A Predictive Machine Learning Model for Maternal Mortality in Delta, State, Nigeria.

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A THESIS WRITTEN IN THE DEPARTMENT OF COMPUTER SCIENCE,
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Certification

This is to certify that the thesis titled: **"A Predictive Ensemble Model for Maternal Mortality in Delta State, Nigeria"** submitted by **Oghenevbaire Efevberha-Ogodo**, in partial fulfillment of the requirements for the award of the degree of Doctor of Philosophy (PhD) in Computer Science, University of Benin, is a record of original research carried out under our supervision.

This work meets the requirements of the Department of Computer Science and the standards of the School of Postgraduate Studies, University of Benin.

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Declaration

I hereby declare that this thesis titled **"A Predictive Ensemble Model for Maternal Mortality in Delta State, Nigeria"** is a record of original research carried out by me under the supervision of my designated academic advisor(s) in the Department of Computer Science, University of Benin.

This work has not been presented in part or full for the award of any degree or diploma in this or any other institution. All sources of information used in this work have been duly acknowledged.

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Dedication

I dedicate this work to every woman and child whose life was lost due to pregnancy-related complications that could have been prevented. May this research serve as a step toward solutions that will save lives and improve maternal health outcomes in Nigeria.

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ABSTRACT

Maternal mortality continues to pose a significant public health challenge in Sub-Saharan Africa, with Nigeria ranking among the countries with the highest burden. The death of women during their reproductive years not only disrupts family structures and causes emotional distress but also places an increased strain on healthcare systems and impedes national economic and developmental progress. In alignment with the United Nations Sustainable Development Goals (SDGs), particularly the goal focused on reducing maternal mortality, this study investigates the application of Artificial Intelligence (AI) in maternal healthcare through the development of a predictive ensemble model for maternal mortality in Delta State, Nigeria.

The objective was to accurately classify maternal health risks, enabling the early identification of high-risk pregnancies and facilitating timely clinical interventions that can reduce preventable maternal deaths. Maternal health data were collected from three healthcare centers across Delta State, Nigeria. Nine supervised machine learning algorithms were employed, including Linear Support Vector Machine (SVM), Gaussian Naïve Bayes, Multilayer Perceptron (MLP), Decision Tree, Random Forest, Gradient Boosting Decision Tree (GBDT), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), and Categorical Boosting (CatBoost).

To improve predictive performance, the models were also integrated into an ensemble learning framework. Among individual models, GBT recorded the highest accuracy (90%) prior to data upsampling, while the Random Forest model achieved 97% accuracy after upsampling. Linear SVM was the least effective both before and after upsampling. The ensemble model outperformed all base classifiers, achieving 98% accuracy and precision, with a notable performance increase following upsampling. These findings demonstrate the potential of AI-powered predictive modeling in enhancing maternal health interventions, optimizing clinical decision-making, and ultimately contributing to the reduction of maternal mortality in Delta State and other states (regions) across Nigeria.

CHAPTER ONE

INTRODUCTION

1.1 Background of Study

Maternal mortality refers to the death of a woman during pregnancy, childbirth, or within six weeks of the termination of pregnancy (WHO 2019). According to data from the World Health Organization (WHO), 1 in 41 women living in Sub-Saharan Africa is likely to die from maternal-related causes in her lifetime, a figure that increases significantly within the Nigerian population (WHO, 2023). With over 900 maternal deaths per 100,000 live births in Nigeria (WHO, 2019), the contrast is stark when compared to countries such as New Zealand and Australia, where the rate is just 4 deaths per 100,000 live births. Alarmingly, up to 70% of all maternal deaths worldwide occur in Africa (WHO, 2023).

Maternal health encompasses the overall physical and mental well-being of the mother and fetus throughout pregnancy and the postpartum period. Proper medical care during this period is critical to reducing the risk of maternal and neonatal death (Azubike & Odagwe, 2015). Common preventable causes of maternal mortality include unsafe abortions, hypertensive disorders such as preeclampsia, hemorrhage, lack of maternal education, and sociocultural practices that discourage medical intervention (Olonade, 2019). Despite the preventability of these conditions, many women continue to face high risks due to systemic gaps in healthcare provision.

Nigeria records over 8 million pregnancies annually, a figure that underscores the urgency of addressing maternal health challenges to prevent a potential public health crisis (WHO, 2023). The situation is exacerbated by the limited number of skilled healthcare personnel. For instance, in 2016, approximately 78% of births with access to skilled health providers were successful, highlighting the lifesaving potential of basic healthcare access (Ogallo *et al*., 2020). According to Rosser *et al.* (2022), the health worker density in Sub-Saharan Africa stands at 13 doctors and 91 nurses/midwives per 100,000 people, figures that fall significantly short of the WHO recommendation of one doctor per 600 people. In Nigeria, this already dire situation is worsened by the ongoing brain drain in the healthcare sector, driven by the mass emigration of medical professionals. The ongoing emigration of Nigerian healthcare workers to more developed countries further threatens the stability of the healthcare system. Other contributing factors

include the lack of prenatal, antenatal, and postnatal care, poverty, and limited maternal education (Ogallo et al., 2020).

Most maternal deaths, however, are preventable if proper and timely medical care is available (Olonade, 2019). In maternal healthcare, early identification of women at risk of pregnancy complications is crucial to prevent adverse outcomes (Mustamin *et al*., 2023). This requires the ability to analyze complex medical data, reports, and diagnostic images with high precision and speed. Often, abnormalities or risk factors may not be immediately visible to the human eye. In these situations, machine learning (ML) becomes instrumental, as it can process large datasets rapidly, uncover hidden patterns, and recognize intricate relationships within the data that may go unnoticed by humans (Jayatilake & Ganegoda, 2021). By leveraging ML techniques, healthcare providers can make more informed, data-driven decisions, ultimately ensuring better outcomes for both mothers and babies during pregnancy (Nirmala & Kambili, 2023). Early risk identification through ML facilitates rapid, targeted interventions, allowing for timely and appropriate care. According to Mondal *et al*. (2023), this proactive approach enhances maternal outcomes by supporting prompt medical responses, data-driven decision-making and optimized resource allocation.

Moreover, the growing volume and complexity of medical data—from electronic health records to diagnostic imaging and real-time monitoring have rendered traditional statistical approaches increasingly inadequate (Mutlu *et al*., 2024). In contrast, ML models excel at handling high-dimensional, heterogeneous datasets, uncovering non-linear and latent relationships that often escape conventional methods. These capabilities make ML highly effective for clinical decision support, early diagnosis, patient risk stratification, and prediction outcome (Mboya *et al*., 2020). By leveraging historical and real-time patient data, machine learning enables the development of intelligent systems that assist clinicians in diagnosing conditions, predicting risks, and recommending treatments (Machoron *et al*., 2022). In maternal healthcare, ML-based decision support systems can analyze a wide array of factors, from demographic and clinical history to socioeconomic variables, helping classify risk levels, guide resource allocation, and ultimately reduce preventable maternal mortality (Dawodi *et al*., 2020).

Researchers have increasingly employed machine learning (ML) models to predict maternal, neonatal, and child mortality. Some studies have focused on specific causes of maternal mortality, including neonatal infections, preeclampsia, sepsis, and caesarean sections (Gomez-Jemes *et al*., 2022; Kopanista *et al*., 2021; Ogallo *et al*., 2020). Others have used standardized or real-world datasets collected at maternal health centers to develop predictive models for maternal outcomes (Nirmala & Kambili, 2023; Mboya *et al*., 2020; Togunwa *et al*., 2023). The outputs of these models have been used to raise awareness and provide pregnant women with relevant information to support safer pregnancies and successful live births (Machoron *et al*., 2022). Despite ongoing ethical and legal concerns regarding patient data privacy, ML holds enormous potential for the future of healthcare, particularly in remote areas where medical facilities are scarce or non-existent (Wahl *et al*., 2018).

1.2 STATEMENT OF PROBLEM

Nigeria has one of the highest maternal mortality rates globally and remains far from achieving the United Nations' Sustainable Development Goal (SDG) of reducing maternal deaths to fewer than 70 per 100,000 live births by 2030 (WHO, 2019). Studies by Izugbara *et al*. (2016) and Azubuike & Odagwe (2015) have shown that an increase in the availability of skilled healthcare workers significantly reduces maternal mortality. However, disparities in healthcare access and infrastructure persist, particularly at the subnational level. In Delta State, the situation is critical. The region reports a health worker density of only 17 doctors and 71 registered nurses per 100,000 people, figures far below the WHO's recommended minimum of one doctor per 600 people (UNDP, 2015). These shortages, combined with inadequate medical infrastructure, place pregnant women at increased risk and further worsen maternal health outcomes.

Traditional maternal risk assessment approaches in Nigeria are largely reactive rather than preventive. Healthcare workers, often overstretched and under-resourced, lack the tools needed to detect and respond to high-risk pregnancies early enough (Azubike & Odagwe, 2015). The absence of data-driven decision-making and real-time risk analysis contributes to missed opportunities for timely interventions. Most maternal deaths, however, are preventable if proper and timely medical care is available (Olonade, 2019). In maternal healthcare, early identification of women at risk of pregnancy complications is crucial to prevent adverse outcomes (Mustamin

et al., 2023). This requires the ability to analyze complex medical data, reports, and diagnostic images with high precision and speed. Moreover, the growing volume and complexity of medical data—from electronic health records to diagnostic imaging and real-time monitoring—have rendered traditional statistical approaches increasingly inadequate (Mutlu *et al*., 2024). In contrast, ML models excel at handling high-dimensional, heterogeneous datasets, uncovering non-linear and latent relationships that often escape conventional methods. These capabilities make ML highly effective for clinical decision support, early diagnosis, patient risk stratification, and prediction outcome (Mboya *et al*., 2020).

The persistent high rate of maternal mortality in Delta State calls for innovative, data-driven solutions. There is a need for a robust predictive model that leverages ensemble learning techniques to improve predictive performance and provide actionable insights for maternal health practitioners. AI technologies have the potential to transform maternal healthcare by identifying at-risk pregnancies before complications arise. However, the adoption and implementation of such technologies in developing countries like Nigeria, remain limited. This study seeks to address this gap by developing a predictive ensemble model capable of classifying maternal health risks into low, medium, and high categories. The model aims to support proactive, data-driven clinical decisions, improve resource allocation, and ultimately reduce maternal mortality in Delta State, Nigeria.

1.3 SIGNIFICANCE OF STUDY

This study holds considerable academic and practical significance, particularly within the field of maternal healthcare and the application of machine learning in low-resource settings. Firstly, by utilizing locally sourced data from Delta State, Nigeria, the research addresses a critical gap often overlooked by models trained on generalized international datasets. This localized approach ensures that the predictive model accounts for the region's unique demographic, socio-economic, and clinical characteristics, thereby improving its accuracy, contextual relevance, and practical utility for healthcare practitioners operating within this environment.

Secondly, the study contributes to the expanding discipline of artificial intelligence and machine learning in healthcare by demonstrating how AI technologies can be applied not merely for

descriptive or retrospective analysis but as proactive tools to predict and potentially prevent maternal mortality. This represents a paradigm shift from traditional reactive risk assessment toward a data-driven, anticipatory model of care.

Furthermore, the research includes the development of a user-friendly interface to deploy the predictive model, thereby ensuring accessibility for non-technical stakeholders such as frontline healthcare providers and pregnant women. By enabling real-time risk assessment, this tool facilitates earlier clinical interventions and supports more informed decision-making, which may help reduce preventable maternal deaths.

Finally, the study aligns with the World Health Organization's strategic emphasis on preventive maternal healthcare rather than reactive measures (WHO, 2023). Beyond its immediate clinical applications, the findings have the potential to inform local health policies, enhance clinical practice, and serve as a model for similar technological interventions in other regions burdened by high maternal mortality rates.

1.4 MOTIVATION OF STUDY

The motivation for this study arises from the urgent need to reduce maternal mortality by leveraging modern data-driven approaches to enhance clinical decision-making and timely interventions. Despite significant global efforts, maternal deaths, many of which are preventable continue to occur, often due to delays in recognizing complications and accessing adequate medical care during pregnancy. The ability to prevent even a single maternal death through early identification of high-risk pregnancies is of profound clinical and societal value.

Machine learning techniques provide an innovative avenue for systematically analyzing clinical, demographic, and laboratory data to predict which women are most at risk of pregnancy-related complications. Such predictive modeling has the potential to support healthcare providers in prioritizing care, allocate limited resources more effectively, and empower pregnant women with information to make informed health-related decisions.

In addition to its technical contribution, this study is motivated by a broader commitment to improving maternal health outcomes within Delta State and similar regions in Nigeria, where

maternal mortality rates remain disproportionately high. By applying artificial intelligence and machine learning to context-specific data, the research seeks to bridge the gap between modern technological capabilities and the pressing public health challenge of maternal mortality. Ultimately, the study aspires to offer a practical, data-driven solution that aligns with global maternal health targets and contributes meaningfully to both academic knowledge and real-world clinical practice.

1.5 AIM AND OBJECTIVES OF STUDY

The aim of this research is to develop a machine learning model to predict pregnancy risks in order to prevent the occurrence of maternal mortality in Delta State, Nigeria. The objectives include:

i. To identify the leading causes of maternal mortality using Delta State as a case study.
ii. To develop a machine learning model to predict high-risk pregnancies, promote safe motherhood and reduce the incidence of maternal deaths.
iii. To implement the model.
iv. To test and evaluate the model's performance.

1.6 SCOPE OF STUDY

Nigeria, located in the western region of Sub-Saharan Africa, is made up of 36 states and the Federal Capital Territory (O'Neil, 2023). Delta State, one of the oil-producing states in southern Nigeria, was officially created in August 1991. It has a population exceeding four million people, with its capital, Asaba, situated in the northern part of the state (UNDP, 2015).

This study will focus on maternal mortality within Delta State, Nigeria, which is divided into three senatorial zones: Delta Central, Delta North, and Delta South. The state comprises 25 Local Government Areas (LGAs), encompassing both urban and rural communities. Table 1.1 shows the three senatorial zones and the local government areas in the State. The research will draw on maternal health data sourced from three selected medical centers in the senatorial zones in the State, which will serve as primary data sources for model training and analysis.

Table 1.1: The list of local government areas in Delta state and their Senatorial districts (O'Neil, 2023).

Delta Senatorial Districts	Local Government Areas
DELTA-CENTRAL	Sapele, Ethiope West, Ughelli North, Ethiope East, Okpe, Udu, , Ughelli South and Uvwie
DELTA-NORTH	Aniocha North, Ika South, Aniocha South, Ika North East, , Ndokwa West, Oshimili North, Oshimili South, Ndokwa East, and Ukwuani.
DELTA-SOUTH	Bomadi, Warri North, Isoko North, Isoko South, Burutu, Patani, Warri South and Warri South West.

Women of childbearing age who are registered at any of the selected health centres has been considered for data collection in this study. However, only maternal cases with verified records has been included in the analysis. Cases that are unregistered or contain incomplete data has been excluded in order to ensure data integrity, maintain model reliability, and uphold the quality of the research outcomes.

1.7 THESIS ORGANIZATION

This thesis is subdivided into five chapters: Chapter One introduces the study; Chapter Two presents the literature review; Chapter Three details the methodology and design; Chapter Four discusses implementation and results; Chapter Five concludes the study with recommendations.

Chapter Two

Literature Review

2.1 Introduction

Maternal mortality remains an acute public health challenge in Sub-Saharan Africa, and Nigeria is among the countries with the highest burden globally. Despite concerted efforts from international organizations, federal and state governments, and private sector initiatives, the maternal mortality ratio (MMR) in Nigeria remains unacceptably high (World Health Organization [WHO], 2023). In stark contrast, countries such as New Zealand and Australia report maternal mortality ratios as low as 4 deaths per 100,000 live births, highlighting an alarming global disparity (WHO, 2019). Furthermore, it is estimated that nearly 70% of all maternal deaths worldwide occur within the African continent (WHO, 2023). “Consequently, there has been a growing focus in recent research on applying machine learning (ML) and predictive analytics to enhance the early identification of high-risk pregnancies (Gomez-Jemes *et al*., 2022). By identifying women most susceptible to adverse maternal outcomes, these advanced analytical techniques seek to aid clinicians in making evidence-based decisions, improve the allocation of limited healthcare resources, and inform the development of targeted preventive strategies (Machoron *et al*., 20222).

2.2 Maternal Mortality: Global and Nigeria Context

According to the World Health Organization (WHO, 2019), maternal mortality refers to the death of a woman resulting from complications related to pregnancy, occurring either during pregnancy or within six weeks of the termination or delivery. Notably, deaths due to accidents or incidental causes are excluded from this definition. The Maternal Mortality Rate (MMR) is typically measured as the number of maternal deaths per 100,000 live births within the same time period (WHO, 2023). Reducing maternal mortality was identified as a priority under the Millennium Development Goals (MDGs) and remains central in the Sustainable Development Goals (SDGs), specifically Goal 3: ‘Ensure healthy lives and promote wellbeing for all at all ages.’

In Nigeria and across much of Africa, maternal mortality rates remain alarmingly high when compared to Europe and other regions (Ogallo *et al*., 2020). As reported by WHO (2019), Nigeria's maternal mortality rate in 2017 was estimated at 917 deaths per 100,000 live births, significantly exceeding the SDG target of fewer than 70 deaths per 100,000 live births (Olonade, 2019). Starkly, a woman in Nigeria is reported to be 500 times more likely to die from maternal causes than a woman in Europe (Olonade, 2019). These figures underscore maternal mortality as an urgent area for research and policy intervention.

According to Fagbemi *et al*. (2024), multiple direct medical factors contribute to maternal mortality. The top factors include severe bleeding (postpartum haemorrhage), infections during pregnancy, hypertensive disorders such as pre-eclampsia, unsafe abortions, sepsis, and obstructed labour (Mboya *et al*., 2023). These are often preventable through timely access to skilled birth attendance, emergency obstetric care, and appropriate medical intervention.

Indirect causes, on the other hand, arise from pre-existing medical conditions or diseases that are not due to direct obstetric complications but are compounded by the physiological changes in pregnancy. These include conditions such as anemia, malaria, HIV/AIDS, cardiac diseases, diabetes, and sickle cell disease (Kenneth & Ezunu, 2021). In low-resource settings like Delta State and other parts of Nigeria, direct causes remain the predominant contributors to maternal deaths, although indirect causes are increasingly significant due to the dual burden of infectious and non-communicable diseases (Clark & Ntuli, 2023). Effective reduction of maternal mortality requires integrated strategies that address both direct obstetric emergencies and broader health system factors impacting women's health before, during, and after pregnancy. These medical factors are compounded by systemic challenges, including inadequate maternal health data, a shortage of skilled healthcare workers, cultural beliefs, and limited access to affordable health facilities (Izugbara *et al*., 2016). According to Rosser *et al*. (2022), Sub-Saharan Africa has a critical shortage of healthcare professionals, with only about 13 doctors and 91 nurses or midwives per 100,000 people, which is far below WHO's recommendation of 1 doctor per 600 people. This shortage is further aggravated by the ongoing emigration of Nigerian medical personnel, which is likely to worsen the crisis.

Beyond medical and systemic factors, high maternal mortality rates have severe socio-economic implications and are widely regarded as indicators of a country's developmental status (Olonade, 2019). Thus, targeted policies and sustained initiatives are critical. For instance, the use of Community Health Workers (CHWs) in rural Ethiopia has significantly improved maternal health outcomes, especially in remote communities often inaccessible by road. The efficiency of this model depends on adequate training, support, and compensation of CHWs within a functioning healthcare system (World Health Organization, 2023).

Governments and stakeholders can also address economic barriers to maternal healthcare. A notable example is the policy introduced in 2007 by the Dr Emmanuel Uduaghan-led government in Delta State, Nigeria. This policy allows women to register for free childbirth services, including consultation, medication and accommodation, at government-run medical centres. Furthermore, children aged 0–5 years receive free consultation and medications (Azubuike & Odagwe, 2015). Such initiatives not only reduce financial barriers but also encourage women to seek skilled care during childbirth. The private sector can complement these efforts through Corporate Social Responsibility (CSR) projects targeting maternal and child health.

Infrastructure, especially road networks, plays an equally critical role. In South Africa, although nearly half the population lives in rural areas, these areas are served by less than 20% of healthcare workers (WHO, 2019). In Malawi, only slightly over 10% of clinics offer 24-hour midwife services, posing a severe risk for women needing emergency care at night. Evidence from Ghana demonstrates that improving road access to health centres led to higher rates of successful deliveries (Olonade, 2019).

According to the World Health Organization (2023), increasing the ratio of healthcare workers to patients is directly linked to reductions in maternal mortality, as it ensures more women have access to skilled medical personnel during pregnancy and childbirth. Additional contributing factors to maternal mortality include lack of prenatal, antenatal, and postnatal care, low household income, and limited maternal education (Ogallo *et al*., 2020).

In summary, although maternal mortality is a multifaceted challenge shaped by clinical, systemic, economic, and infrastructural factors, meaningful progress requires holistic and context-sensitive interventions. These should include strengthening the healthcare workforce, enhancing medical infrastructure, implementing targeted policies, promoting education, and leveraging modern technology like artificial intelligence.

2.3 Artificial Intelligence and Machine Learning in Healthcare

The field of artificial intelligence (AI) has witnessed remarkable advancements since 1956, when the term was first introduced by a group of pioneering researchers (Wahl *et al*., 2018). AI can be broadly defined as a branch of computer science focused on endowing machines with intelligent behavior. According to experts, a machine is said to act intelligently when its actions align with its goals and it can adapt appropriately to changes in its environment. Equally important is the machine's capacity to observe and learn from its experiences—an essential characteristic of intelligence (Wahl *et al*., 2018).

A prevalent form of AI, particularly in healthcare applications, is Artificial Narrow Intelligence (ANI). ANI systems are designed to excel at specific tasks, allowing researchers to reduce system complexity by building AI solutions tailored to particular problems. This focus helps mitigate potential errors and can significantly shorten the time medical professionals spend on various duties (Panesar, 2020).

One of the most transformative branches of AI is Machine Learning (ML). ML emerged from the idea that computers can 'learn' from data without being explicitly programmed with fixed instructions, moving beyond traditional rule-based computing (Mueller & Massaron, 2016). This concept grew out of earlier work in pattern recognition. In Machine Learning, data is fundamental: by applying specialized algorithms to large datasets, computers can uncover new insights previously unknown to humans. Just as humans learn in diverse ways by following instructions, observing, or reflecting on past experiences, machines too, can learn using various methods known as algorithms. These algorithms generally fall into four broad categories: supervised, unsupervised, semi-supervised, and reinforcement learning (Panesar, 2020).

Sometimes, multiple algorithms are combined to build a more robust predictive model, an approach known as an ensemble method.

Supervised learning is the most widely used ML category in practice (Brownlee, 2016). It mirrors the process of a teacher guiding a student by continuously correcting mistakes until the student's performance improves. In supervised learning, the algorithm is provided with both input and corresponding output variables; it then learns to predict outcomes based on this dataset. Typical problems addressed by supervised learning include classification (e.g., predicting categories) and regression (e.g., predicting numerical values). Popular supervised algorithms include Support Vector Machines, Logistic Regression, and Random Forest (Panesar, 2020).

In contrast, unsupervised learning algorithms operate without explicit output labels or guidance (Brownlee, 2016). The system analyzes input data to detect hidden patterns or structures without knowing the correct answers in advance. This can lead to discoveries of insights that were previously undetected by human analysts (Mueller & Massaron, 2016). Common tasks in unsupervised learning include clustering and association (Panesar, 2020).

Semi-supervised learning combines elements of both supervised and unsupervised approaches (Brownlee, 2016). It leverages a small amount of labeled data (from supervised learning) alongside a larger set of unlabeled data (from unsupervised learning). This approach helps the model find meaningful patterns and make accurate predictions while reducing the cost of labeling large datasets. Semi-supervised learning is commonly applied to problems involving classification and regression (Panesar, 2020).

Reinforcement learning focuses on learning through interaction and feedback. Here, an algorithm (often called an 'agent') makes sequential decisions in a dynamic environment, learning from the positive or negative outcomes of its past actions (Panesar, 2020). The goal is to maximize cumulative rewards over time. Reinforcement learning has found applications in fields such as robotics, where systems must adapt and improve their performance based on real-world feedback (Mueller & Massaron, 2016).

Machine learning has moved far beyond a theoretical concept and is now integral to many aspects of daily life. In the financial sector, ML models help detect fraudulent transactions.

Social media platforms like Facebook use ML for features such as automatic friend tagging through face recognition. Self-driving car manufacturers like Tesla rely heavily on ML to navigate roads safely. Similarly, ride-sharing services such as Uber, Bolt, and Taxify use ML to optimize routes and pricing. Virtual assistants like Siri and Alexa demonstrate ML's capabilities in understanding and responding to human speech (Mueller & Massaron, 2016).

Healthcare, which is the major focus of this research, has also benefited significantly from machine learning. By analyzing large volumes of medical data, ML algorithms can identify patterns that help improve clinical decision-making (Gomez-Jemes *et al*., 20222). Researchers have used ML to predict the onset of various diseases, including COVID-19 and diabetes. Importantly, ML models have also been applied to predict maternal, neonatal, and child mortality. These models often analyze risk factors like neonatal infections, preeclampsia, and caesarean sections to assess mortality risks. The results have been used to raise awareness and guide interventions, ultimately aiming to improve maternal and child health outcomes (Machoron *et al*., 2022).

Applications of machine learning (ML) have led to notable advancements in the management of pregnancy-related conditions such as postpartum hemorrhage, preeclampsia, intrauterine growth restriction (IGR), preterm birth, gestational diabetes, and overall maternal health (Gomez-Jemes et al., 2022). By leveraging data-driven insights, ML models enhance the prediction of high-risk pregnancies, thereby improving clinical decision-making and maternal outcomes. For example, Machoron *et al*. (2022) applied semi-supervised algorithms to improve supervised learning models designed to predict high-risk pregnancies in the Philippines. Their study evaluated six supervised ML algorithms—Decision Tree, Random Forest, Support Vector Machine, Multilayer Perceptron, Naïve Bayes, and K-Nearest Neighbors—using local health center data containing attributes such as age, gravida, parity, and risk level. The Decision Tree model initially achieved the best performance with an accuracy of 93.7%. The application of a semi-supervised learning approach further enhanced the model's accuracy to 97.01%, demonstrating the critical role of high-quality input data in building effective prediction models.

Similarly, Togunwa *et al*. (2023) proposed a hybrid model that integrates Artificial Neural Networks (ANN) with Random Forest (RF) to improve maternal health risk classification. Using

a standardized dataset from the UCI Machine Learning Repository and a 75/25 train-test split, their model achieved an accuracy of 95%, with evaluation based on F1 Score, Precision, and Recall metrics. These results emphasize the potential of combining ML algorithms to boost predictive performance.

Gomez-Jemes *et al*. (2022) also examined the detection of high-risk pregnancies, specifically focusing on predicting preeclampsia and intrauterine growth restriction (IGR). Using a dataset of 95 pregnant women collected by the University Medical Center of Ljubljana, Slovenia, they applied a multi-label classification approach to capture the presence of either, both, or none of the conditions. Among the tested classifiers, the Decision Tree outperformed others, highlighting ML's role not only in prediction but also in identifying underlying conditions that may compromise maternal and fetal health.

In Bangladesh and India, Nirmala and Kambili (2023) developed an ensemble prediction model targeting the detection of maternal mortality risk due to preeclampsia. Using data from the UCI Machine Learning Repository (Marzia, 2023), they applied algorithms including Random Forest, K-Nearest Neighbors, Neural Networks, and Naïve Bayes. Random Forest individually achieved the highest accuracy, and further improvement was realized through a stacked ensemble model. This approach enabled the classification of pregnant women into different risk categories based on multiple patient features, thereby supporting healthcare providers in timely intervention.

Fredrikson *et al*. (2022) focused on predicting the likely delivery location—at home or in a healthcare facility—for pregnant women in Zanzibar. Using data from 38,787 women enrolled in the 'Safer Deliveries' program, their study implemented Random Forest, LASSO-regularized logistic regression, Artificial Neural Network, and logistic regression models, which collectively achieved predictive accuracies between 68% and 77%. The predictions enabled community health workers (CHWs) to proactively reach out to high-risk women, thereby reducing the likelihood of home deliveries associated with elevated maternal and neonatal mortality.

Raja *et al*. (2022) addressed the challenge of preterm births in rural communities, where barriers such as limited awareness, cost of care, and insufficient health infrastructure persist. Using medical records and features such as maternal age and educational awareness, they evaluated

Decision Tree, Support Vector Machine, and Logistic Regression algorithms. The SVM model demonstrated the highest predictive accuracy of 90.9%, aiding early identification of preterm birth risk and informing both healthcare workers and pregnant women for timely action.

Beyond maternal outcomes, ML applications extend to infant mortality prediction. In Rwanda, Mfaneza *et al*. (2022) utilized data mining techniques and ML algorithms—Decision Tree, Random Forest, Logistic Regression, and Support Vector Machine—to predict infant mortality risk based on data from the Rwanda Demographic Health Survey. The models were assessed using precision, recall, F1 score, accuracy, and AUROC metrics, with Random Forest achieving the highest accuracy of 84.3%. Significant predictors identified included marital status, wealth index, birth order, and number of children ever born, illustrating ML's ability to uncover patterns that may remain hidden in traditional statistical analyses. Gomez-Jemes *et al*. (2022) argue that ML can improve maternal care by monitoring mothers' health status during pregnancy, ultimately enhancing safety for both mother and child. While the successful application of ML models depends on robust datasets and knowledge of local contexts, their potential to transform maternal healthcare is significant (Dawodi *et al*., 2022).

In summary, the integration of machine learning into maternal healthcare research and practice has led to demonstrable improvements in predicting and managing complications such as preeclampsia, postpartum hemorrhage, preterm birth, and IGR. By supporting timely interventions and resource optimization, ML holds promise for further reducing maternal and neonatal morbidity and mortality, especially in low-resource settings. Despite ethical and legal concerns over patient data privacy, scholars such as Wahl *et al.* (2018) highlight that ML is reshaping healthcare delivery—particularly in underserved regions where access to specialized care is limited.

2.4 Ensemble Learning Techniques: Bagging, Boosting and Stacking

According to Mienye & Sun (2022), conventional machine learning (ML) algorithms often underperform when trained on imbalanced datasets. To address this limitation, researchers have increasingly turned to advanced learning approaches, including ensemble methods and deep learning techniques, which are better suited to handle class imbalance and improve predictive

performance. Ensemble learning is founded on the principle that combining a group of weak learners in an appropriate manner can achieve or even surpass the predictive performance of a single strong learner. Techniques such as bagging, stacking and boosting have demonstrated significant improvements in predictive accuracy across diverse domains, including medicine, finance, image classification, and natural language processing (Shah *et al*., 2025).

Bootstrap aggregating, or bagging, is a technique that involves dividing the training dataset into multiple subsets and training each base model on a different subset. The final prediction is obtained by averaging the outputs (for regression) or taking a majority vote (for classification) from all the base models (Fan *et al*., 2025). Bagging is particularly effective at improving the performance of base learners when the underlying algorithm is unstable—meaning its generalization ability varies significantly with small changes in the input data. This technique primarily targets the reduction of variance among ensemble members, rather than addressing bias (Mienye & Sun, 2022).

Boosting is a sequential learning process in which each new model is trained to correct the errors made by its predecessor. It combines multiple weak learners adaptively, with each model in the sequence placing greater emphasis on observations that were previously misclassified or inaccurately predicted (Mohammed & Kora, 2023). Typically, boosting begins by training a weak learner on the input data. After predictions are generated, misclassified samples are identified and assigned greater weight. The next weak learner is then trained on this adjusted dataset, focusing more on the difficult instances. This iterative process continues until a predefined number of base learners is reached. Finally, the individual learners are aggregated through a weighted approach to form the final predictive model (Mienye & Sun, 2022).

Stacking ensemble learning is a type of meta-learning approach in which predictions generated by multiple base models are combined and used as inputs to a higher-level model, commonly referred to as a meta-learner or blender. The meta-learner synthesizes these inputs to produce the final predictions. By integrating the diverse strengths and complementary perspectives of different base models, stacking can substantially enhance predictive accuracy, model robustness, and generalization to unseen data (Fan *et al*., 2025). The primary advantage of stacking is its ability to combine the strengths of multiple high-performing, heterogeneous algorithms, unlike bagging and boosting, which typically rely on homogeneous models. This diverse combination

allows stacking to deliver predictions that often outperform those of any individual model within the ensemble. Stacked models typically achieve high accuracy, which is a key reason they have been widely adopted and have won numerous machine learning competitions (Mienye & Sun 2022). Stacking ensemble was chosen in this study for its ability to combine heterogeneous algorithms. A block diagram outlining the framework of the stacking ensemble technique is presented in Figure 2.1.

Overall, ensemble learning has been widely utilized to improve disease detection, risk prediction, optimize therapeutic recommendations and enhance system performance across various domains within healthcare.

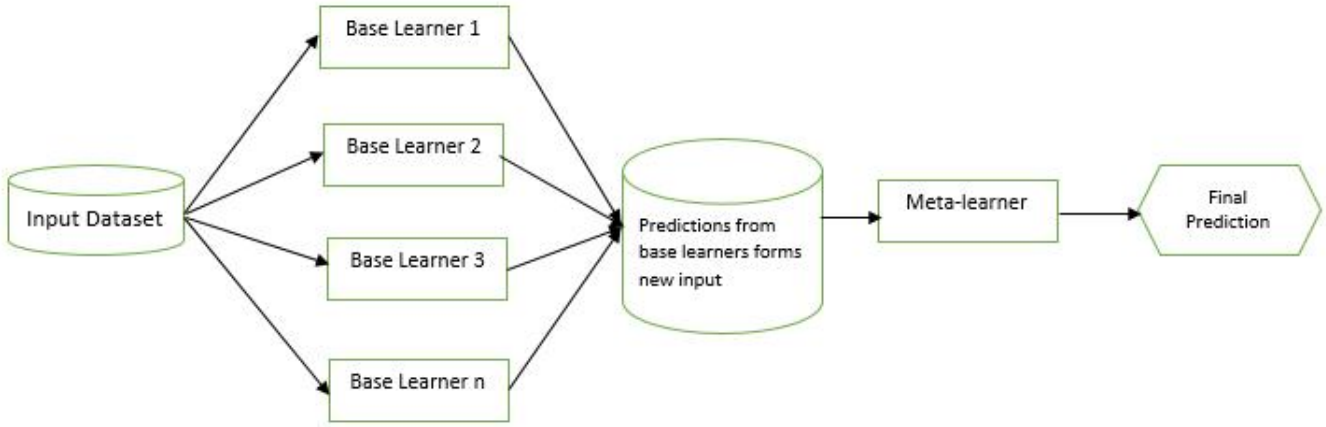

Figure 2.1: Framework for stacking ensemble technique.

The stacking ensemble process begins with an input dataset that is simultaneously fed into multiple base learners. These base learners are individual machine learning models, each trained on the same dataset. As shown in figure 2.1, models such as Base Learner 1, Base Learner 2, Base Learner 3, up to Base Learner *n*, illustrate the flexibility to incorporate various models. Importantly, these learners can be heterogeneous, for example, decision trees, support vector machines, or neural networks. The predictions generated by each base learner are then aggregated to form a new dataset, known as meta-features. This new dataset serves as the input for a higher-level model called the meta-learner. The meta-learner is trained to combine the predictions of the base models in an optimal way to produce a more accurate final output.

Ultimately, the final prediction of the stacking ensemble comes from this meta-learner (Mohammed & Kora, 2023).

Ensemble learning is a powerful and widely used technique in machine learning, recognized for its ability to tackle complex learning challenges. It is highly effective in boosting predictive accuracy, minimizing overfitting, and enhancing generalization across a variety of datasets (Fan *et al*., 2025)

A summary of key related studies is as shown in Table 2.1.

Table 2.1: Summary of Related Works

S/N	Article	Research Goal	Research Methodology	Results	Limitations
1	Gomez-Jemes *et al.*(2022) Machine Learning to predict Pre-eclampsia Intrauterine Growth Restriction in Pregnant women	Build a machine learning model to predict the occurrence of pre-eclampsia and intrauterine growth restriction	Public dataset gotten from 95 pregnant women. A multi-label approach was applied to several classifiers including RF, DT, SVM, K-Neighbors and Gaussian Naïve Bayes.	Decision Tree (DT) was the best performing classifier model.	The model may fail occasionally to detect a pregnant woman who is at risk of both pre-eclampsia and intra-uterine growth.
2	Mfaneza *et al.*(2022) Application of Machine Learning methods for predicting Infant mortality in Rwanda	Predicting Infant mortality using Machine Learning methods rather than conventional regression analysis methods.	Data was collected from Rwanda Demographic & Health Survey. STATA version 13 was used for convention analysis. Python software was also used to implement machine learning methods through SVM, RF, LR and DT,	Random Forest(RF) predicting ability and accuracy was more than the other methods	The research was conducted under the guidelines provided by the Rwanda Demographic Health Survey.
3	Machoron *et al.*(2022) A semi-supervised learning approach in Predicting High risk pregnancies in the Philippines.	The goal is to predict high risk pregnancies so that the pregnant woman involved will be given special care from conception to delivery and afterwards.	Multiple supervised learning algorithms were analyzed to identify the best performing one which was then fed with data records from a health center.	DT showed best performance with a score of over 93%	The model's performance is highly influenced by the precision of the data it is trained on.
4	Fredrickson *et*	The goal of this study was to	The data used in this study was	The models predicted	About 14% of women enrolled were not

	al.(2022) Machine Learning for Maternal health: Predicting delivery location in a community health worker program in Zanzibar	accurately predict the delivery location of a pregnant woman in order for CHWs to be alerted in case of risks complications aggravated by pregnancy.	collected as at the time the pregnant women were enrolled for ante-natal care by CHWs who used smartphones containing the model. Four different ML models were evaluated. The model is embedded in a smartphone application so CHWs are alerted to pregnant women who are at a high risk if delivery is performed at home rather than in a health center.	accurately 68%-77% of the delivery locations of pregnant women.	included in the analysis as they did not have any data recorded for place of delivery and they were hesitant to inform the CHWs of their place of delivery.
5	Raja *et al.*(2022) A machine learning-based Prediction model for Pre-term Birth in Rural India.	The objective of the authors was to build a machine learning model that takes into account key maternal features in the dataset influencing preterm birth in India.	In this study the novel approach of selecting the best maternal features was applied to data from previous Pre-term birth cases and obstetric data from community health centers in rural areas. SVM, DT AND LR classifiers were analyzed evaluated.	The SVM performed better than the other two algorithms with over 90% accuracy.	The small size of data set can be increased to improve efficiency of the model. PTB risk factors outlined in the study are also limited in size.
6	Coleman, A.(2014) The use of ICT Tools (Mobile Phones) to improve awareness of	To provide a level of danger signs and symptoms awareness amongst pregnant women in rural communities in	The data used in this study was collected via open-ended interviews of fifteen (15) women selected out of the number of women who attended at least one of 5	The PDSMAF is set to not only improve pregnancy danger signs awareness but also improve the quality of primary health care (PHC)	It is recommended that network service providers enhance their connection signals in rural areas. Pregnant women should also be trained weekly on application of mobile

	Pregnancy Danger Signs among Pregnant Women in Rural Communities of South Africa.	South Africa	prenatal care clinics (three from each) in a rural setting. Findings from the interviews revealed that over 90% of the women in the rural area had mobile phones therefore a mobile framework, Pregnancy Danger Signs Mobile Architectural Framework (PDSMAF) was proposed to provide awareness in a systematic way by educating pregnant women via their mobile phone on the pregnancy-related danger signs.	services in management of pregnancy cases.	phones.
7	Hasan *et al*.(2017) Mobile Application can be an Effective Toll for Reduction of Maternal Mortality	To develop a Mobile Tool to monitor and detect complications during labour stages.	Using physiological detail of the mother including obstetric history. The mobile application also collects data during labor and stores for future reference. Java is used to implement this android app.	It ensures improved care during labour thereby reducing the occurrence maternal mortality especially in low resource settings.	This application is not employed in the duration of pregnancy that precedes labour.
8	Thomas *et al*.(2018) Pregnancy Complication Prediction Based on Machine	A Framework for a Cloud based Smart Assistant to monitor to monitor a woman's health during	Data of pregnant women is collected during routine antenatal checks in order to detect any abnormalities in	The C4.5 machine learning algorithm used for classification problems performed better when predicting risks than the	The Model's goal was to predict pregnancy risks and was not aimed at monitoring.

	Learning	pregnancy in order to detect risks.		Support Vector Machine (SVM) algorithm.	
9	Okoronkwo *et al*.(2019) Maternal Mortality Rate Monitoring Model using Knowledge Discovery Databases (KDD).	To develop a Model to monitor maternal mortality rate using Knowledge Discovery Databases.	Object-Oriented Analysis and Design Methodology (OOADM).	This monitoring model will cause health care delivery to be more effective and efficient and even lower operating costs.	Model was targeted at monitoring only. Lack of real- time or primary data.
10	Jhee et al.(2019) Prediction Model development of late-onset Pre-eclampsia using Machine Learning-Based Methods.	To develop a prediction model for late-onset of Pre-eclampsia.	Medical records of Women who were registered at a University Hospital were used to train and test the model. The data excluded women who were not at late-onset preeclampsia risk based on gestational age.	The Stochastic Gradient Boosting algorithm had the best performance over 97% when compared to other machine learning algorithms.	Records of women in their first trimester was excluded since the late on-set of preeclampsia could not be accurately predicted until second trimester.
11	Westcott *et al*.(2020) Prediction of Maternal Haemorrahge: Using Machine Learning to Identify Patients at Risk.	To utilize machine learning techniques to identify patients at risk for postpartum haemorrhage (PPH) at obstetric delivery.	The data used for this study was collected from a major medical center for a period of 5 years of women aged 18 – 55 years with over 400 variables.	Out of all algorithms used Gradient Boosted Decision Tree (XGBoost) performed better that RF, SVM and LR.	Model performance was limited to available data.
12	Tesfaye et al.(2022) Predicting skilled delivery service use in	To predict the use of skilled delivery service using statistical and machine learning	Data used in this research study was obtained from 2016 Ethiopia Demographic and Health Survey	SVM , J48, ANN and Naïve Bayes algorithms were analyzed and J48 performed better than the others	The study employed secondary data, Authors were not privy to factors such as how cases were excluded before data was analysed.

	Ethiopia: dual application of logistic regression and machine learning algorithms.	methods.	(EDHS). Women in the age group of 15 -49 were interviewed and response rate was over 90%.	with 98% accuracy	
13	Dejene et al. (2022) Predicting the level of anemia among Ethiopian pregnant women using homogenous ensemble machine learning algorithm	Ensemble machine learning algorithms were employed to predict anemia severity in pregnant women in Ethiopia.	Data from EDHS was utilized in this study. Three different algorithms were analysed separately and together as an ensemble. They are Random Forest, Extreme Gradient (XGB) Boosting and Cat boost.	This study resulted in Cat Boost one versus all class decomposition as the best performing algorithm with 97.6% accuracy.	This study employed secondary data.
14	Koivu & Sairanen (2020) Predicting risk of stillbirth and preterm pregnancies with machine learning.	The objective of this research was to discover novel risk predictive models for stillbirth and preterm pregnancies.	A large data set from the Center for Diseases Control (CDC), with about 16 million observations, was used in this study. The following machine learning classifies were used as standalone and as ensemble learning techniques.	The ensemble learning classifiers performed similarly to the individual machine learning models for predicting stillbirth and preterm pregnancies.	This study was conducted to target prediction of only stillbirth and preterm pregnancies.
15	Aljameel et al.(2023) Prediction of Preeclampsia using Machine Learning and Deep Learning Models: A	The goal was to define machine learning and deep learning techniques that are accurate for predicting preeclampsia.	The works of several researchers on machine learning and deep learning for predicting preeclampsia was analyzed, clearly stating the algorithms used and	Random Forest (RF), Support Vector Machine (SVM) and Logistic Regression proved to be the most popularly used models.	The study noted some factors that may limit meaning outcomes in the use of machine and deep learning. They include inaccurate choice of data features, data privacy issues, missing values in data set and lack of diversity in training data.

	Review		limitations.		
16	Nirmala & Kambili (2023) Maternal Risk Level Prediction Using Ensemble Model	The aim was to evaluate the risk levels of preeclampsia using machine learning algorithms.	The study dataset was retrieved from UCI machine learning repository. Risk levels were categorized as low risk, mid risk and high risk.	RF algorithm had a96% accuracy of prediction that exceeded KNN, Naïve Bayes, Neural Network and an ensemble algorithm known as stacking.	The model can be more accurate if more relevant attributes are added.
17	Kopanitsa et al.(2021) Prediction of Sepsis in Pregnancy Uisng Machine Learning Methods.	The study's objective was to design a model that can predict sepsis in its early stages using real world data	Electronic Health Records (EHR) were analyzed and 15,000 birth cases were extracted for use as training and testing data for the model.	Gradient Boosting algorithm had an accuracy rate of 95% in predicting early sepsis. The number of predictors was also reduced compared to previous studies.	Further research on risk factors of maternal sepsis is needed to mitigate its occurrence.
18	Shah et al.(2023) Prediction of Post-Partum Hemorrhage (PPH) using Machine Learning algorithms in a Kenyan population.	To predict the possibility of postpartum hemorrhage using data from antenatal and post natal visits.	Data was obtained from a Kenyan research center and split into two for training and validation.	The Naïve Bayes (NB) algorithm performed better than the LR, DT and RF with 95% accuracy.	Data used for this study contained a small sample size of 40 PPH cases. There was also the case of missing data.
19	Mekster et al.(2020) Prediction of Childbirth Mortality using Machine Learning	The objective of this research study was to build a model that predicts the occurrence of mortality at childbirth resulting for	Both structured and unstructured medical data set was used to train the predictive model. The data was from electronic health records.	After validation the model was measured to be 92% precise.	The study showed some methodological flaws.

		complications			
20	Akbulut et al.(2018) Fetal Haelth Status Prediction based on maternal clinical history using machine learning techniques.	To help health workers and parents of new born to better predict fetal anomalies using machine learning techniques.	Data used for this study was collected from 96 pregnant women from a maternal questionnaire with evaluation from 3 clinicians.	The Decision Forest (DT) algorithm performed better than other algorithms considered with an accuracy of 89.5%.	The data set was collected from a small sample of women. Results may be more accurate with a large dataset.

2.5 Research Gap

Despite global efforts to curb maternal mortality, Sub-Saharan Africa continues to experience the highest rates, with Nigeria accounting for an outstanding percentage of maternal deaths. This persistent crisis underscores systemic challenges in the delivery of maternal healthcare, particularly in rural and underserved communities.

In Nigeria, maternal health strategies are largely reactive rather than preventive, with interventions often initiated only after complications arise. This limits the opportunity for early detection and timely intervention, which are essential in preventing maternal deaths. Moreover, the integration of advanced technologies, such as Machine Learning (ML), into maternal health decision-making remains notably absent.

Globally, Machine Learning has demonstrated considerable potential in healthcare through risk prediction, diagnostics, and personalized treatment. However, its application within Nigeria's maternal health system is still underexplored, leaving a critical technological gap in data-driven maternal risk assessment and intervention.

Another significant limitation is the lack of representative datasets. Many existing maternal health datasets used in research are not reflective of the socio-demographic and clinical diversity

present in regions like Delta State. This restricts the generalizability and effectiveness of predictive models, rendering them less applicable to local populations (Zinzuwadia *et al*., 2024).

Therefore, there is a critical need for context-aware, data-driven approaches that can predict high-risk pregnancies before fatal complications arise. This study aims to address these gaps by developing a predictive ensemble machine learning model based on locally sourced data from Delta State, thereby enhancing model relevance, promoting preventive care, and contributing to the broader goal of reducing maternal mortality in Nigeria.

Chapter Three

Research Methodology

3.0 Methodology

The structured machine learning process in Machoron *et al*. (2022) was adopted in this study. This following key stages were followed to achieve the research objectives: data collection, data pre-processing, model selection, model training, model testing and evaluation.

3.1 Standardized Data

This section outlines the process of sourcing standardized data for this study, given the limited availability of relevant datasets in this field within Nigeria. It also covers data pre-processing and other analytical procedures applied to prepare and analyze the standardized dataset for model development.

3.1.1 Data Collection and Description for Standardized Data

Maternal dataset was sourced from the University of California, Irvine (UCI) Machine Learning Repository (Marzia, 2023). Table 3.1 shows a description of the dataset used in developing the model, while Table 2 depicts excerpt of some instances of the dataset showing the six features and their corresponding risk level.

Table 3.1: Description of dataset (Marzia, 2023)

Variable Name	Role	Type	Demographic	Description	Units
Age	Feature	Integer	Age	Any age in years when a woman during pregnant.	
SystolicBP	Feature	Integer		Upper value of Blood Pressure in mmHg, another significant attribute during pregnancy.	
DiastolicBP	Feature	Integer		Lower value of Blood Pressure in mmHg, another significant attribute during pregnancy.	

BS	Feature	Integer		Blood glucose levels is in terms of a molar concentration	Mmol/L
BodyTemp	Feature	Integer			F
HeartRate	Feature	Integer		A normal resting heart rate	Bpm
RiskLevel	Target	Categorical		Predicted Risk Intensity Level during pregnancy considering the previous attribute.	

The features captured in Table 1 include Age (in years), Systolic Blood Pressure as SystolicBP, Diastolic Blood Pressure as DiastolicBP, Blood Sugar as BS, Body Temperature as BodyTemp, the rate of heart beat as HeartRate and the maternal health risk level as RiskLevel. With 1014 instances, there are no missing values in the data.

Table 3.2: Excerpt of Instances in Dataset showing the six features and Corresponding Risk Level

Age	Systolic BP	Diastolic BP	Blood Sugar	Body Temp	Heartrate	Risk Level
35	120	60	6.1	98	76	Low risk
23	140	80	7.01	98	70	High risk
23	130	70	7.01	98	78	Mid risk
35	85	60	11	102	86	High risk
32	120	90	6.9	98	70	Mid risk

Table 3.2 presents an excerpt from the dataset used in this study, highlighting six key features identified as potential predictors of the corresponding maternal risk levels. Each row in the table represents an individual instance (i.e., a pregnant woman) and is categorized according to a corresponding Risk Level — classified as Low, Mid, or High.

3.1.2 Data Preprocessing for Standardized Data

Data cleaning and other preprocessing tasks were performed using Python libraries within the Google Colaboratory environment (Google, 2025). To prepare the dataset for analysis, data transformation was conducted to ensure variables were represented in formats suitable for machine learning modelling. Specifically, the target (response) variable, originally represented as

categorical labels ("low risk," "mid risk," and "high risk"), was converted into numerical codes, as most machine learning algorithms require numerical input for model training. By encoding the target variable into numerical form, the model can correctly interpret the risk categories and learn patterns that distinguish between them during training. This transformation ensures the target variable is compatible with the algorithms and helps achieve accurate and reliable predictions. Details of this transformation process are presented in Table 3.3.

Table 3.3: Target Variables and Corresponding Numeric Values

Target Variable	Numeric value
Low Risk	0
Mid Risk	1
High Risk	2

Low, Mid and High risk is depicted by 0, 1 and 2, respectively, in order to enable computation. A Comma Separated Value (CSV) format was applied to data file to operate with Pandas library.

The dataset pre-processing procedures included normalization, handling missing values and encoding categorical variables. To ensure balanced representation across target classes, Stratified K-fold Sampling is employed. This technique divides the data into 10 subsets while preserving the percentage of samples for each class in every fold, which is crucial for imbalanced datasets typically found in maternal health records. Data was split into 90% training data (913 instances) and 10% validation data (101 instances). In ten (10) iterations, the dataset was divided into 10 parts and each time k-1 fold (9 folds) was trained then validated with the remaining one (1) fold. With respect to feature selection, the features found in the dataset were sufficient for developing the model, thus no new features were added or removed.

3.1.3 Model Selection and Design

Figure 3.1 shows the design of the model as presented in seminar II, dubbed ‘Safe Motherhood Predictor (SMP)’. Stratified k-Fold sampling technique was applied to the data to prevent overfitting and ensure that all data samples are sufficiently represented in the model prediction.

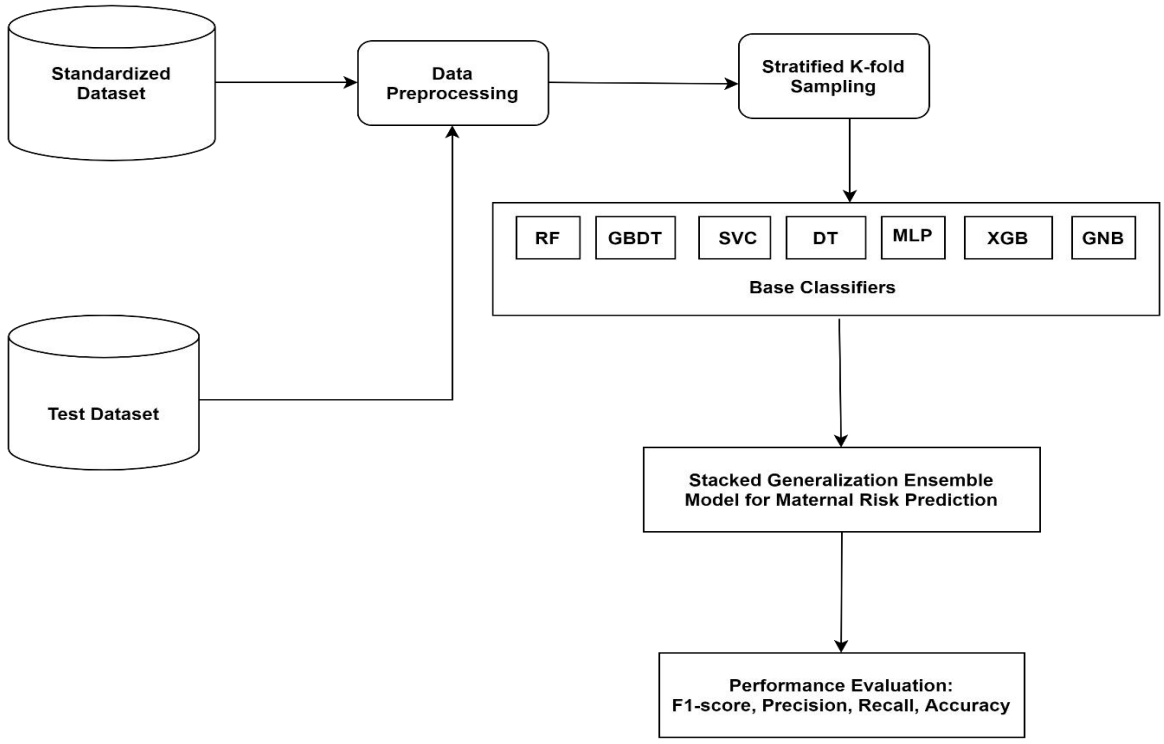

Figure 1: Ensemble Model Design in Seminar II

This model design in Figure 3.1 presents a methodological framework for developing a stacked generalization ensemble model aimed at predicting maternal risk. The architecture is built upon the integration of multiple machine learning classifiers selected (Uddin *et al*., 2019) based on their performance in other studies. The specific classifiers are Support Vector Classification (SVC), Gaussian Naïve Bayes (GNB), Multilayer Perceptron (MLP), Decision Tree (DT), Random Forest (RF), Gradient Boosting Decision Tree (GBDT) and Extreme Gradient Boosting (XGB). The predictions from the base classifiers are used as input features for a meta-classifier, forming the stacked generalization ensemble model**.** This higher-level learner combines the strengths of individual models to improve predictive performance on maternal risk classification tasks. The individual models and the ensemble model were evaluated based relevant performance metrics such as F1-Score, Precision, Recall, and Accuracy.

3.1.4 Model Evaluation and Adaptability

In order to test the model and adapt it to our environment, primary data was collected from the three (3) health facilities managed by the government in each of the senatorial districts in Delta State. A comparison of the standardized dataset and primary dataset is depicted in Table 7.

Table 7: Feature Comparison of Standardized and Primary Data from Delta State Health Centers

S/N	Standardized Data set	Primary Data set
1	Age (Maternal)	Maternal Age
2	Systolic BP	Systolic BP
3	Diastolic BP	Diastolic BP
4	Blood Sugar	Weight
5	Body Temperature	Height
6	Heart Rate	Body Mass Index (BMI)
7		Gestational Age
8		Parity
9		Urine Analysis
10	RiskLevel	RiskLevel

Maternal Age is retained as Age (Maternal), while Systolic BP and Diastolic BP remain unchanged in both datasets. Variables such as Blood Sugar, Body Temperature, and Heart Rate appear in the standardized dataset but are absent in the primary dataset. Conversely, variables like Weight and Height, which are included in the primary dataset led to the derivation of the variable, BMI. Notably, demographic variables including Gestational Age, Parity, and Urine

Analysis are present in the primary dataset but do not appear in the standardized dataset's renamed section. The target variable, Risk Level, remains unchanged across both datasets to ensure consistency and comparability in classification tasks.

According to Dockes *et al*. (2021), the differences in the variables between the two datasets could significantly affect the model's evaluation. The proposed model may be unable to generate predictions if only partially available variables from the primary dataset are provided. As a result, testing and evaluating a model developed with the standardized dataset using the primary data could compromise the validity of the evaluation and obscure the model's true predictive performance. This mismatch in feature availability may lead to biased accuracy estimates, reduced generalizability, and ultimately, misleading conclusions about the model's effectiveness (Luijken *et al*., 2018). Utilizing a localized dataset collected directly from the specific population, region, or context where the predictive model is intended to be applied is critical for several reasons. A major reason for this is that localized data capture the unique demographic, socio-economic, cultural, and clinical characteristics inherent to the target population. This enables the model to learn patterns that are genuinely reflective of the local context, thereby enhancing its predictive accuracy and ensuring greater relevance to real-world applications (Zinzuwadia *et al*., 2024). Owing to inconsistencies between the existing (standardized) dataset features and the dataset of the target demographic, a revised model was developed utilizing primary data specifically collected to align with the intended population for accurate and effective implementation.

3.2 Primary Dataset

This section describes the process of collecting the primary dataset used in this study, addressing the lack of existing data in this area within Nigeria. It also details the data preprocessing steps and analytical techniques applied to ensure the dataset is clean, consistent, and suitable for analysis.

3.2.1 Data Collection for Primary Dataset

Maternal dataset was sourced from three (3) different medical centers in Delta State, Nigeria. Nigeria, a country in Sub-Saharan Africa, is located in the western region of the continent. It

comprises 36 states and the Federal Capital Territory (O'Neil, 2023). Delta State, one of Nigeria's oil-producing states, is situated in the southern region of the country and was officially created in August 1997. "The state has a population of over 4 million people, and its capital city, Asaba, is located in the northern part of the state (UNDP, 2015).

The centers were chosen from each Senatorial districts in the state, all managed by the state government. Ethical approval for data collection was obtained from corresponding research ethics committee: Health Research Ethics Committee of Delta State University Teaching Hospital (HREC DELSUTH) in Oghara (Delta Central), The Ethics and Research Committee of Central Hospital, Warri (Delta South) and Model Health Care Center, Oshimili South (Delta North) representing the three Senatorial districts in Delta State. The data was collected with the aid of research assistants from ante-natal records in the selected health facilities according to ethical principles in accordance with the guidelines and regulations of the ethics committee. The data was anonymised to ensure that there was no breach of confidentiality. Consent was also not required from the patients. Data was manually inputted into Microsoft Excel sheets due to the absence of Electronic Health Records (EHR) systems in all the health centers. Each patient's information was maintained in a serialized physical file stored in cabinets, which was retrieved during hospital visits for reference and updates.

The data was localized and the features captured include Maternal Age (Age of pregnant woman), Gestational Age (Number of weeks pregnant), Systolic Blood Pressure as Systolic BP, Diastolic Blood Pressure as Diastolic BP, Parity (the number of times as a woman has given birth), Weight (weight of woman as at ante-natal visit, Height (Height of women as at visit), Body Mass Index (Derived from Height and Weight), Urine analysis (to show the presence of glucose or protein which pose harm to pregnant woman) and the maternal health risk level as Risk Level (derived from medical consultation).

3.2.2 Data Preprocessing

Data preprocessing is a crucial step that involves cleaning, transforming, and organizing raw data to enhance its suitability for analysis. In this study, preprocessing was performed to handle missing values, normalize numerical features, encode categorical variables and address class

imbalance. These steps were vital to improve model accuracy, reduce bias, and ensure that the algorithms could learn meaningful patterns from the maternal health data. Table 3.1 shows a description of the dataset used in developing the model.

Table 3.4: Description of dataset features

Variable Name	**Role**	**Type**	**Description**
Maternal Age	Feature	Integer	Maternal age in years at the time of pregnancy
Gestational Age	Feature	Integer	Duration of pregnancy in weeks
Parity	Feature	Integer	Number of previously live births
Weight	Feature		Weight of Patient at ante-natal visit in kg
Height	Feature		Height of patient at ante-natal visit in cm
Body Mass Index (BMI)	Derived Feature	Float	Derived from weight and height of patient
Systolic BP	Feature	Integer	Upper value of Blood Pressure in mmHg, a significant feature in maternal health.

Diastolic BP	Feature	Integer	Lower value of Blood Pressure in mmHg, a significant feature in maternal health.
Urine Analysis	Feature	Integer	The Presence of Glucose and/or Protein in Urine
Risk Level	Target	Categorical	Predicted Risk Intensity Level of pregnant woman

The dataset features captured include Maternal Age (Age of pregnant woman), Gestational Age (Number of weeks pregnant), Systolic Blood Pressure as Systolic BP, Diastolic Blood Pressure as Diastolic BP, Parity (the number of times as a woman has given birth), Weight (weight of woman as at ante-natal visit, Height (Height of women as at visit), Body Mass Index (Derived from Height and Weight), Urine analysis (to show the presence of glucose or protein which pose harm to pregnant woman) and the maternal health risk level as Risk Level (derived from medical consultation). With 1582 instances, there were some missing values in the height features of patients. This was filled with the highest occurring height value (mode value) in the data set (Togunwa *et al*., 2023). Table 3.5 shows an excerpt of some instances in the dataset and their corresponding risk levels.

	MATERNAL AGE	GESTATIONAL AGE	PARITY	WEIGHT	HEIGHT	BMI	SYSTOLIC BP	DIASTOLIC BP	URINE ANALYSIS	RISK LEVEL
0	25	41.0	0	67.0	1.71	22.913033	180	90	NEGATIVE	High
1	31	21.0	0	76.0	1.61	29.319856	130	80	NEGATIVE	Mid
2	40	16.0	0	90.0	1.65	33.057851	140	90	NEGATIVE	High
3	30	19.0	0	57.0	1.33	32.223416	130	80	NEGATIVE	Mid
4	33	25.0	3	78.0	1.61	30.091432	120	60	NEGATIVE	Mid

Table 3.5: Excerpt of some instances of the dataset showing the features and their corresponding Risk level.

The data was subsequently classified into three (3) categories based on specific features. The categories are as follows: Low (representing women at mild risk of maternal mortality), Mid (representing women at a moderate risk of maternal mortality), and High (representing women at a significant risk of maternal mortality). Table 3.3 shows the categorization process, which was conducted under the supervision of a Domain Expert in Obstetrics and Gynaecology to ensure accuracy and reliability. According to WHO (2019) and Mashrafi et al. (2024), the clinical features present in the dataset are sufficient for accurately classifying maternal health risk levels.

Table 3.6: Categorization of Risk levels based on Clinical features

	Low risk	Mid risk	High risk
Maternal Age	<16>39 (years)	>40<45 (years)	>45 years
Systolic Blood Pressure	<140 (mmhg)	>140<160 (mmhg)	>160 (mmhg)
Diastolic Blood Pressure	<90 (mmhg)	>90<110 (mmhg)	>110 (mmhg)
Parity	2 – 4	0	>4
BMI	18.5 – 24.9 (Normal)	>25<29.9 (Overweight)	>30 (Obesity) or <18.5 (Underweight)
Gestational Age (at booking)	Less than 16 weeks	16 – 26 weeks	More than 26 weeks
Urinalysis	Absence of Protein and/or Glucose	Trace values of Protein and/or Glucose	High levels of Protein and/or Glucose

Data cleaning procedures carried out on the dataset included the removal of invalid entries, such as instances where characters or strings were mistakenly entered in place of numeric values. Additionally, outlier detection was carried out using the Interquartile Range (IQR) method to identify and handle anomalous data points. Data transformation was performed to prepare the dataset for effective analysis and modeling. The target variable, representing maternal health risk levels (originally categorized as Low Risk, Mid Risk, and High Risk), was not immediately suitable for most machine learning algorithms, which usually necessiates numerical input. To address this, the categorical risk levels were encoded into numerical values—High Risk, Mid Risk, and Low Risk were mapped to 0, 1, and 2, respectively. This encoding facilitated computational processing and model compatibility, as shown in Table 3.7.

Table 3.7: Risk Levels and Corresponding Numeric Values.

Target Variable	**Numeric value**
Low Risk	2
Mid Risk	1
High Risk	0

A stratified 10-fold cross-validation, a variation of the standard K-fold validation technique, was employed to assess model performance. In this approach, the dataset was partitioned into ten (10) equally sized folds. For each iteration, the model was trained on nine (9) folds and validated on the remaining one (1) fold, repeating this process 9 more times to ensure that every instance in the dataset is used for both training and validation exactly once. The stratification ensures that the distribution of the target variable (maternal health risk levels) is proportionally maintained across all folds, thereby minimizing sampling bias. This method improves the reliability of model evaluation by providing a more representative performance estimate and reducing the risk of overfitting, especially given the relatively small dataset size (Togunwa et al., 2023).

3.2.3 Feature Engineering

To enhance the predictive capability of the model, a new binary feature titled ‘Non Negative Urine Analysis’ was introduced. This feature was derived from the original ‘Urine Analysis’ variable, which contains numerical or categorical indicators of various urine test results. The engineered feature simplifies the information by encoding whether or not the urine analysis result indicated a non-normal (abnormal) condition. Specifically, values indicating any abnormality were assigned a value of 1 (non-negative), while normal results were assigned 0 (negative). This transformation enables the model to focus on the presence of clinically relevant deviations without being affected by the scale or variability of the original urine analysis variable.

3.2.4 Correlation Analysis

In this study, Pearson’s correlation coefficient was employed to evaluate pairwise correlations among numerical features in the maternal health dataset. The results were visualized using a correlation matrix heatmap to facilitate intuitive interpretation. This analysis served as a foundational step for selecting relevant features and improving the robustness and interpretability of the predictive models. Figure 3.1 shows the Correlation Analysis of Dataset features.

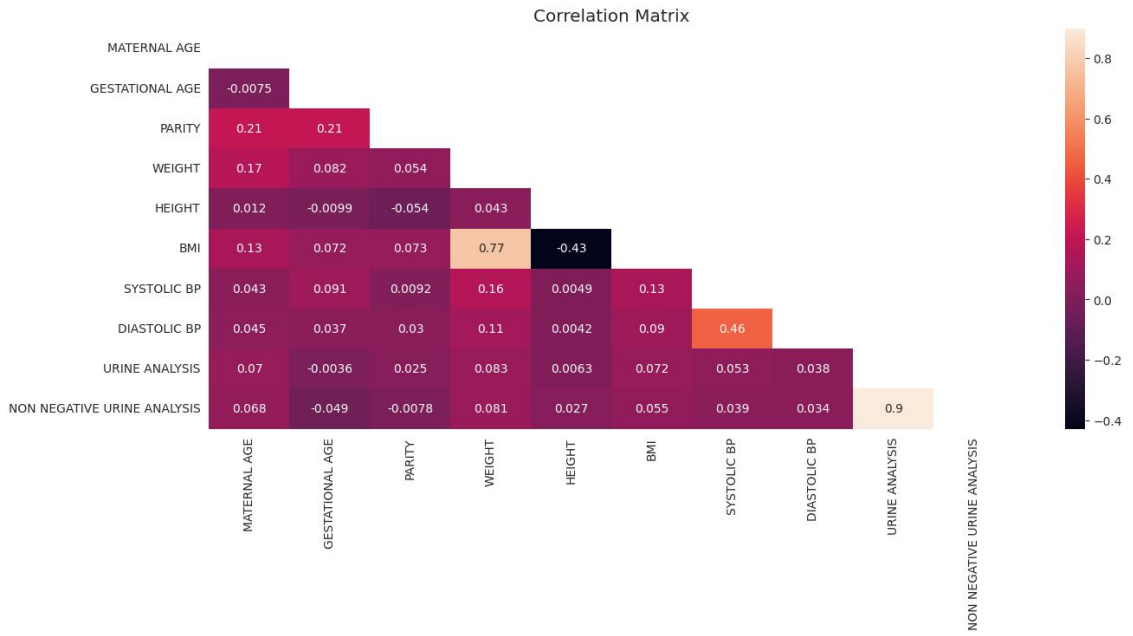

Figure 3.2: Correlation Analysis of Dataset features.

The Pearson correlation coefficient (r) in the correlation matrix provides insight into the strength and direction of linear relationships among clinical features in the maternal health dataset. The highest positive correlation is observed between Urine Analysis and Non-Negative Urine Analysis (r = 0.90), indicating a strong association and potential overlap in the information these features convey. Similarly, BMI and Weight are highly correlated (r = 0.77), which is consistent with the fact that BMI is calculated from weight and height. A moderate correlation exists between Systolic and Diastolic Blood Pressure (r = 0.46), reflecting their physiological connection. In contrast, features such as Maternal Age, Parity, and Gestational Age exhibit low or negligible correlations with other variables (ranging approximately from -0.05 to 0.21), suggesting that they contribute independently and with minimal redundancy to the dataset.

3.2.5 Exploratory Data Analysis

Exploratory Data Analysis (EDA) serves as a foundational step in understanding the underlying structure and characteristics of the dataset. It involves the use of statistical summaries and visualizations to uncover patterns, detect anomalies, identify correlations, and evaluate the distribution of variables. In this study, EDA was conducted to gain insights into maternal health indicators, assess feature relevance, and guide subsequent modelling decisions.

Feature Average Per Risk Level Analysis

To better understand the relationship between clinical features and maternal risk classification, the average values of each feature were computed and compared across three risk levels (0 = Low, 1 = Medium, 2 = High). This grouped bar chart provides a visual comparison of how variables such as age, blood pressure, body mass index (BMI), and urine analysis vary across different risk categories.

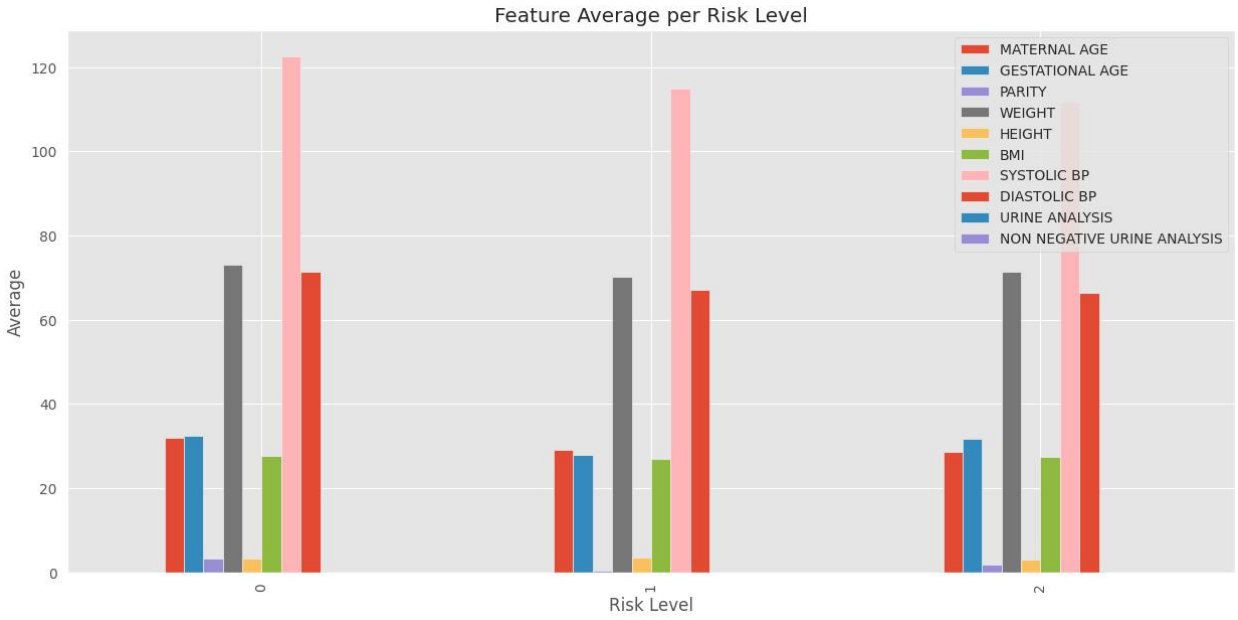

Figure 3.2: Feature Average Per Risk Level Analysis.

From the chart in figure 3.2, it is evident that systolic blood pressure and diastolic blood pressure show noticeable increases from low to high risk categories, suggesting a strong association between elevated blood pressure and maternal risk. Similarly, BMI and non-negative urine analysis values are slightly higher in higher-risk categories, which aligns with known clinical indicators such as preeclampsia. Interestingly, features like height and parity remain relatively consistent across risk levels, indicating limited influence in this particular dataset.

Boxplot Analysis of Dataset Features

Figure 3.3 presents the boxplots of key numerical variables in the maternal health dataset, including maternal age, gestational age, parity, anthropometric measurements (weight, height, and BMI), blood pressure (systolic and diastolic), urine analysis results, and the binary risk level outcome. Each subplot represents the distribution of a variable using a boxplot**,** which highlights the median, interquartile range (IQR), and potential outliers.

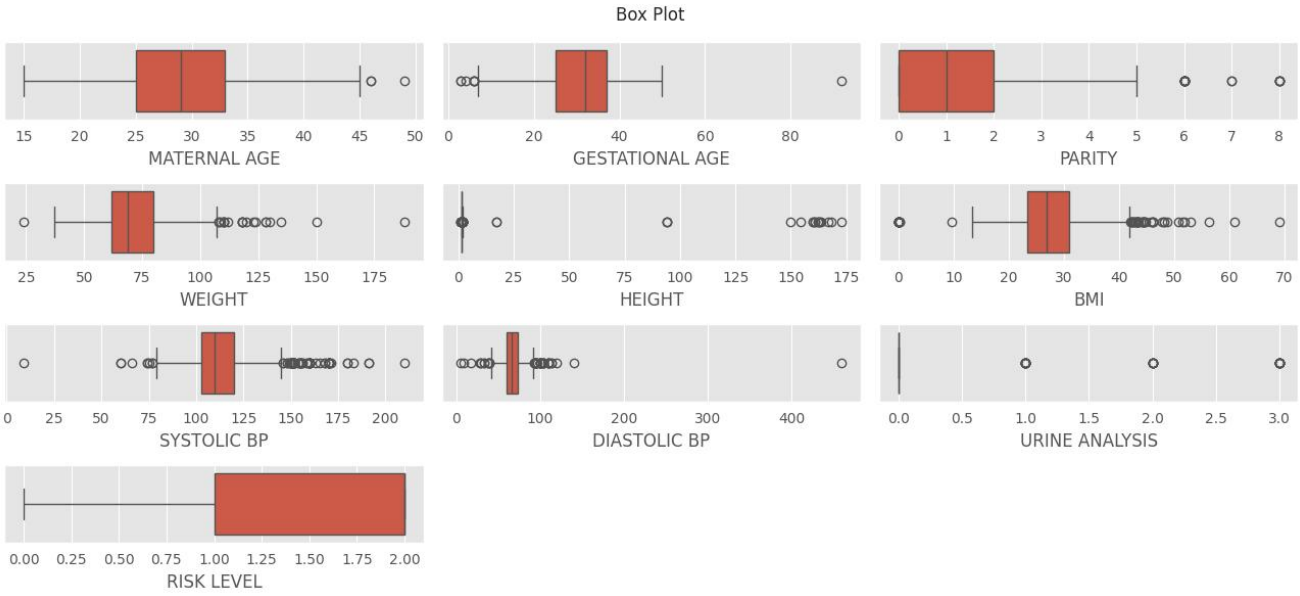

Figure 3.3: Boxplot Analysis of Dataset features.

The boxplot analysis reveals important data characteristics, such as the presence of outliers, potential data quality issues (especially in height and gestational age), and skewed distributions in variables like BMI and blood pressure. These insights guided subsequent preprocessing steps, including outlier treatment and feature scaling. Moreover, the class imbalance observed in the risk level variable highlights the necessity for synthetic sampling techniques such as Random Oversampling to improve classifier performance.

Feature Distribution Analysis

This feature distribution analysis provides crucial insights into the nature and behavior of each variable. It highlights skewness for variables that may need transformation and the presence of imbalanced classes that justify the need for upsampling techniques. These insights directly

informed the feature engineering, model selection, and preprocessing strategies applied in the study. Figure 3.4 presents the feature distribution of the variables in the maternal health dataset, including maternal age, gestational age, parity, anthropometric measurements (weight, height, and BMI), blood pressure (systolic and diastolic), urine analysis results, and the binary risk level outcome.

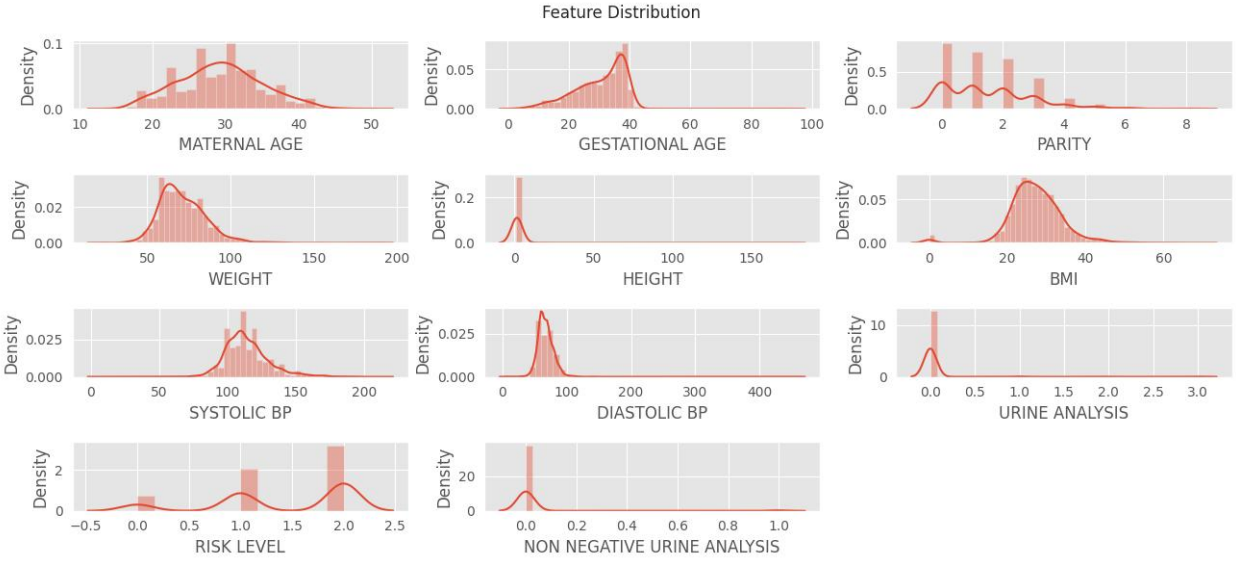

Figure 3.4: Features Distribution

3.2.6 Data Upsampling (Random Oversmapling)

In data analysis and machine learning, imbalanced datasets, where some categories have significantly fewer instances than others, can lead to biased models that perform inaccurately on the minority classes. In such cases, data upsampling is a widely used method to address class imbalance (Okpono *et al*., 2024). It is an oversampling technique that increases the number of samples of the minority class simply by duplicating existing samples of the same minority class until all classes are balanced (Mashrafi *et al,* 2024). Figure 3.5 shows the result of the risk variables before and after Upsampling.

Table 3.5: Target variables before and after Upsampling

	Classes	Before Sampling	After Sampling
1	Low Risk	844	844
2	Mid Risk	540	844
3	High Risk	192	844

Prior to upsampling, the dataset exhibited class imbalance, with the 'High Risk' class containing only 192 samples and the 'Mid Risk' class 540 samples, compared to 844 samples in the 'Low Risk' class. This imbalance could bias the model toward predicting the majority class ('Low Risk') more frequently, thereby reducing its ability to accurately classify minority classes. To address this, upsampling was applied, resulting in all three classes—'High Risk', 'Mid Risk', and 'Low Risk'—having equal representation of 844 samples each. The statistical distribution of the risk levels before and after Upsampling are as shown in Figure 3.5 and Figure 3.6.

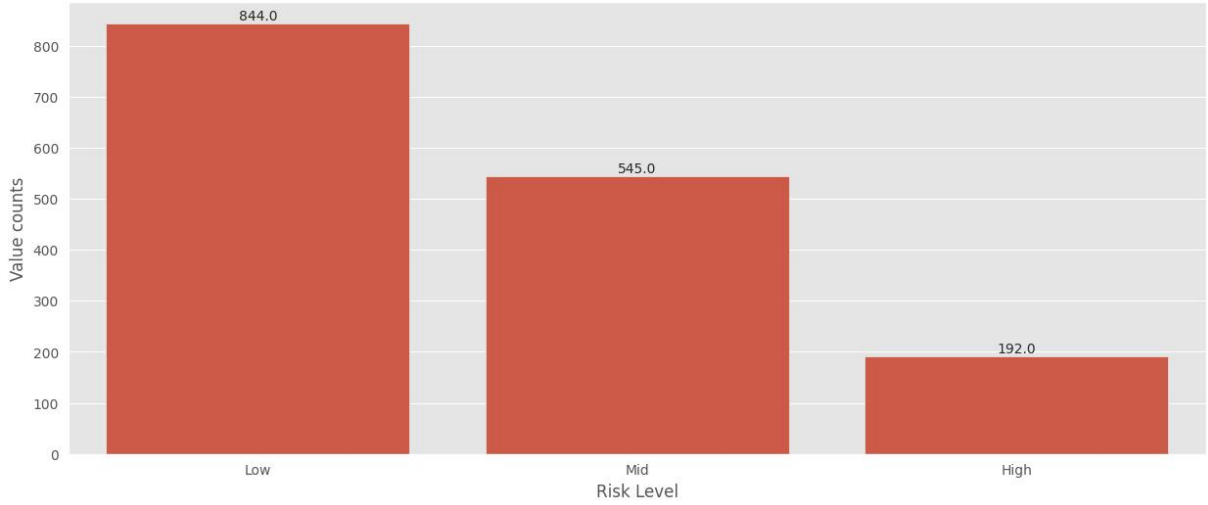

Figure 3.5: Statistical Distribution of Risk Level in Dataset before Upsampling

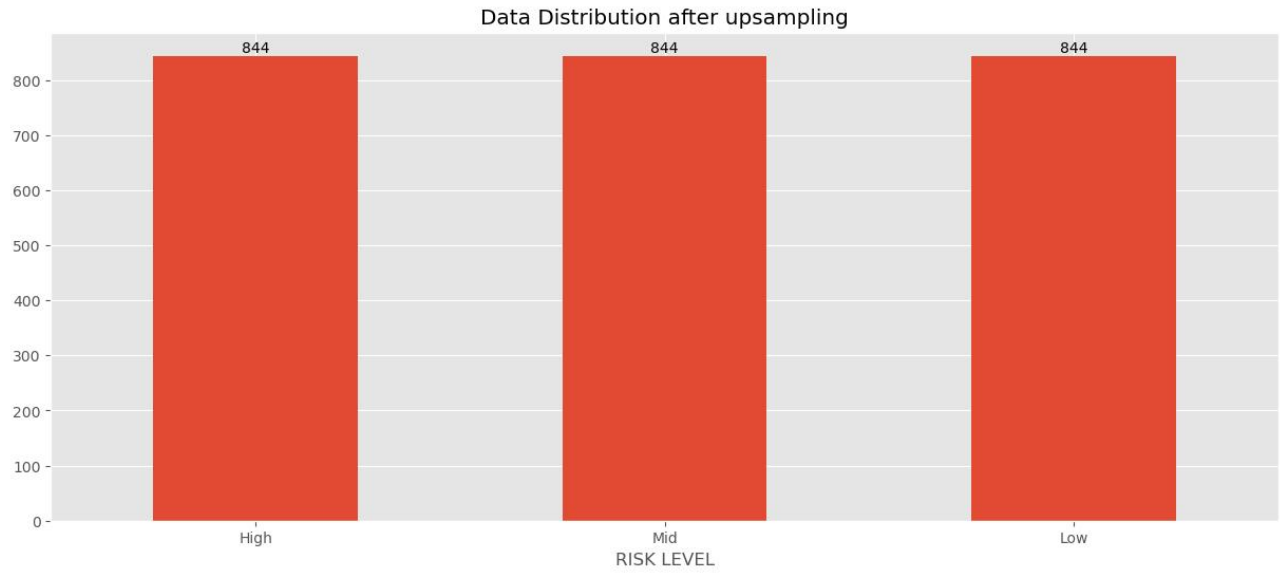

Figure 3.6: Statistical Distribution of Risk Level in Dataset after Upsampling

3.2.7 Model Selection

The selection of suitable machine learning algorithms is a pivotal step in building a robust and reliable predictive model for maternal mortality. Due to the complex and sensitive nature of healthcare data, this process requires careful consideration of multiple factors, including predictive accuracy, model interpretability, and the ability to generalize across diverse populations. To ensure optimal performance, the study evaluated both individual base classifiers and ensemble learning techniques, allowing for a comprehensive comparison of different algorithmic approaches.

Support Vector Classification (SVC): Support Vector Classification (SVC) is the implementation of the Support Vector Machine (SVM) algorithm for classification tasks. It is designed to construct an optimal hyperplane in a high-dimensional space to separate data into distinct classes (Uddin *et al.*, 2019). SVC operates by identifying support vectors, data points that are closest to the decision boundary and uses them to maximize the margin between classes. One of the key strengths of SVC lies in its ability to handle both linear and non-linear classification problems. SVC is especially effective in high-dimensional spaces and is robust to overfitting, particularly when the number of dimensions exceeds the number of samples. Its

flexibility and precision make it a suitable algorithm for complex classification problems in domains such as healthcare, finance, and text categorization.

Gaussian Naïve Bayes (GNB): Naïve Bayes is a simple yet effective probabilistic classification algorithm based on Bayes' Theorem. It assigns class labels to instances represented as vectors of feature values, selecting from a predefined set of discrete classes. Rather than relying on a single training approach (Nirmala & Kambili, 2023). Naïve Bayes encompasses a family of algorithms, like the Gaussian Naïve Bayes, that operate under a common assumption: the conditional independence of features. The GNB algorithm operates under the key assumption that the continuous features follow a Gaussian (normal) distribution. This statistical assumption allows the algorithm to compute the likelihood of features given a class using the probability density function of the normal distribution. By leveraging this distributional property, Gaussian Naïve Bayes efficiently estimates class probabilities, enabling accurate and scalable classification even in high-dimensional datasets (Mustamin *et al*., 2023). This method is particularly effective when the normality assumption approximately holds and is commonly applied in medical and biological datasets where features tend to exhibit Gaussian-like behavior.

Multilayer Perceptron (MLP): The Multilayer Perceptron (MLP) is a type of Artificial Neural Network (ANN) widely applied in classification and regression tasks across domains such as speech recognition, pattern recognition, and medical diagnosis (Ramchoun et al., 2016). An MLP consists of an input layer, one or more hidden layers, and an output layer, with each layer composed of interconnected perceptrons (neurons). Often referred to as the multilayer backpropagation method, MLP operates through two main phases: forward propagation, where input data is passed through the network to generate an output, and backward propagation, where the prediction error is propagated backward through the network to update weights and minimize loss using gradient descent (Putra et al., 2021). The ability of MLP to model complex non-linear relationships makes it a powerful tool in data-rich environments, such as healthcare analytics, where prediction accuracy is critical.

Decision Tree (DT): Decision Trees are widely used machine learning algorithms known for their ability to analyze datasets by generating a hierarchy of decision rules. These rules are structured in a tree-like format, where each internal node represents a decision based on a

specific feature, and each branch corresponds to an outcome of that decision (Mutlu *et al.,* 2023). Decision Trees offer several advantages, including their ability to handle both categorical and continuous variables, ease of interpretation, and relatively fast computation. These characteristics make them especially useful in healthcare settings, where transparency and speed are essential (Mondal *et al*., 2023).

Random Forest (RF): The Random Forest Classifier is a tree-based ensemble learning method that constructs a large number of individual decision trees during training. It builds upon the traditional bagging approach by incorporating both bootstrap sampling and random feature selection, thereby creating a diverse and uncorrelated ensemble of trees (Gomez-Jemes *et al*., 2022). This design significantly enhances predictive accuracy and reduces the risk of overfitting, which is a common limitation of single decision trees. In classification tasks, the Random Forest model produces its output through majority voting, where the class predicted by the majority of individual trees is selected as the final decision (Raja *et al*., 2022). Unlike standard decision trees that evaluate all possible feature splits at each node, Random Forests randomly select a subset of features at each split. This randomness improves computational efficiency and further reduces correlation among the trees, contributing to the model's robustness and generalization ability (Miranda *et al*., 2022).

Gradient Boosting Decision Tree (GBDT): Gradient Boosting Decision Trees is one of the machine learning models employed in this study due to its proven effectiveness and widespread application in medical datasets. GBDT is a powerful ensemble learning technique that builds a predictive model in a stage-wise fashion, combining the strengths of multiple weak learners, typically decision trees, to create a strong and robust classifier (Khadidos *et al*., 2024). The GBDT algorithm follows a forward learning approach, where each subsequent tree attempts to correct the errors made by the previous ones. By minimizing a loss function using gradient descent, the model incrementally improves its performance with each iteration. This method allows GBDT to capture complex patterns and interactions within the data, making it highly effective for both classification and regression tasks. GBDT's ability to handle heterogeneous data, model non-linear relationships, and reduce bias and variance makes it a suitable choice for analyzing high-dimensional and noisy healthcare data (Mbali, 2024).

Extreme Gradient Boosting (XGBoost): Extreme Gradient Boosting (XGBoost) is a highly popular and efficient machine learning framework introduced by Chen et al. (2014). It has gained widespread recognition for its exceptional performance across a broad spectrum of machine learning tasks (Okpono et al., 2024). XGBoost is based on the principle of ensemble learning, where multiple weak learners, typically decision trees are combined to form a robust and accurate predictive model. The framework incorporates several optimization techniques, including regularization, parallel processing, and tree pruning, which contribute to its high accuracy and computational efficiency. Due to its scalability and strong predictive capabilities, XGBoost has been extensively applied in fields such as healthcare, finance, and bioinformatics, making it a suitable candidate for this study's classification task.

Light Gradient Boosting Machine (LightGBM): In this study, LightGBM (Light Gradient Boosting Machine) was also employed for the analysis of the dataset. LightGBM is a high-performance implementation of the gradient boosting framework, specifically designed to be efficient with large-scale datasets (Mutlu *et al*., 2023). It achieves faster training speeds and lower memory usage through techniques such as histogram-based decision tree learning and leaf-wise tree growth. One of LGBM's key advantages lies in its ability to handle large volumes of data with high dimensionality while maintaining competitive accuracy (Mustamin *et al*., 2023). This makes it particularly suitable for complex classification tasks in domains like healthcare, where data can be both voluminous and heterogeneous.

Categorical Boosting (CatBoost): CatBoost is a gradient boosting algorithm designed to handle both categorical and numerical features efficiently. One of its key advantages lies in its ability to automatically process categorical variables without requiring manual encoding, which reduces the risk of information loss and simplifies the preprocessing pipeline (Mutlu *et al*., 2023). Additionally, CatBoost is known for its high predictive accuracy and relatively faster training times compared to other boosting algorithms. Due to its robustness and native support for categorical data, CatBoost is well-suited for classification tasks across a wide range of application domains, including healthcare (Okpono *et al*., 2023).

3.2.8 Updated Model Architecture for Primary Dataset

Figure 3.7 illustrates the design of the model. The dataset was preprocessed to prepare it for modeling. The data was divided into two subsets, with 90% allocated for training and 10% reserved for testing**.** To prevent over fitting and ensure that all data samples were adequately represented in the model's predictions, the Stratified k-Fold sampling technique was applied. This approach maintained the proportion of the different risk categories across each fold, enhancing the model's robustness and reliability.

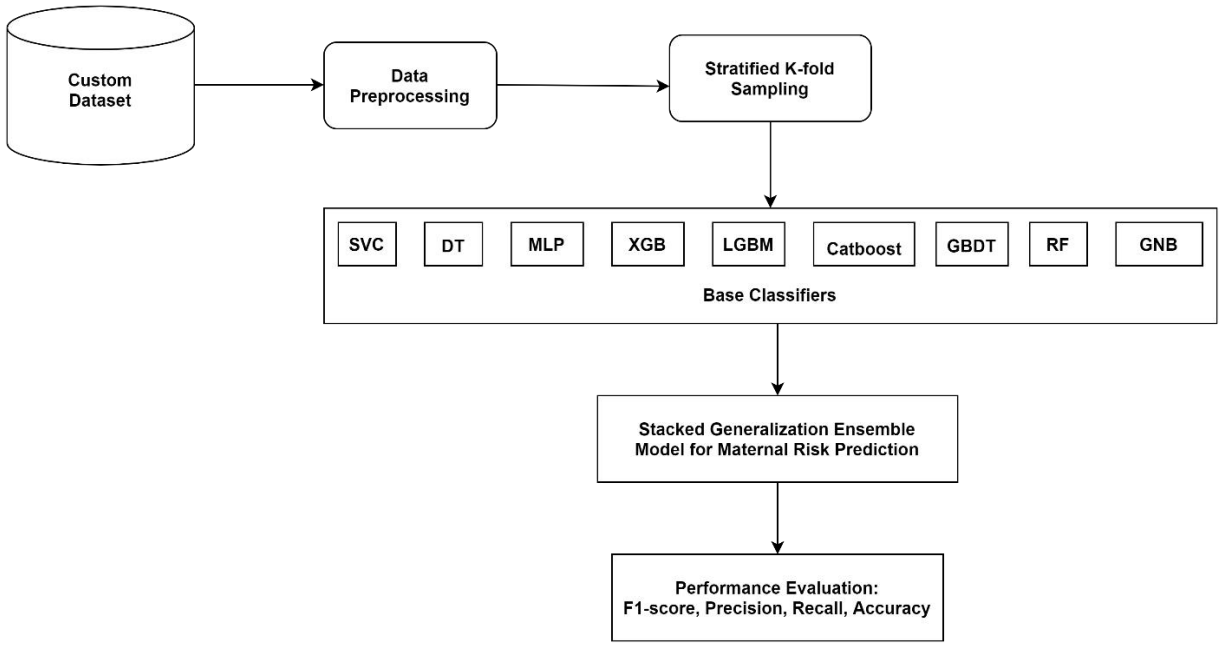

Figure 3.7: Ensemble Model Design

The design incorporates a representation of all the selected classifiers, which include: Random Forest (RF), Gradient Boosted Decision Tree (GBDT), Support Vector Classifier (SVC) (a linear variant of Support Vector Machine), Decision Tree (DT), Multilayer Perceptron (MLP) (a type of Artificial Neural Network), Extreme Gradient Boosting (XGB), Gaussian Naïve Bayes (GNB), Light Gradient Boosting Machine (LightGBM), and Categorical Boosting (CatBoost)." To enhance the overall performance beyond that of any individual classifier, an ensemble model was constructed using these nine classifiers as base learners. The performance of the developed model was evaluated using key metrics, including F1 Score, Precision, Accuracy, and Recall.

Stacking Ensemble Formula

Let the **level-0 base models** be:

$$\{h_1, h_2, h_3 \ldots h_g\} = \{\text{SVC, MLP, GNB, DT, RF, XGB, GBDT, LGBM, CatBoost}\}$$

For an input sample x_i, each base model produces a prediction:

$$\hat{y}_{i1} = h_1(x_i), \quad \hat{y}_{i2} = h_2(x_i), \ldots, \hat{y}_{ig} = h_g(x_i) \tag{1}$$

The **meta-dataset** is defined as:

$$\widetilde{x_i} = [h_1(x_i),\ h_2(x_i),\ h_3(x_i), \ldots h_g(x_i) \tag{2}$$

$$\widetilde{y_i} = y_i$$

The **level-1 meta-model** $\hat{h}$— here, a Random Forest (RF) — is trained on $\{(\widehat{x_i},\ \widehat{y_i})\}_{i=1}^{N}$

The final stacked model prediction for a new instance x is:

$$H(x) = \hat{h}(h_1(x_i),\ h_2(x_i),\ h_3(x_i), \ldots h_g(x_i)) \tag{3}$$

Where:

- h_j are base classifiers (level-0 learners)
- $\widehat{h}$ is the meta-learner (level-1 model; here, RF)
- x is the input feature vector

3.2.9 Model Performance Measure

To assess the effectiveness of the classification models used in this study, four standard performance metrics were employed: Accuracy, Precision, Recall, and F1 Score. These metrics are widely accepted for evaluating classification models, particularly in imbalanced datasets where reliance on a single metric like accuracy may be misleading.

Accuracy, as defined by Rabbi *et al*. (2023), represents the proportion of true positives and true negatives among all observations in the dataset. This metric provides a general indication of a model's overall predictive performance, particularly when the data is balanced.

$$Accuracy = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \tag{4}$$

Recall measures a model's ability to correctly identify all actual positive instances in the dataset. It reflects the proportion of true positives captured out of the total number of genuine positives, serving as an indicator of the model's sensitivity in detecting relevant cases (Rabbi et al., 2023).

$$Recall = \frac{T_p}{T_p + F_n} \tag{5}$$

Precision assesses the accuracy of positive predictions by calculating the proportion of true positives among all positive predictions. It reflects how many of the model's positive predictions are truly accurate, thus serving as a measure of the model's reliability in identifying relevant cases (Rabbi et al., 2023).

$$Precision = \frac{T_p}{T_p + F_p} \tag{6}$$

F1 Score combines precision and recall into a single metric by calculating their harmonic mean, effectively balancing false positives and false negatives. It is particularly useful when evaluating model performance on imbalanced datasets, as it offers a more comprehensive view of classification effectiveness (Rabbi et al., 2023).

$$F_1 = 2 \times \frac{precision \times recall}{precision + recall} \tag{7}$$

The final model was selected based on its optimal balance between sensitivity and specificity, with a particular emphasis on accurately identifying high-risk pregnancies with precision. This

approach ensured that the chosen model not only minimized false negatives but also maintained reliable overall classification performance.

3.3 Machine Learning Tools and Techniques

This section outlines the computational tools, software, programming libraries, and machine learning techniques utilized for the development, evaluation, and interpretation of the maternal health risk classification models.

3.3.1 Programming Language

Python was employed as the primary programming language in this study due to its simplicity, versatility, and widespread adoption within the machine learning and data science communities. Python's clear syntax and ease of use make it especially suitable for rapid prototyping and iterative experimentation, which were essential during the development of the maternal mortality predictive model. One of Python's greatest strengths lies in its rich ecosystem of libraries, many of which were leveraged in this study to support various stages of the machine learning process.

3.3.2 Model Development Environment

Google Colaboratory (Colab) was employed as the primary development environment for interactive code execution, data analysis, model development, and visualization. Colab provides a cloud-based platform that supports Python programming and comes pre-configured with key machine learning libraries such as Scikit-learn, Pandas, NumPy, TensorFlow, and Matplotlib, among others (Google, 2025)

Its integration with Google Drive allowed seamless storage, sharing, and collaboration across devices and researchers. One of its significant advantages is the free access to Graphical Processing Units (GPUs) computing resources, which significantly accelerated the training of computationally intensive models such as ensemble classifiers and Multilayer Perceptrons (MLPs). Additionally, Colab's support for Jupyter Notebook formatting enabled clear documentation of code, results, visualizations, and interpretations within a single environment. This made it an ideal platform for conducting reproducible experiments and model evaluations throughout the course of the study (Google, 2025).

3.3.3 Libraries and Frameworks

i. Pandas and NumPy: For data loading, cleaning, transformation, and numerical operations.
ii. Matplotlib: Used for data visualization, including boxplots, histograms, correlation matrices, and confusion matrices.
iii. Scikit-learn: The primary machine learning library used for implementing classical algorithms such as Decision Tree, , Naïve Bayes, Random Forest, , Multilayer Perceptron and Support Vector Machine
iv. XGBoost: A high-performance gradient boosting framework used to implement the Extreme Gradient Boosting model.
v. LightGBM: Employed to build the Light Gradient Boosting Machine model, optimized for speed and performance on large datasets.
vi. CatBoost: Used to handle categorical variables natively while implementing gradient boosting.
vii. SHAP (SHapley Additive exPlanations)**:** An Explainable AI library used to interpret the contributions of individual features to the model's predictions.
viii. Imbalanced-learn: For handling class imbalance in the dataset using techniques such as Random Oversampling and SMOTE (Synthetic Minority Over-sampling Technique).

3.3.4 Streamlit

Streamlit is an open-source Python-based framework that enables the rapid development and deployment of interactive web applications for machine learning. In this study, Streamlit was employed as a key tool to build a user-friendly interface that allows healthcare practitioners and other stakeholders to interact directly with the predictive maternal mortality model.

Its intuitive design allows developers to transform Python scripts into shareable web applications with minimal code. Streamlit supports dynamic user inputs through sliders, forms, dropdowns, and file upload components, making it ideal for real-time data entry and instant prediction generation. This feature is particularly valuable in clinical settings, where frontline healthcare workers can input patient data (e.g., age, blood pressure, maternal age) and immediately receive model predictions regarding maternal health risk. Streamlit was not only instrumental in

deploying the final model but also in bridging the gap between complex machine learning techniques and practical, real-world usability in maternal health interventions.

3.4 Ethical Considerations in Machine Learning for Healthcare

The integration of machine learning (ML) into healthcare introduces a number of ethical considerations that must be carefully addressed to ensure its safe, equitable, and responsible use. Central to ethical ML deployment is the quality and integrity of the data used for training and validation. The performance and reliability of predictive models are fundamentally dependent on the accuracy, completeness, and consistency of input data (Tilala *et al*., 2024). Given that healthcare systems generate vast amounts of information both from manual records and electronic health systems, ensuring data privacy and protection becomes paramount. Any breach of privacy, unauthorized access, or misuse of sensitive patient data can significantly erode public trust in healthcare systems and emerging technologies. Such erosion of trust may lead to reluctance among patients to share data, thereby limiting the potential of ML applications in clinical practice and research (Ganesan & Somasiri, 2024).

Another critical ethical issue is the need for fairness and representativeness in the datasets used to train machine learning models. If the training data lacks diversity across key demographic groups such as gender, ethnicity, geographic location, or socio-economic status, the resulting models may produce biased or discriminatory predictions. These biases can lead to misdiagnoses, inappropriate treatments, and ultimately reinforce existing health disparities (Saputro *et al*., 2024). Therefore, it is essential that datasets are inclusive and reflective of the populations they are intended to serve.

Furthermore, many ML models, especially those based on deep learning and ensemble approaches, suffer from a lack of interpretability (Tilala *et al*., 2024). Often regarded as "black boxes," these models can produce accurate predictions without providing a clear rationale for their decisions (Ganesan & Somasiri, 2024). This lack of explainability poses a significant ethical concern, particularly in clinical settings where transparency is critical for informed decision-making. The adoption of Explainable AI (XAI) methods is therefore essential to enhance transparency, foster trust among clinicians, and support accountability.

Accountability is another pressing ethical concern. When ML-based decisions lead to negative outcomes, it remains unclear who bears the responsibility, the developers, the healthcare providers, or the institution deploying the technology (Olabiyi & Frank, 2024). This ambiguity underscores the need for well-defined ethical and legal frameworks that establish clear lines of accountability and liability in the event of harm (Tilala *et al*., 2024).

According to Saputo *et al*. (2024), the ethical use of ML in healthcare also requires mechanisms for informed consent, algorithmic auditability, and ongoing monitoring. AI systems must be transparent in how patient data is used, subject to regular audits for bias or errors, and continuously updated to reflect evolving medical knowledge, clinical guidelines, and patient populations. Static models may become outdated, posing risks to patient safety and quality of care (Ganesan & Somasiri, 2024). In summary, the ethical deployment of machine learning in healthcare must be grounded in the principles of transparency, accountability, and non-maleficence. Proactively addressing these concerns is essential for building trust, ensuring equitable outcomes, and facilitating the sustainable and responsible use of AI in health systems.

Chapter Four

Results and Discussion

4.0 Introduction

This chapter presents the results obtained from training and testing individual classifiers, as well as the ensemble model with the standardized and primary datasets.

4.1 Results for Standardized dataset

The follow tables show the results for the individual classifiers and stacking ensemble of all base classifiers using the standardized dataset.

Table 4.1: Summary of Training Results

Model	F1_Score	Precision	Recall	Accuracy
Support Vector Classification (SVC)	0.7133	0.7328	0.7202	0.7216
Gaussian Naïve Bayes	0.5703	0.6171	0.5892	0.6082
Multilayer Perceptron (MLP)	0.7321	0.7434	0.7362	0.7361
Decision Tree	0.9270	0.9253	0.9299	0.9261
Random Forest	0.9273	0.9260	0.9293	0.9261
Gradient Boosting Decision Trees (GBDT)	0.8683	0.8700	0.8678	0.8662
Extreme Gradient Boosting (XGB)	0.9271	0.9261	0.9289	0.9261

Table 4.1 presents the performance metrics of various machine learning classifiers during the validation phase, reporting their respective F1-Score, Precision, Recall, and Accuracy.

Table 4.2: Summary of Validation Results

Model	F1_Score	Precision	Recall	Accuracy
Support Vector Classification (SVC)	0.6830	0.7051	0.6961	0.6971
Gaussian Naïve Bayes	0.5611	0.6054	0.5821	0.5996
Multilayer Perceptron (MLP)	0.6720	0.6854	0.6822	0.6813
Decision Tree	0.8154	0.8345	0.8260	0.8105
Random Forest	0.8479	0.8645	0.8532	0.8430
Gradient Boosting Decision Trees (GBDT)	0.7526	0.7614	0.7556	0.7436
Extreme Gradient Boosting (XGB)	0.8268	0.8490	0.8360	0.8213

Table 4.3 presents the performance results of the final stacked ensemble, reporting their respective F1-Score, Precision, Recall, and Accuracy scores. The results indicate that ensemble-based models outperformed traditional classifiers in predicting maternal health risks.

Table 4.3: Performance Results for Stacked Ensemble Model

Performance Metric	Result
F1_Score	0.9133
Precision	0.9189
Recall	0.9182
Accuracy	0.9121

The training results showed Random Forest and Extreme Gradient Boosting with approximately 92.61% accuracy, and highest F1-scores as the best forming algorithms. However, Random Forest was slightly higher in terms of F1-score. The least performing algorithm during training was the Gaussian Naïve Bayes with 60.82% accuracy and 57.03% F1-score. The validation results in Table 4.2 further show that Random Forest with 84.30% accuracy and 84.79% F1-score is the best forming algorithm followed by the Extreme Gradient Boosting with 82.13% accuracy and 82.68% F1-score. The least performing algorithm again was the Gaussian Naïve Bayes with 59.96% accuracy and 56.11% F1-score. The findings presented in Table 4.2 suggests that by implementing bagged and boosted Decision Tree algorithms (such as Random Forest and XGB) with the employed dataset, model prediction of Maternal mortality can be improved (Mienye & Sun, 2022; Mbali, 2024).

Table 4.3 shows the prediction scores of the ensemble model with the maternity dataset. Higher results are obtained compared to all the individual classifiers considered in Table 4.2. It presents an accuracy of 91.21% and F1-score of 91.33%, which values are higher than corresponding ones for both Random Forest and XGB considered earlier. This outcome shows that by developing an ensemble model through stacking the individual classifiers considered, model prediction of Maternal mortality could be enhanced (Mienye & Sun, 2022; Khadka, 2024).

4.2 Performance Results for Primary Dataset

This section presents the performance results of the individual models and the ensemble developed using the primary dataset. It evaluates each model based on key performance metrics, providing insights into their predictive accuracy, robustness, and overall effectiveness.

4.2.1` Performance of Individual Models

Table 4.4 summarizes the training results, Table 4.5 provides an overview of the testing results and Table 4.6 showcases the performance of the ensemble model.

Table 4.4: Summary of Training Performance Results

Classifiers	F1_Score	Precision	Recall	Accuracy
Support Vector Classification (SVC)	0.308959	0.395001	0.369074	0.564936
Gaussian Naïve Bayes	0.675902	0.711995	0.71662	0.685548
Multilayer Perceptron (MLP)	0.629312	0.77701	0.619302	0.737177
Decision Tree	1	1	1	1
Random Forest	1	1	1	1
Gradient Boosting Decision Trees (GBDT)	0.947148	0.958796	0.936851	0.955654
Extreme Gradient Boosting (XGB)	1	1	1	1
Light Gradient Boosting Machine (LightGBM)	1	1	1	1
Categorical Boosting (CatBoost)	0.999212	0.999387	0.99904	0.999013

The training results revealed that Decision Tree, Random Forest, Extreme Gradient Boosting, and Light Gradient Boosting Machine all achieved perfect scores (1.0) across all evaluated performance metrics. This indicates that these tree-based models have likely memorized the training data—a phenomenon common when working with relatively small datasets, such as the 1,582 samples used in this study (Okpono *et al*., 2024).

Table 4.5: Summary of Testing Performance Results

Classifier	F1_Score	Precision	Recall	Accuracy
Support Vector Classification (SVC)	0.289605	0.338474	0.352927	0.541244
Gaussian Naïve Bayes	0.655454	0.707669	0.697896	0.670261
Multilayer Perceptron (MLP)	0.607645	0.698405	0.607162	0.720765
Decision Tree	0.789993	0.797832	0.790753	0.82553
Random Forest	0.842325	0.86714	0.834894	0.886427
Gradient Boosting Decision Trees (GBDT)	0.85694	0.873463	0.851552	0.897226
Extreme Gradient Boosting (XGB)	0.840721	0.85875	0.835387	0.879444
Light Gradient Boosting Machine (LightGBM)	0.842733	0.864576	0.834895	0.884528
Categorical Boosting (CatBoost)	0.839259	0.860744	0.83322	0.883254

As shown in Table 4.2, the testing results displayed a slight decline in performance, though they remained exceptionally high (above 95%). This minor drop is expected but can be partially attributed to the fact that the testing was not conducted on a truly independent dataset, previously unseen by the models, which may have led to optimistic performance estimates (Mutlu *et al*., 2024). The results in Table 4.4 indicate that Gradient Boosting Decision Tree was the best-performing algorithm, with an accuracy of 89.72% and an F1-score of 85.62%. The Support Vector Classification ranked as the lowest-performing algorithm, with 54.12% accuracy and a 28.96% F1-score.

4.2.3 Performance of Stacking Ensemble Model

To enhance the overall performance beyond that of any individual classifier, an ensemble model was constructed using these nine classifiers with Random Forest as the meta learner. The performance of the developed model was evaluated using key metrics, including F1 Score, Precision, Accuracy, and Recall. The results (before upsampling) are as shown in Table 4.3.

Table 4.5: Performance Results for Stacked Ensemble Model before Upsampling

Performance Metric	Result
F1_Score	0.975485
Precision	0.975137
Recall	0.977912
Accuracy	0.982166

Table 4.5 highlights the performance of the ensemble model without upsampling applied to the maternity dataset. The ensemble model outperformed all individual classifiers, achieving an accuracy of 98.21% and an F1-score of 97.55%. These values are higher than that of Gradient Bosting Decision Tree previously considered. This outcome demonstrates that by stacking individual classifiers into an ensemble model, the prediction of maternal mortality can be significantly enhanced (Mienye & Sun, 2022; Khadka, 2024).

Table 4.6: Performance Results for Stacked Ensemble Model after Upsampling

Performance Metric	Result
F1_Score	0.998422
Precision	0.998485

Recall	0.998431
Accuracy	0.998419

The upsampled data performed slightly better as an ensemble than the ensemble without upsampling, achieving an accuracy and FI-score both of 99.84%. The comparison between Table 4.3 and Table 4.4 shows that the upsampling conducted on the data improved the performance of the ensemble.

Table 4.7: Performance Results for Stacked Ensemble Model after dropping low performing models (SVC, GNB, MLP).

Performance Metric	**Result**
F1_Score	0.975991
Precision	0.975744
Recall	0.978309
Accuracy	0.982803

Table 4.8: Performance Results for Stacked Ensemble Model for standardized Dataset using the same base models as Primary Dataset.

Performance Metric	**Result**
F1-Score	0.906666
Precision	0.914547
Recall	0.911048
Accuracy	0.905193

Table 4.8 presents the performance results of the stacked ensemble model developed using the standardized dataset, employing the same base models previously used for the primary dataset. The evaluation metrics, F1-Score, Precision, Recall, and Accuracy, were used to assess the model's predictive performance. The ensemble model trained on the primary dataset outperformed the one developed using the standardized dataset, demonstrating significantly better performance across key evaluation metrics. This comparison provides insights into the consistency and adaptability of the ensemble model across different types of datasets.

4.4 Confusion Matrix Analysis of Ensemble Model with Primary Dataset

To obtain a more detailed understanding of each model's classification performance beyond aggregate metrics like Accuracy and F1-Score, a confusion matrix analysis was carried out. The confusion matrix breaks down predictions into four categories: True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN)**.** This allows for a more granular evaluation of how accurately each model classified individual instances, particularly in distinguishing between high-risk, mid-risk and low-risk maternal health cases. Figure 4.1 depicts the confusion Matrix showing performance of the model after dropping less performing.

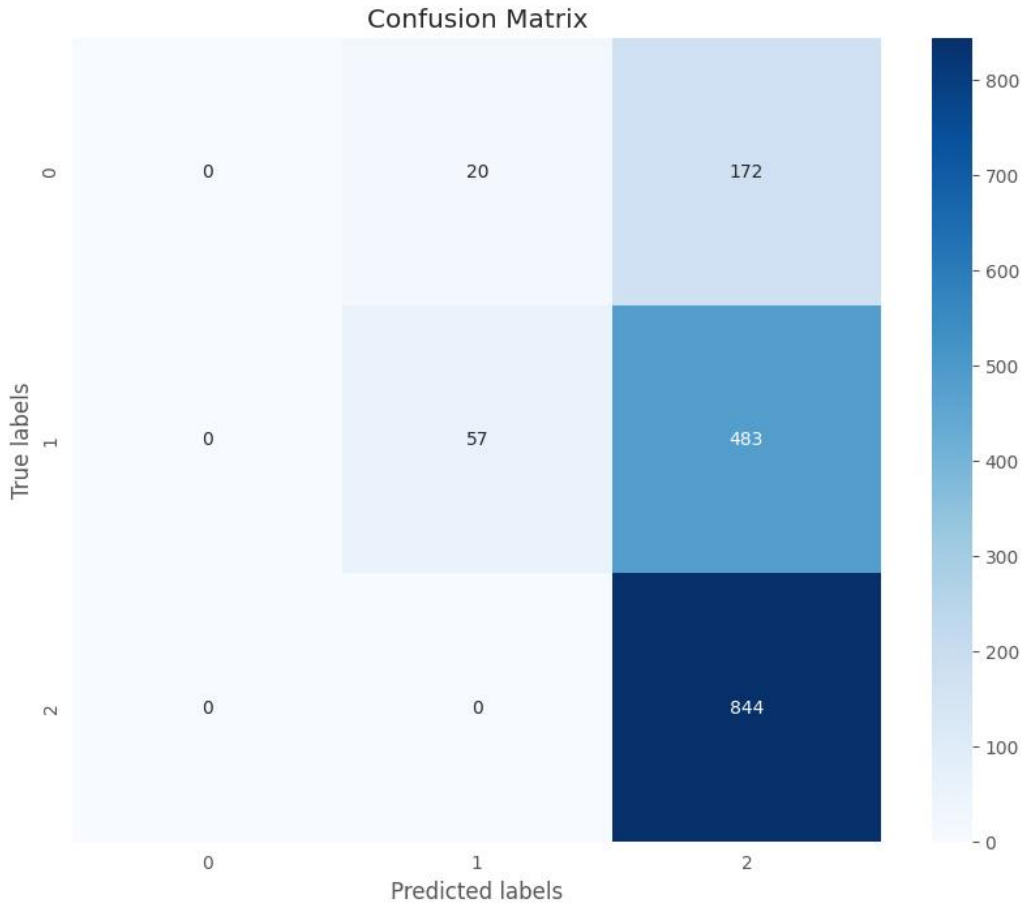

Figure 4.1: Confusion Matrix showing performance of the model before Upsampling.

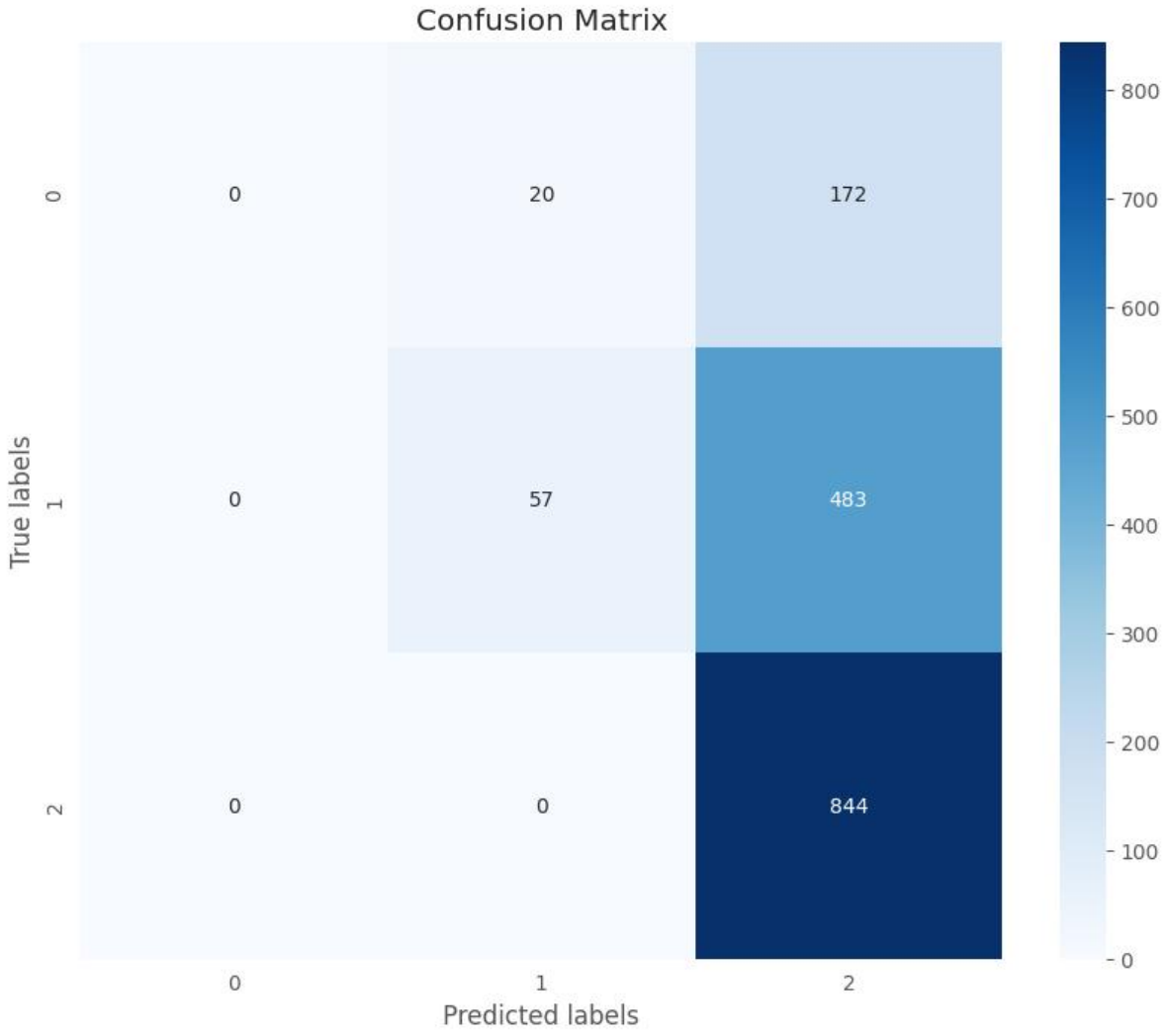

Figure 4.2: Confusion Matrix showing performance of the model before Upsampling

Figure 4.2 presents the confusion matrix for the model's performance on the imbalanced dataset. The diagonal values represent correct predictions for each maternal health risk class. The model achieved perfect accuracy for the low-risk class, correctly classifying all 844 instances. However, it failed entirely to identify any high-risk cases, misclassifying 172 instances as low risk and 20 instances as mid risk. For the mid-risk class, only 57 out of 540 instances were correctly predicted, with the remainder likely misclassified as low risk. These results highlight a significant bias toward the majority class (low risk), a common issue in imbalanced datasets. The model's inability to accurately detect high-risk cases is particularly concerning in clinical applications, as it can lead to poor diagnosis and increased patient risk. Moreover, this skewed performance distorts the overall interpretation of model effectiveness and underscores the

necessity of addressing class imbalance during training. Figure 4.3 depicts the Confusion Matrix showing performance of the model after Upsampling

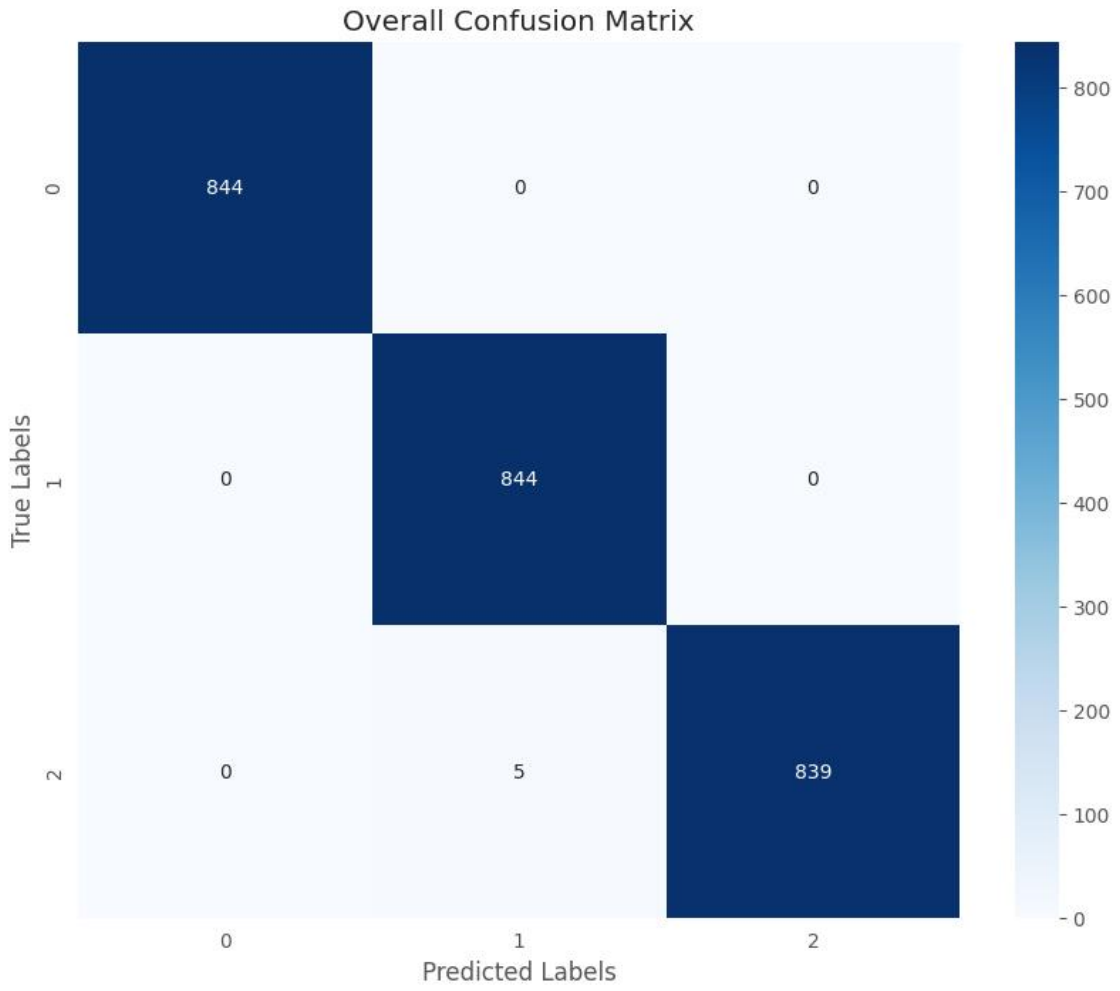

Figure 4.3: Confusion Matrix showing performance of the model after Upsampling.

The confusion matrix in figure 4.3 shows that there were no misclassifications in the High and Mid risk levels. Low risk pregnancies were accurately classified 839 times out of 844 instances. This models displays over 90% rate of accurately classified instances. The higher the accuracy of the model, the better its performance.

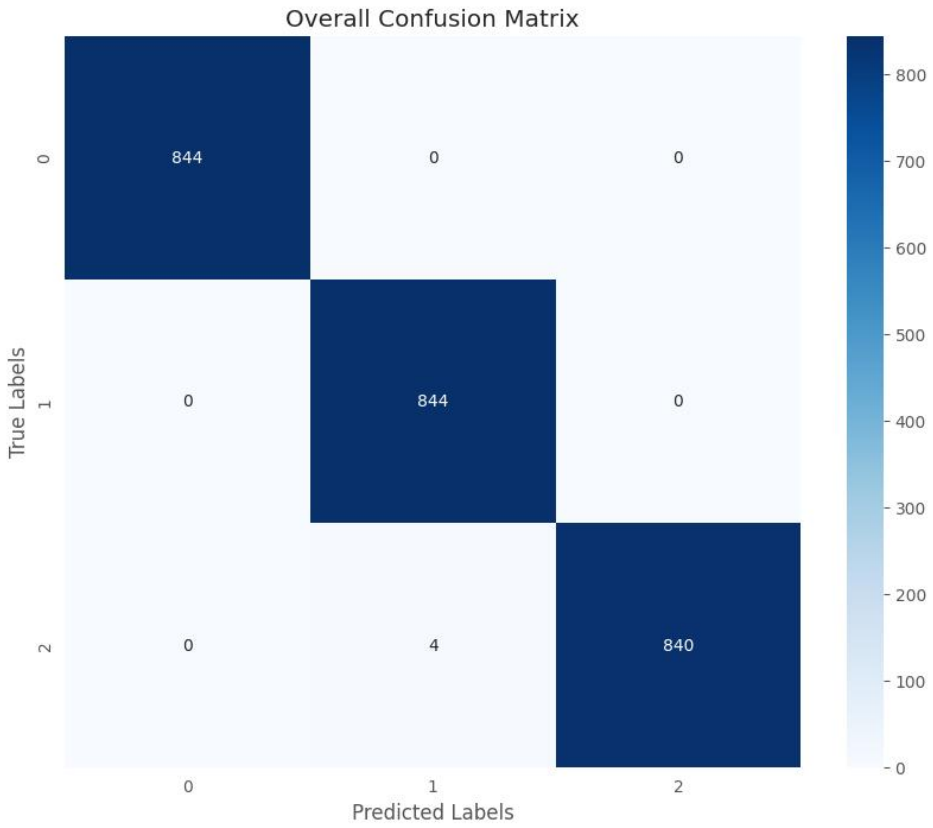

Figure 4.4: Confusion Matrix showing performance of the model after Upsampling and dropping low performing models.

The confusion matrix in figure 4.4 shows that there were no misclassifications in the High and Mid risk levels. Low risk pregnancies were accurately classified 840 times out of 844 instances. The model performed slightly better when low performing models (SVC, MLP and GNB) were removed from the ensemble.

4.5 Explainable Artificial Intelligence (XAI)

As machine learning models, particularly ensemble and deep learning approaches, grow in complexity, their internal decision-making processes increasingly resemble a "black box," thereby limiting transparency and interpretability (Saputro *et al*., 2024). This opacity presents a critical challenge in high-stakes domains such as healthcare, where explainability is essential for fostering trust, ensuring accountability, and supporting clinical decision-making. Explainable Artificial Intelligence (XAI) encompasses a suite of methodologies and tools aimed at enhancing

the interpretability of machine learning model outputs. In this study, SHAP (SHapley Additive exPlanations) was employed to quantify and visualize the contribution of individual features to the model's predictions (Tilala *et al*., 2024).

Figure 4.4 illustrates the feature importance scores generated by the SHAP analysis for the final predictive model. BMI is identified as the most important predictor, followed by Maternal Age**,** Systolic Blood Pressure**,** and Gestational Age. These features consistently contribute high value to the model's learning process. Diastolic Blood Pressure**,** Weight**,** Height**,** and Parity also showed notable influence, while Urine Analysis and the engineered binary feature Non-Negative Urine Analysis exhibited minimal importance, indicating limited impact on the model's predictive decisions.

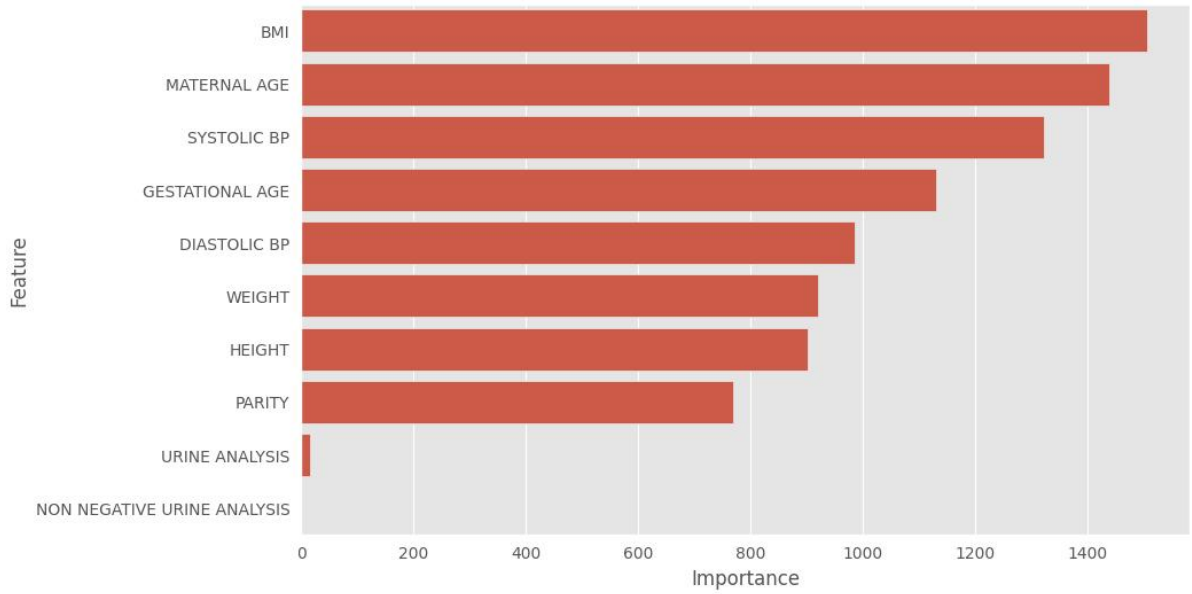

Figure 4.4: Feature Importance scores of the Predictive Model

For feature engineering, a new binary feature, Non-Negative Urine Analysis**,** was engineered from the original Urine Analysis variable to enhance model interpretability and risk classification. The rationale behind creating this feature was to simplify the representation of complex urine test results into a clinically meaningful risk indicator. Incorporating this binary indicator allows for

easier integration into machine learning models and aligns with clinical practice, where any abnormal urine finding typically triggers closer monitoring and intervention. BMI is identified as the most important predictor, followed by Maternal Age**,** Systolic Blood Pressure**,** and Gestational Age**.** These features consistently contribute high value to the model's learning process. Diastolic Blood Pressure**,** Weight**,** Height, and Parity also showed notable influence, while Urine Analysis and the engineered binary feature Non-Negative Urine Analysis exhibited minimal importance, indicating limited impact on the model's predictive decisions.

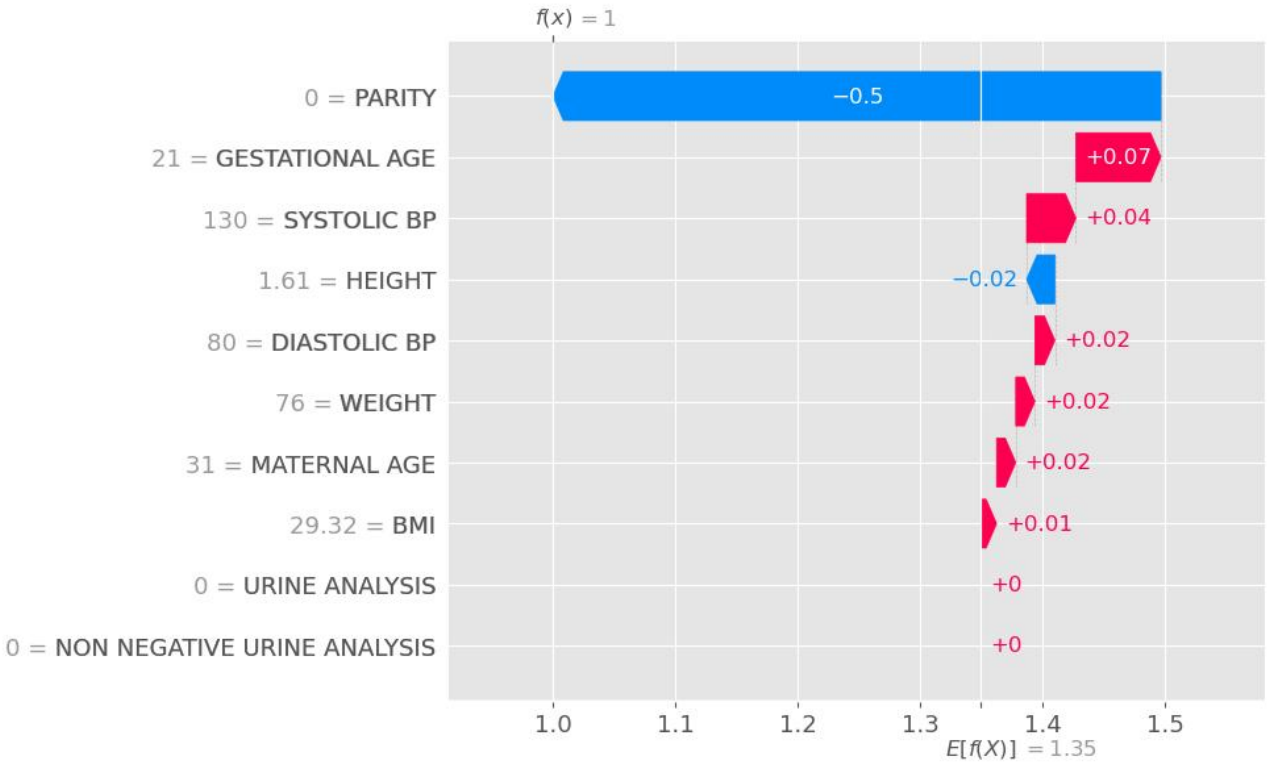

Figure 4.5: SHapely Additive Explanations (SHAP) plot illustrating the contribution of data set features in the prediction model

The feature importance rankings in figure 4.4 align with the Shapely Additive Explanations (SHAP) results in figure 4.5 from individual predictions, where features like Parity**,** Gestational Age, and Systolic Blood Pressure showed significant directional influence (positive or negative)

on the model output. Specifically, SHAP analysis revealed Parity had the strongest negative contribution in one case, while Gestational Age and Systolic BP pushed the prediction higher. Meanwhile, Urine Analysis and Non-Negative Urine Analysis had SHAP values close to zero, reinforcing their limited interpretive and predictive relevance.

4.6 MODEL DEPLOYMENT

To demonstrate the practical application of the developed predictive ensemble model, a user-friendly web-based interface was implemented using Streamlit, an open-source Python framework designed for deploying machine learning models and interactive data applications. Streamlit enables real-time interaction between the user and the predictive model by allowing healthcare providers or users to input key maternal health indicators such as Maternal age, Gestational age, blood pressure (systolic and diastolic), and other relevant parameters. Upon submission, the model processes the inputs and returns a risk classification—Low, Medium, or High—indicating the likelihood of maternal complications. Figure 4.6a and Figure 4.6b show the model implementation results for high risk pregnancy classification.

Figure 4.6a: Model implementation for High risk pregnancy classification

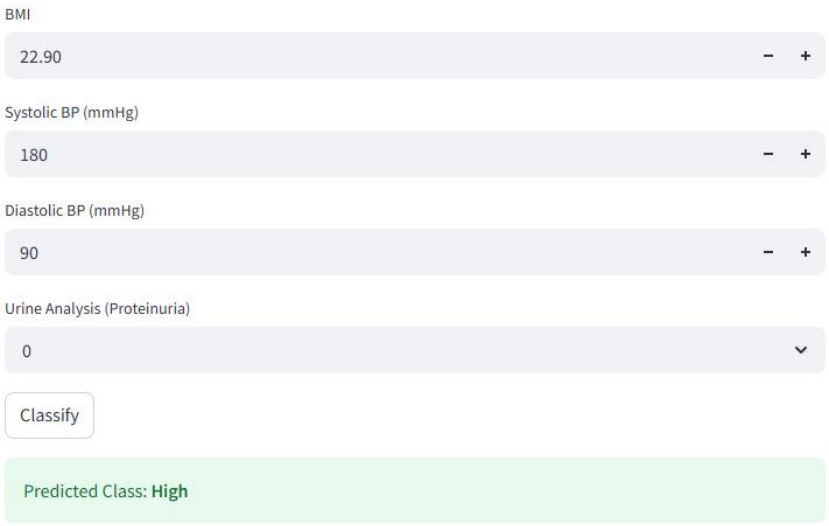

Figure 4.6b: Model implementation for High risk pregnancy classification

Figures 4.7a and 4.7b show the model implementation results for Mid risk pregnancy classification.

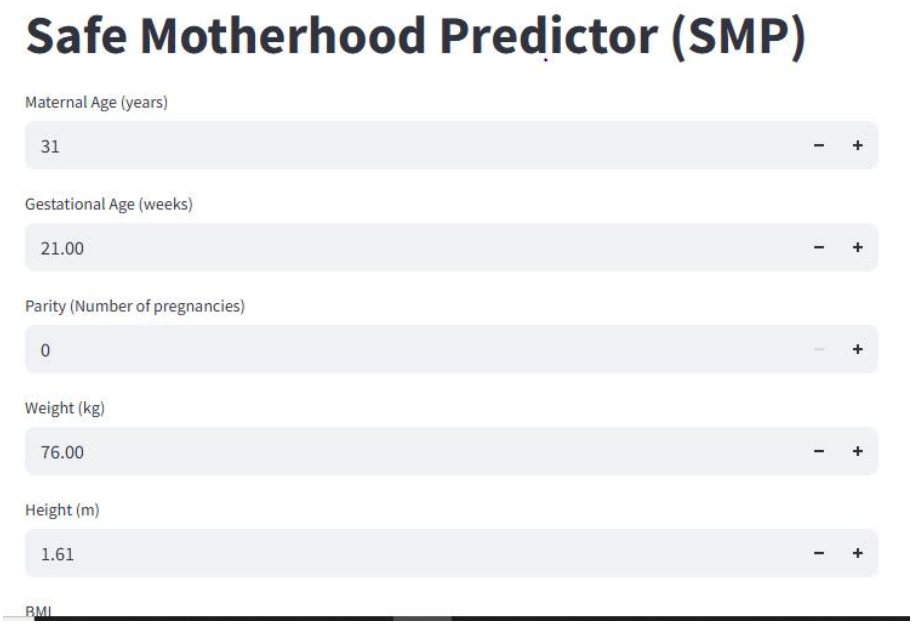

Figure 4.7a: Model implementation for Mid risk pregnancy classification

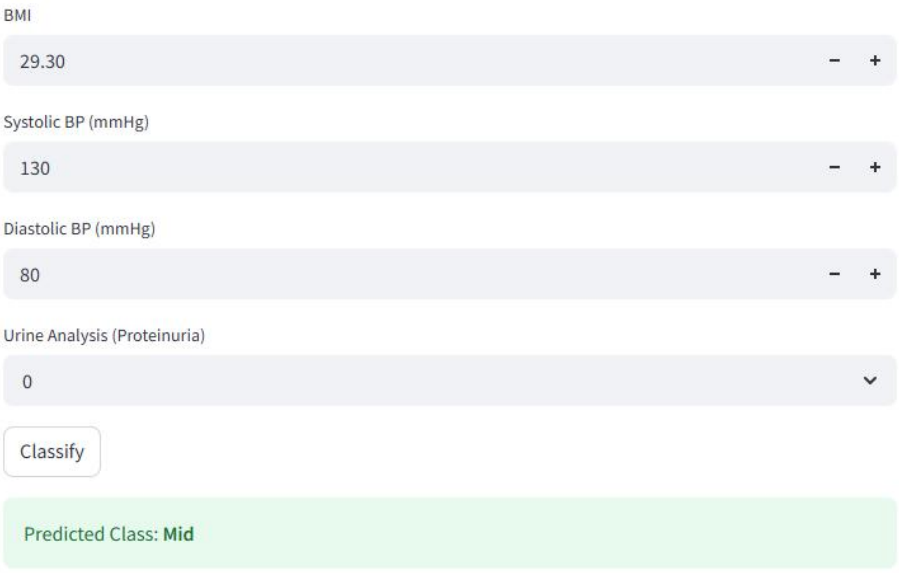

Figure 4.7b: Model implementation for Mid risk pregnancy classification

Figure 4.8a and Figure 4.8b show the model implementation results for Low risk pregnancy classification.

Figure 4.8a: Model implementation for Low risk pregnancy classification

Figure 4.8b: Model implementation for Low risk pregnancy classification

Figures 4.6a–4.8b illustrate the results of the model deployment using the Streamlit interface. These figures demonstrate the model's ability to classify pregnancy risk into three distinct levels: low**,** mid, and high risk. Each classification is based on input variables such as Maternal age, Gestational age, Parity, Weight, Height, Body Mass Index (BMI), blood pressure (systolic and diastolic) and urine analysis (proteinuria). The interface allows for real-time input and risk prediction, providing a user-friendly platform for maternal health risk assessment. The model can be hosted locally or deployed to a cloud platform such as Streamlit Community Cloud, making it accessible to healthcare workers in field locations via web browsers. This implementation serves as a proof-of-concept for integrating AI into maternal healthcare services and lays the foundation for future integration with electronic health records (EHR) or mobile health platforms.

Chapter Five

Summary and Conclusion

Maternal mortality remains a critical challenge in Sub-Saharan Africa, with Nigeria ranking among the countries with the highest rates. If Nigeria is to attain Sustainable Development Goals (SDG) by 2030, increased measures to reduce maternal mortality rate must be implemented. This study employed machine learning to classify maternal health risk during pregnancy using Nine (9) base classifiers, namely, Linear Support Vector Machine, Gaussian Naïve Bayes, Multilayer Perceptron, Decision Tree, Random Forest, Gradient Boosting Decision Tree, Extreme Gradient Boosting, Light Gradient Boosting Machine, and Categorical Boosting. Accurate classification of maternal health risk can bring about individualized maternal care (especially for high risk pregnancies), optimize the use of scare resources and reduce adverse outcomes in pregnancy. The successful implementation and usage of machine learning models should involve the knowledge of the locality of its use therefore real-world data was collected at three (3) different health centers in Delta State during ante-natal visits. Standardized dataset as used in a number of studies (Marzia, 2023; Nirmala & Kambili, 2023; Mutlu *et al*., 2023; Mondal *et al*., 2023; Mustamin *et al*., 2023; Mashrafi *et al*., 2024) may not be a true reflection of the Nigerian populace. This is not the case in this study as real-world data was collected from local health centers and preprocessed for model development.

The accuracy results of the ensemble model is significantly higher than any individual classifier considered. The implementation of the ensemble model can potentially optimize healthcare resources by targeting pregnant women at high risk, facilitate timely clinical decision-making, and consequently improve maternal health outcomes. This model can also be adapted to other states and regions in Nigeria. Future research will focus on expanding the dataset (and range of features) and implementing the model in real-world healthcare environments.

5.1 Research Findings

The research findings from the study are as follows:

i. The leading causes of maternal mortality in Delta State include severe bleeding (postpartum haemorrhage), pregnancy-related infections, hypertensive disorders such as pre-eclampsia, unsafe abortions, sepsis, and obstructed labour. These identified clinical factors have commonly served as input features in various machine learning studies and informed the selection of base classifiers aimed at predicting maternal health risks in this study.

ii. The deployment of the ensemble model has the potential to optimize healthcare resource allocation by accurately identifying high-risk pregnancies, thereby facilitating timely and informed clinical decision-making. This can significantly contribute to improved maternal health outcomes. The model demonstrated strong predictive performance in correctly classifying high-risk cases. Furthermore, its design allows for adaptability and scalability, making it applicable to other states and regions across Nigeria. Future research will focus on expanding the dataset to include a broader range of features and validating the model's effectiveness within real-world clinical settings.

iii. To improve predictive performance, multiple classifiers were integrated using a stacking ensemble learning approach. Among the individual models, the Gradient Boosting Decision Tree (GBDT) recorded the highest accuracy prior to upsampling, achieving 90%, while the Random Forest classifier attained 97% accuracy following upsampling. In contrast, the Linear Support Vector Machine (SVM) demonstrated the lowest performance both before and after upsampling. Notably, the ensemble model outperformed all standalone classifiers, achieving 98% accuracy and precision, with over a 1% increase in accuracy post-upsampling.

iv. To demonstrate the practical application of the developed predictive ensemble model, a user-friendly web-based interface was implemented using Streamlit**,** an open-source Python framework optimized for deploying machine learning models and interactive data applications. This platform facilitates real-time interaction between users and the predictive model by allowing healthcare professionals or end-users to input key maternal

health indicators—such as maternal age, gestational age, systolic and diastolic blood pressure, among other relevant parameters. Upon submission, the model processes these inputs and generates a risk classification output; Low, Medium, or High, indicating the predicted likelihood of maternal complications.

5.2 Contributions to Knowledge

The following listed are the study's contributions to knowledge:

i. A novel machine learning model to reduce maternal mortality in Nigeria by identifying high-risk patients early was developed. This will help maternal healthcare providers to efficiently allocate limited resources for timely interventions to prevent adverse pregnancy outcomes. Addressing high-risk cases proactively will prevent complications that may lead to long-term morbidity and mortality.
ii. The study established a methodological framework for building machine learning models that are sensitive to the unique demographic, clinical, and socio-economic characteristics of specific regions. This framework can be adapted in other under-resourced areas seeking to leverage cutting-edge AI methods for healthcare improvements.

5.3 Conclusion

This study presents a novel approach to predicting maternal health risks using machine learning techniques, specifically through the development of an ensemble model trained on real-world data collected from local health centers in Delta State, Nigeria. The findings demonstrate that machine learning algorithms, particularly ensemble models, can significantly enhance the accuracy of maternal risk classification, enabling the identification of high-risk pregnancies that may otherwise go undetected. By focusing on locally sourced data, this study ensures that the model is tailored to the specific demographic and clinical characteristics of the Nigerian population, which has often been underrepresented in international datasets. This approach is crucial for improving the relevance and applicability of predictive models in real-world healthcare settings. The use of primary data collected from local health centers in Delta State

enhances the contextual accuracy of the model by ensuring that the input features reflect the unique demographic and clinical characteristics of the target population. This localization increases the model's relevance and effectiveness in real-world applications within the region.

The successful implementation of this predictive model has the potential to optimize healthcare resources, guide timely clinical interventions, and ultimately reduce maternal mortality in Delta State. Furthermore, the model's adaptability makes it a promising tool for scaling to other regions within Nigeria and similar low-resource settings in Sub-Saharan Africa. Future research will build on these findings by expanding the dataset, incorporating additional features, and working toward real-world deployment in healthcare environments. As machine learning continues to evolve, its application in maternal healthcare holds immense potential to revolutionize the way maternal risks are managed, improving both maternal and infant health outcomes.

5.4 RECOMMENDATIONS FOR FURTHER STUDIES

The following are recommendations for future research:

i. Healthcare institutions should emphasize the collection of clean, standardized, and representative data from both rural and urban areas. The adoption of Electronic Health Records (EHRs) should be promoted over manual data entry systems to enhance data quality, accessibility, and reliability.
ii. The inclusion of additional features such as medical history, nutritional status, socio-economic factors, and lifestyle behaviors could enhance model accuracy and provide deeper insight into maternal risk factors.
iii. It is recommended that future work involves the deployment of the model in clinical or public health settings to evaluate its effectiveness in real-time decision support systems. This would also help assess the model's usability, interpretability, and impact on maternal health outcomes.
iv. Government health agencies and other stakeholders in healthcare should integrate machine learning tools into maternal health programs for early detection and prevention strategies. Medical personnel should be trained to understand and interpret ML-based decision-support systems, particularly those involving Explainable Artificial Intelligence (XAI) tools.

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- Efevberha-Ogodo, O., Egbokhare, F. A. & Chete, F. O. (2025). Towards the Development of a Predictive Machine Learning Model for Maternal Mortality in Nigeria. *NIPES Journal of Science and Technology Research*, 7(*2*). (Published/Scopus-Indexed)
- Efevberha-Ogodo, O., Egbokhare, F. A. & Chete, F. O. (2025). An Ensemble Model for Maternal Health Risk Classification in Delta State, Nigeria. *Applied Computer Science (ACS) Journal*, 21(*3*). Pp 53-64. ISSN: 2353-6977. (Published/Scopus-Indexed)
- Efevberha-Ogodo, O., Egbokhare, F. A. & Chete, F. O. (2025). Classification of Pregnancy Health Risk using Tree-based Ensemble Models. *Library Progress International*,45(*1*). ISSN:0970-1052. (Accepted/Scopus-Indexed)

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Appendix A: Compiled Maternal Dataset

MATERNAL AGE	GESTATIONAL AGE	PARITY	WEIGHT	HEIGHT	BMI	SYSTOLIC BP	DIASTOLIC BP	URINE ANALYSIS	RISK LEVEL
25	41	0	67	1.71	22.91303	180	90	NEGATIVE	High
31	21	0	76	1.61	29.31986	130	80	NEGATIVE	Mid
40	16	0	90	1.65	33.05785	140	90	NEGATIVE	High
30	19	0	57	1.33	32.22342	130	80	NEGATIVE	Mid
33	25	3	78	1.61	30.09143	120	60	NEGATIVE	Mid
31	14	1	82	1.6	32.03125	110	80	NEGATIVE	Low
28	24	3	72	1.66	26.12861	110	60	NEGATIVE	Low
20	13	0	53	1.69	18.55677	110	60	POSITIVE	Mid
33	24	2	87	1.62	33.15043	130	90	NEGATIVE	Low
28	19	1	85	1.72	28.73175	114	59	NEGATIVE	Low
26	40	1	67	1.75	21.87755	100	70	NEGATIVE	Low
27	20	1	60	1.73	20.04745	110	80	NEGATIVE	Low
27	20	1	60	1.5	26.66667	110	70	NEGATIVE	Low
29	37	0	62	1.5	27.55556	100	70	NEGATIVE	Mid
31	16	1	84	1.75	27.42857	100	70	POSITIVE	Low
34	24	3	85	1.65	31.2213	120	80	NEGATIVE	Low
30	24	0	74	1.54	31.20256	120	80	NEGATIVE	Mid
36	29	2	59	1.62	22.48133	110	30	NEGATIVE	Low
37	34	1	75	1.63	28.22839	120	80	NEGATIVE	Low
35	18	4	66	1.68	23.38435	100	60	NEGATIVE	High
31	13	1	67	1.63	25.21736	120	80	NEGATIVE	Low

24	14	0	56	1.63	21.0772	110	70	NEGATIVE	Mid
21	22	0	64	1.71	21.88708	110	60	NEGATIVE	Mid
23	6	0	56	1.6	21.875	110	80	NEGATIVE	Mid
32	20	5	58	1.55	24.14152	110	50	NEGATIVE	High
41	15	0	77	1.65	28.28283	110	60	NEGATIVE	High
37	32	1	74	160	0.002891	100	60	POSITIVE	Low
26	17	0	84	1.63	31.61579	110	80	NEGATIVE	Mid
31	37	2	77	1.6	30.07813	90	60	NEGATIVE	Low
23	21	3	72	1.61	27.77671	110	60	NEGATIVE	Low
35	15	1	55	1.5	24.44444	146	100	NEGATIVE	Mid
24	37	0	65	1.74	21.46915	110	70	NEGATIVE	Mid
33	19	2	90	1.69	31.5115	110	70	NEGATIVE	Low
30	18	1	75	1.6	29.29688	100	60	NEGATIVE	Low
30	23	0	55	1.64	20.44914	100	50	NEGATIVE	Mid
30	28	1	60	1.64	22.30815	100	60	NEGATIVE	Low
29	25	0	124	1.67	44.46197	130	80	NEGATIVE	Mid
29	25	2	84	1.6	32.8125	140	80	NEGATIVE	Mid
28	14	0	67	1.6	26.17188	110	60	NEGATIVE	Mid
34	19	1	67	1.63	25.21736	100	70	NEGATIVE	Low
28	13	0	63	1.69	22.05805	120	80	NEGATIVE	Mid
34	17	2	70	1.73	23.38869	105	70	NEGATIVE	Low
32	24	0	62	1.65	22.77319	110	60	NEGATIVE	Mid
33	13	2	72	1.8	22.22222	100	60	NEGATIVE	Low
36	15	0	56	1.69	19.60716	90	60	NEGATIVE	Mid

22	38	1	52	1.45	24.732 46	150	100	NEGATIVE	Mid
39	34	5	73	1.62	27.815 88	110	60	NEGATIVE	High
27	33	1	75	1.52	32.461 91	140	90	NEGATIVE	Mid
34	18	0	73	1.59	28.875 44	120	78	NEGATIVE	Mid
20	32	0	64	1.69	22.408 18	100	70	NEGATIVE	Mid
40	12	3	52	1.59	20.568 81	170	100	NEGATIVE	High
33	13	1	45	1.31	26.222 25	110	70	NEGATIVE	Mid
30	12	0	62	1.32	35.583 1	100	80	NEGATIVE	Mid
32	34	1	65	1.56	26.709 4	100	60	NEGATIVE	Mid
35	37	1	85	1.58	34.049 03	120	70	NEGATIVE	Mid
32	24	0	67	1.32	38.452 71	98	70	NEGATIVE	Mid
26	35	0	55	1.57	22.313 28	100	70	NEGATIVE	Mid
35	30	0	65	1.56	26.709 4	122	79	NEGATIVE	Mid
34	38	1	57	1.55	23.725 29	104	60	NEGATIVE	Mid
33	7	1	78	1.62	29.721 08	120	80	NEGATIVE	Mid
35	24	3	68	1.58	27.239 22	100	60	NEGATIVE	Mid
26	17	0	56	1.68	19.841 27	120	80	NEGATIVE	Mid
27	3	1	91	1.5	40.444 44	148	90	NEGATIVE	Mid
30	26	2	72	1.32	41.322 31	122	63	NEGATIVE	Low
39	31	0	60	1.31	34.963	120	70	NEGATIVE	Mid
21	38	0	64	1.62	24.386 53	160	120	NEGATIVE	High
29	18	0	63	1.66	22.862 53	110	60	NEGATIVE	Mid
25	18	0	92	1.68	32.596 37	110	60	NEGATIVE	Mid
25		0	77	1.57	31.238 59	120	60	NEGATIVE	Mid

28	18	3	62	1.34	34.52885	120	60	NEGATIVE	Low
36	36	3	98	1.7	33.91003	110	70	NEGATIVE	Low
34	40	2	90	1.69	31.5115	99	57	NEGATIVE	Low
21	30	0	59	162	0.002248	120	60	NEGATIVE	Mid
33	37	3	54	1.44	26.04167	120	86	NEGATIVE	Low
37	33	2	78	1.57	31.64429	110	70	NEGATIVE	Low
21	30	0	63	1.61	24.30462	100	56	NEGATIVE	Low
32	31	1	90	1.58	36.05191	110	80	NEGATIVE	Mid
40	25	3	63	1.38	33.08129	100	70	NEGATIVE	Mid
42	23	1	68	1.46	31.90092	100	60	NEGATIVE	Mid
27	17	1	70	1.54	29.51594	140	80	NEGATIVE	Mid
27	32	1	69	1.63	25.97012	111	73	NEGATIVE	Low
32	30	3	98	1.7	33.91003	120	70	NEGATIVE	Low
33	18	0	85	1.63	31.99217	160	100	NEGATIVE	High
19	31	1	56	1.52	24.23823	100	60	NEGATIVE	Mid
27	29	0	51	1.76	16.46436	110	70	NEGATIVE	Low
31	19	1	65	1.68	23.03005	110	70	NEGATIVE	Low
21	19	0	60	1.67	21.51386	120	60	NEGATIVE	Mid
30	32	0	76	1.31	44.28646	116	60	NEGATIVE	Mid
42	10	1	90	1.64	33.46222	120	90	NEGATIVE	Low
20	34	0	87	1.62	33.15043	100	60	POSITIVE	Mid
21	15	0	65	1.62	24.76757	100	70	NEGATIVE	Mid
37	17	2	78	1.59	30.85321	100	60	POSITIVE	Mid
23	19	0	92	1.74	30.387	130	80	NEGATIVE	Mid

					11				
22	38	0	56	1.65	20.56933	150	110	NEGATIVE	High
30	23	0	104	1.4	53.06122	130	90	NEGATIVE	Mid
39	18	3	89	1.7	30.79585	100	60	NEGATIVE	Low
30	31	0	64	1.67	22.94812	100	80	NEGATIVE	Mid
25	23	1	70	1.72	23.66144	116	65	NEGATIVE	Low
27	40	0	84	1.64	31.23141	111	70	NEGATIVE	Mid
32	14	1	66	1.65	24.24242	110	80	POSITIVE	Low
23	34	1	67	161	0.002585	100	50	NEGATIVE	Low
46	36	1	90	1.63	33.87406	120	80	NEGATIVE	High
34	26	2	74	1.38	38.85738	90	60	NEGATIVE	Mid
26	25	2	64	1.72	21.63332	120	80	NEGATIVE	Mid
39	19	0	74	1.72	25.01352	120	70	NEGATIVE	Mid
29	40	0	92	1.66	33.38656	168	110	NEGATIVE	High
36	21	2	90	1.66	32.66076	109	73	NEGATIVE	Mid
29	19	1	58	1.61	22.37568	110	70	NEGATIVE	Low
31	37	0	63	1.65	23.1405	130	70	NEGATIVE	Mid
31	27	0	75	1.58	30.04326	110	60	NEGATIVE	Mid
37	34	1	60	1.59	23.73324	100	70	POSITIVE	Low
35	16	2	81	1.6	31.64063	100	70	NEGATIVE	Mid
31	24	0	89	1.61	34.3351	120	75	NEGATIVE	Mid
38	25	0	73	1.5	32.44444	130	60	NEGATIVE	Mid
36	12	2	59	1.32	33.86134	120	60	NEGATIVE	Mid
36	13	2	76	1.59	30.0621	90	60	NEGATIVE	Mid

23	12	3	72	1.7	24.91349	110	70	NEGATIVE	Low
28	11	0	52	1.51	22.80602	90	70	NEGATIVE	Mid
24	22	0	58	1.53	24.7768	90	50	NEGATIVE	Mid
32	39	1	81	1.63	30.48666	110	60	NEGATIVE	Low
34	23	1	67	1.71	22.91303	120	80	NEGATIVE	Low
39	25	3	71	1.69	24.85907	100	60	NEGATIVE	Low
38	10	2	37	1.67	13.26688	100	60	NEGATIVE	Mid
33	23	3	91	1.67	32.62935	110	60	POSITIVE	Low
22	17	0	60	1.31	34.963	120	60	NEGATIVE	Mid
30	20	2	62	1.62	23.62445	110	60	NEGATIVE	Mid
28	34	1	74	1.63	27.85201	120	60	NEGATIVE	Low
26	13	0	62	1.59	24.52435	98	61	POSITIVE	Mid
19	35	0	63	1.59	24.9199	120	60	NEGATIVE	Mid
37	26	0	50	1.5	22.22222	110	60	NEGATIVE	Mid
38	29	2	64	1.64	23.79536	107	67	NEGATIVE	Mid
36	22	0	57	1.66	20.68515	100	70	NEGATIVE	Mid
30	16	2	67	1.64	24.91077	120	60	NEGATIVE	Mid
32	13	3	53	1.64	19.70553	120	80	NEGATIVE	Low
31	28	0	90	1.69	31.5115	160	90	NEGATIVE	Mid
39	19	1	74	1.64	27.51338	120	70	NEGATIVE	Low
34	25	6	67	1.71	22.91303	110	60	NEGATIVE	High
38	12	0	81	1.61	31.24879	120	80	POSITIVE	Mid
40	22	1	82	1.49	36.93527	120	80	NEGATIVE	Mid
37	9	1	79	1.57	32.04998	110	60	NEGATIVE	Low

38	23	0	71	1.68	25.1559	130	50	NEGATIVE	Mid
36	34	2	76	1.67	27.25089	145	90	NEGATIVE	High
36	26	0	76	1.61	29.31986	130	80	POSITIVE	Mid
29	34	0	83	1.66	30.12048	100	60	NEGATIVE	Mid
28	14	1	66	1.48	30.13148	110	60	NEGATIVE	Low
21	22	1	94	1.7	32.52595	110	70	POSITIVE	Low
28	11	0	56	1.3	33.13609	100	70	NEGATIVE	Mid
28	29	1	57	1.6	22.26563	110	60	NEGATIVE	Low
24	25	2	44	1.49	19.81893	100	60	NEGATIVE	Mid
26	22	6	82	1.62	31.24524	100	80	NEGATIVE	High
29	34	1	91	1.65	33.42516	110	70	NEGATIVE	Low
39	38	0	84	1.65	30.85399	110	60	POSITIVE	Mid
29	27	1	75	1.64	27.88519	97	62	NEGATIVE	Low
19	20	0	41	1.5	18.22222	100	60	NEGATIVE	Low
26	22	1	64	1.62	24.38653	120	70	NEGATIVE	Low
28	17	1	75	1.53	32.03896	120	70	NEGATIVE	Low
29	21	1	60	1.57	24.34176	120	70	POSITIVE	Low
31	33	1	62	1.63	23.33547	155	88	NEGATIVE	Mid
21	30	1	43	1.65	15.79431	140	60	NEGATIVE	Low
31		1	61	1.62	23.24341	165	75	NEGATIVE	Mid
31	23	0	52	1.63	19.57168	98	62	POSITIVE	Mid
29	38	1	79	1.64	29.3724	110	60	NEGATIVE	Low
33	33	3	78	1.62	29.72108	120	70	NEGATIVE	Low
33	13	0	45	1.3	26.627	110	70	NEGATIVE	Mid

					22				
19	18	1	55	1.59	21.75547	120	60	NEGATIVE	Low
40	10	0	81	1.65	29.75207	170	100	POSITIVE	High
40	13	0	83	1.61	32.02037	120	80	NEGATIVE	High
38	21	1	65	1.62	24.76757	100	60	NEGATIVE	Low
21	17	1	93	1.63	35.0032	120	80	POSITIVE	Low
28	27	0	69	1.68	24.44728	120	70	POSITIVE	Mid
26		2	52	1.72	17.57707	118	74	NEGATIVE	Mid
33	25	2	82	1.67	29.40227	110	60	NEGATIVE	Mid
31	11	1	67	1.63	25.21736	120	80	NEGATIVE	Mid
32	23	0	77	1.65	28.28283	120	80	NEGATIVE	Mid
23	24	0	62	1.61	23.91883	120	70	NEGATIVE	Mid
31	33	3	91	1.58	36.45249	100	60	NEGATIVE	Low
24	32	2	69	1.62	26.29172	102	80	NEGATIVE	Mid
21	32	0	60	1.64	22.30815	100	60	NEGATIVE	Mid
30	6	0	59	1.52	25.5367	100	60	NEGATIVE	Mid
28	27	0	70	1.64	26.02617	108	80	NEGATIVE	Mid
24	3	3	65	1.54	27.40766	100	80	NEGATIVE	Low
29	13	3	71	1.59	28.08433	110	60	NEGATIVE	Low
30	27	4	60	1.52	25.96953	102	80	NEGATIVE	Mid
26	26	2	61	1.72	20.61925	100	70	NEGATIVE	Low
32	31	3	58	1.56	23.833	90	60	NEGATIVE	Low
35	32	2	59	1.65	21.67126	110	70	NEGATIVE	Low
34	34	0	81	1.59	32.03987	110	80	NEGATIVE	Mid

31	38	4	75	1.63	28.22839	120	60	NEGATIVE	High
29	24	4	84	1.57	34.07846	110	50	NEGATIVE	High
30	18	4	75	1.53	32.03896	105	70	NEGATIVE	High
26	12	5	66	1.49	29.72839	100	60	NEGATIVE	High
30	34	3	48	1.57	19.47341	100	60	NEGATIVE	Low
24	34	4	24	1.57	9.736703	120	80	NEGATIVE	High
31	24	2	64	1.59	25.31545	110	80	NEGATIVE	Low
26	20	1	59	1.6	23.04688	140	70	NEGATIVE	Low
21	32	0	58	1.62	22.10029	120	60	NEGATIVE	Mid
21	32	3	59	1.58	23.63403	100	80	NEGATIVE	Low
26	38	5	62	1.6	24.21875	110	80	NEGATIVE	High
23	22	3	85	1.8	26.23457	110	80	NEGATIVE	Low
32	28	2	66	1.6	25.78125	98	100	NEGATIVE	Low
35	30	0	58	1.62	22.10029	120	90	NEGATIVE	Mid
29	15	2	72	1.67	25.81663	100	70	NEGATIVE	Low
30	33	2	68	1.54	28.67263	100	80	NEGATIVE	Low
26	33	0	61	1.67	21.87242	100	80	NEGATIVE	Mid
30	29	0	81	94	0.009167	100	70	NEGATIVE	Mid
34	30	1	68	1.6	26.5625	110	60	NEGATIVE	Low
29	30	0	52	1.57	21.09619	100	70	NEGATIVE	Mid
23	23	1	85	1.7	29.41176	110	70	NEGATIVE	Low
26	27	0	68	1.58	27.23922	125	80	NEGATIVE	Mid
35	24	1	81	1.66	29.39469	110	80	NEGATIVE	Low
41	30	3	68	1.58	27.239	100	60	NEGATIVE	Low

					22				
24	34	2	69	1.55	28.72008	120	70	NEGATIVE	Low
34	24	1	76	1.56	31.22945	110	70	NEGATIVE	Low
31	11	0	67	1.58	26.83865	106	60	NEGATIVE	Mid
29	4	0	75	1.73	25.05931	109	43	NEGATIVE	Mid
21	21	2	72	1.58	28.84153	105	53	NEGATIVE	Low
30	34	2	80	1.62	30.48316	130	60	NEGATIVE	Low
27	32	0	90	1.67	32.27079	109	68	NEGATIVE	Mid
32	20	0	61	1.64	22.67995	111	69	NEGATIVE	Mid
30	21	0	64	1.52	27.70083	113	67	NEGATIVE	Mid
32	26	2	63	1.56	25.88757	96	60	NEGATIVE	Low
30	32	0	49	1.66	17.78197	112	57	NEGATIVE	Mid
32	34	3	85	1.62	32.38836	116	70	NEGATIVE	Low
26	27	1	69	1.67	24.74094	132	77	NEGATIVE	Low
34	28	3	59	1.66	21.41094	121	57	NEGATIVE	Low
25	26	2	53	1.57	21.50189	107	65	NEGATIVE	Low
26	36	1	54	1.59	21.35991	86	50	NEGATIVE	Low
31	38	2	54	1.54	22.76944	115	61	NEGATIVE	Low
22	17	2	52	1.66	18.87066	94	69	NEGATIVE	Low
17	24	7	53	1.61	20.44674	106	59	NEGATIVE	High
32	32	0	62	1.52	26.83518	102	52	NEGATIVE	Mid
34	36	3	71	1.51	31.13899	140	80	NEGATIVE	Low
27	30	2	71	1.55	29.55255	120	70	NEGATIVE	Low
32	32	3	68	1.57	27.58733	110	65	NEGATIVE	Low

24	28	0	65	1.64	24.16716	95	58	NEGATIVE	Mid
18	30	0	63	1.68	22.32143	106	60	NEGATIVE	Mid
26	27	0	86	1.6	33.59375	105	51	NEGATIVE	Mid
25	17	2	60	1.6	23.4375	105	59	NEGATIVE	Low
25	32	3	66	1.61	25.46198	113	64	NEGATIVE	Low
26	24	0	63	1.6	24.60938	117	70	NEGATIVE	Mid
34	24	0	80	1.56	32.87311	138	75	NEGATIVE	Mid
32	20	0	80	1.82	24.15167	111	60	NEGATIVE	Mid
24	30	0	50	1.61	19.28938	121	72	NEGATIVE	Mid
27	31	1	89	1.66	32.29787	128	77	NEGATIVE	Low
32	34	0	62	1.7	21.45329	114	88	NEGATIVE	Mid
32	18	0	88	1.65	32.32323	115	71	NEGATIVE	Mid
24	25	1	65	1.56	26.7094	103	57	NEGATIVE	Low
25	22	2	60	1.67	21.51386	109	57	NEGATIVE	Mid
31	20	1	64	1.71	21.88708	111	67	NEGATIVE	Low
21	32	1	95	1.48	43.37107	111	81	NEGATIVE	Low
23	20	0	79	1.56	32.4622	115	70	NEGATIVE	Mid
24	36	0	65	1.54	27.40766	118	67	NEGATIVE	Mid
26	18	2	60	1.66	21.77384	107	62	NEGATIVE	Low
24	30	1	60	1.64	22.30815	171	69	NEGATIVE	Low
22	27	0	95	1.63	35.75596	140	81	NEGATIVE	Mid
21	20	3	79	1.59	31.24876	104	65	NEGATIVE	Low
22	38	2	78	1.58	31.24499	115	76	NEGATIVE	Low
19	35	0	68	1.57	27.587	116	78	NEGATIVE	Mid

					33				
40	33	0	80	1.61	30.86301	115	71	NEGATIVE	Mid
21	33	1	60	1.62	22.86237	152	89	NEGATIVE	Low
32	28	2	85	1.61	32.79194	141	74	NEGATIVE	Low
21	35	1	118	1.65	43.34252	113	51	NEGATIVE	Low
32	32	2	51	1.56	20.95661	114	71	NEGATIVE	Low
29	28	1	73	1.66	26.49151	106	51	NEGATIVE	Low
30	8	3	74	1.58	29.64269	115	71	NEGATIVE	Low
32	27	2	58	1.55	24.14152	106	65	NEGATIVE	Low
26	42	0	79	1.59	31.24876	106	61	NEGATIVE	Mid
31	15	0	81	1.71	27.70083	121	77	NEGATIVE	Mid
36	20	1	86	1.65	31.58861	102	47	NEGATIVE	Low
23	20	1	49	1.56	20.13478	117	63	NEGATIVE	Low
33	37	2	68	1.56	27.94214	86	50	NEGATIVE	Low
21	22	3	54	1.58	21.63115	105	61	NEGATIVE	Low
27	29	2	52	1.64	19.33373	120	77	NEGATIVE	Low
27	33	0		1.69	0	94	69	NEGATIVE	Mid
17	29	0	53	1.72	17.91509	106	59	NEGATIVE	Mid
32	24	1	62	1.68	21.96712	102	52	NEGATIVE	Low
34	30	1	71	1.5	31.55556	140	80	NEGATIVE	Low
27	29	2	79	1.61	30.47722	120	70	NEGATIVE	Low
32	20	0	68	1.62	25.91068	110	65	NEGATIVE	Mid
24	16	0	65	1.65	23.87511	95	58	NEGATIVE	Mid
18	30	0	63	1.55	26.22268	106	60	NEGATIVE	Mid

26	19	0	86	1.66	31.20917	105	51	NEGATIVE	Mid
25	28	3	60	1.71	20.51913	105	59	NEGATIVE	Low
25	42	2	66	1.63	24.84098	113	64	NEGATIVE	Low
26	32	0	63	1.59	24.9199	117	70	NEGATIVE	Mid
34	34	0	80	1.76	25.82645	132	75	NEGATIVE	Mid
32	30	1	80	1.51	35.08618	111	60	NEGATIVE	Low
24	36	2	50	1.52	21.64127	121	72	NEGATIVE	Low
27	29	1	89	1.61	34.3351	128	77	NEGATIVE	Low
32	32	2	62	1.62	23.62445	114	88	NEGATIVE	Low
32	30	2	88	1.63	33.12131	120	63	NEGATIVE	Low
26	34	3	86	1.75	28.08163	96	55	NEGATIVE	Low
23	37	2	63	1.56	25.88757	125	74	NEGATIVE	Low
30	35	0	60	1.57	24.34176	108	54	NEGATIVE	Mid
35	34	0	58	1.54	24.45606	84	38	NEGATIVE	Mid
35	32	1	58	1.6	22.65625	118	64	NEGATIVE	Low
36	28	1	92	1.48	42.00146	110	70	NEGATIVE	Low
18	36	0	85	1.66	30.84628	124	70	NEGATIVE	Mid
28	28	0	70	1.54	29.51594	130	80	NEGATIVE	Mid
22	32	1	86	1.57	34.88985	100	64	NEGATIVE	Low
24	36	0	76	1.66	27.5802	74	69	NEGATIVE	Mid
17	32	2	55	1.67	19.72104	101	51	NEGATIVE	Low
23	28	0	59	1.68	20.9042	125	70	NEGATIVE	Mid
27	40	4	78	1.81	23.8088	120	72	NEGATIVE	High
18	27	1	89	1.67	31.912	114	63	NEGATIVE	Low

					22				
32	15	0	65	1.6	25.39063	97	40	NEGATIVE	Mid
35	33	2	58	1.67	20.79673	106	69	NEGATIVE	Low
32	40	1	64	1.56	26.29849	127	56	NEGATIVE	Low
29	31	0	108	1.53	46.1361	107	44	NEGATIVE	Mid
23	28	1	43	1.58	17.2248	115	63	NEGATIVE	Low
18	36	1	63	1.56	25.88757	115	63	NEGATIVE	Mid
26	30	3	86	1.67	30.83653	99	65	NEGATIVE	Low
45	10	1	68	1.52	29.43213	117	64	NEGATIVE	Low
28	22	2	83	1.68	29.4076	116	66	NEGATIVE	Low
31	22	1	64	1.52	27.70083	101	53	NEGATIVE	Low
32	34	0	77	1.65	28.28283	98	49	NEGATIVE	Mid
29	32	0	78	1.59	30.85321	139	56	NEGATIVE	Mid
34	33	0	107	1.55	44.53694	100	55	NEGATIVE	Mid
29	17	1	101	1.66	36.65263	119	59	NEGATIVE	Low
29	28	0	92	1.68	32.59637	87	47	NEGATIVE	Mid
31	19	2	55	1.66	19.95936	102	50	NEGATIVE	Low
21	22	2	66	1.6	25.78125	128	58	NEGATIVE	Low
32	50	2	49	1.69	17.15626	117	53	NEGATIVE	Low
30	23	2	69	1.57	27.99302	110	70	NEGATIVE	Low
37	35	0	62	1.56	25.47666	86	42	NEGATIVE	Mid
23	20	0	65	1.67	23.30668	107	56	NEGATIVE	Mid
43	40	0	66	1.52	28.56648	152	90	NEGATIVE	Mid
35	30	0	85	1.68	30.11621	120	70	NEGATIVE	Mid

32	40	4	78	1.52	33.76039	97	58	NEGATIVE	High
18	37	0	62	1.65	22.77319	127	74	NEGATIVE	Mid
24	31	0	75	1.59	29.66655	123	75	NEGATIVE	Mid
30	30	3	63	1.55	26.22268	120	70	NEGATIVE	Low
35	32	1	75	1.66	27.2173	135	62	NEGATIVE	Mid
32	30	1	70	1.68	24.80159	95	45	NEGATIVE	Low
29	29	1	62	1.66	22.49964	113	60	NEGATIVE	Low
27	37	0	76	1.6	29.6875	117	55	NEGATIVE	Mid
23	31	0	40	1.69	14.00511	107	62	NEGATIVE	Mid
23	26	0	68	1.57	27.58733	109	63	NEGATIVE	Mid
25	38	0	79	1.58	31.64557	110	70	NEGATIVE	Mid
24	30	0	68	1.68	24.09297	104	65	NEGATIVE	Mid
17	32	0	59	1.68	20.9042	139	76	NEGATIVE	Mid
33	34	0	128	1.63	48.17645	130	72	NEGATIVE	High
25	30	2	59	1.58	23.63403	110	54	NEGATIVE	Low
22	29	4	84	1.67	30.1194	156	84	NEGATIVE	High
32	37	0	79	1.65	29.01745	110	58	NEGATIVE	Mid
29	31	0	67	1.63	25.21736	118	55	NEGATIVE	Mid
21	25	2	73	1.61	28.16249	117	61	NEGATIVE	Low
23	37	4	57	1.65	20.93664	108	62	NEGATIVE	High
26	28	0	60	1.63	22.58271	101	84	NEGATIVE	Mid
27	36	1	83	1.68	29.4076	113	60	NEGATIVE	Low
27	8	1	76	1.65	27.91552	110	79	NEGATIVE	Low
32	28	6	81	1.63	30.486	124	86	NEGATIVE	High

					66				
31	18	2	91	1.69	31.86163	101	59	NEGATIVE	Low
23	22	3	73	1.57	29.61581	110	72	NEGATIVE	Low
26	32	2	59	1.68	20.9042	116	66	NEGATIVE	Low
25	27	0	64	1.69	22.40818	109	62	NEGATIVE	Mid
32	37	1	79	1.53	33.7477	111	86	NEGATIVE	Low
28	29	3	80	1.6	31.25	136	84	NEGATIVE	Mid
29	18	2	79	1.57	32.04998	99	55	NEGATIVE	Mid
32	13	0	68	1.62	25.91068	139	89	NEGATIVE	Mid
34	12	2	85	1.64	31.60321	110	74	NEGATIVE	Low
37	35	6	78	1.58	31.24499	111	70	NEGATIVE	High
35	34	0	62	1.57	25.15315	170	104	NEGATIVE	High
34	27	0	66	1.71	22.57105	101	64	NEGATIVE	Mid
32	27	0	83	1.66	30.12048	119	63	NEGATIVE	Mid
28	37	1	82	1.56	33.69494	115	63	NEGATIVE	Low
36	32	0	63	1.57	25.55885	102	58	NEGATIVE	Mid
28	31	1	60	1.59	23.73324	116	60	NEGATIVE	Low
31	30	0	90	1.58	36.05191	120	63	NEGATIVE	Mid
26	36	0	86	1.53	36.73801	96	55	NEGATIVE	Mid
23	30	3	63	1.56	25.88757	125	74	NEGATIVE	Low
30	28	0	60	1.53	25.63117	108	54	NEGATIVE	Mid
35	30	0	58	1.56	23.833	84	38	NEGATIVE	Mid
35	27	0	58	1.64	21.56454	118	64	NEGATIVE	Mid
35	24	0	92	1.61	35.49246	110	70	NEGATIVE	Mid
18	36	0	85	1.64	31.603	124	70	NEGATIVE	Mid

					21				
28	27	0	86	1.59	34.01764	130	80	NEGATIVE	Mid
22	34	2	86	1.68	30.47052	109	64	NEGATIVE	Low
24	26	0	76	1.64	28.25699	74	69	NEGATIVE	Mid
17	38	6	55	1.61	21.21832	101	51	NEGATIVE	High
23	31	0	59	1.62	22.48133	128	70	NEGATIVE	Mid
32	23	3	78	1.65	28.65014	120	72	NEGATIVE	Mid
27	30	0	89	1.62	33.91251	114	64	NEGATIVE	Mid
18	36	0	65	1.61	25.07619	97	40	NEGATIVE	Mid
32	36	2	58	1.71	19.83516	106	70	NEGATIVE	Low
35	18	6	60	1.52	25.96953	105	69	NEGATIVE	High
32	30	0	64	1.66	23.22543	127	56	NEGATIVE	Mid
29	32	0	108	1.59	42.71983	107	44	NEGATIVE	Mid
23	32	2	43	1.64	15.98751	86	50	NEGATIVE	Low
31	25	4	54	1.54	22.76944	105	61	NEGATIVE	High
22	24	1	52	1.52	22.50693	94	69	NEGATIVE	Low
22	27	2	53	1.62	20.19509	106	59	NEGATIVE	Low
17	28	2	62	166/158	#VALUE!	102	52	NEGATIVE	Low
32	20	1	71	1.61	27.39092	140	80	NEGATIVE	Mid
34	25	3	79	1.64	29.3724	120	70	NEGATIVE	Low
27	18	2	68	1.59	26.89767	110	65	NEGATIVE	Low
32	27	2	65	1.51	28.50752	95	58	NEGATIVE	Low
24	26	0	63	1.5	28	106	60	NEGATIVE	Mid
18	30	0	86	1.61	33.17773	109	51	NEGATIVE	Mid

26	27	1	60	1.51	26.31464	105	59	NEGATIVE	Low
25	35	0	66	1.65	24.24242	113	64	NEGATIVE	Mid
26	33	0	63	1.63	23.71184	117	70	NEGATIVE	Mid
34	36	0	80	1.53	34.17489	138	75	NEGATIVE	Mid
32	26	1	80	1.65	29.38476	111	60	NEGATIVE	Low
24	29	1	60	1.64	22.30815	121	72	NEGATIVE	Low
27	25	1	89	1.66	32.29787	128	77	NEGATIVE	Low
32	36	4	62	1.55	25.80645	114	82	NEGATIVE	High
32	31	3	88	1.57	35.70125	115	63	NEGATIVE	Low
18	26	0	63	1.54	26.56434	115	63	NEGATIVE	Mid
26	24	2	86	1.6	33.59375	99	55	NEGATIVE	Low
43	16	0	68	1.72	22.9854	115	63	NEGATIVE	Mid
28	35	1	86	1.62	32.76939	99	55	NEGATIVE	Mid
31	32	3	68	1.61	26.23356	119	70	NEGATIVE	Low
32	26	1	62	1.63	23.33547	101	66	NEGATIVE	Low
29	18	0	64	1.6	25	98	49	NEGATIVE	Mid
34	24	1	70	1.7	24.22145	139	56	NEGATIVE	Mid
29	16	4	107	1.56	43.96778	100	55	NEGATIVE	High
29	30	4	101	1.68	35.78515	119	59	NEGATIVE	High
31	28	2	92	1.51	40.34911	87	47	NEGATIVE	Low
21	34	0	55	1.67	19.72104	102	50	NEGATIVE	Mid
32	22	0	66	1.68	23.38435	128	58	NEGATIVE	Mid
30	26	4	49	1.68	17.36111	115	53	NEGATIVE	High
37	26	4	69	1.67	24.74094	110	70	NEGATIVE	High

23	34	0	62	1.58	24.83576	86	42	NEGATIVE	Mid
43	20	2	65	1.66	23.58833	107	56	NEGATIVE	Mid
35	24	0	66	1.62	25.14861	152	70	NEGATIVE	Mid
32	29	1	85	1.66	30.84628	97	58	NEGATIVE	Low
18	26	3	62	1.62	23.62445	107	74	NEGATIVE	Low
24	28	0	75	1.58	30.04326	123	75	NEGATIVE	Mid
30	29	2	63	1.64	23.42356	120	70	NEGATIVE	Low
35	30	0	75	1.63	28.22839	135	62	NEGATIVE	Mid
32	11	0	60	1.67	21.51386	95	45	NEGATIVE	Mid
29	15	1	62	1.68	21.96712	113	60	NEGATIVE	Low
27	33	0	76	1.63	28.60476	117	55	NEGATIVE	Mid
23	23	1	40	1.69	14.00511	102	62	NEGATIVE	Low
23	22	0	68	1.66	24.67702	109	62	NEGATIVE	Mid
25	36	0	79	1.61	30.47722	110	70	NEGATIVE	Mid
24	26	0	68	1.67	24.38237	111	63	NEGATIVE	Mid
17	18	1	45	1.55	18.73049	139	76	NEGATIVE	Low
33	15	2	128	1.57	51.92908	130	72	NEGATIVE	Low
25	9	1	59	1.66	21.41094	110	54	NEGATIVE	Low
22	22	0	84	1.58	33.64845	130	84	NEGATIVE	Mid
32	22	0	79	1.56	32.4622	110	58	NEGATIVE	Mid
29	24	2	67	1.6	26.17188	118	55	NEGATIVE	Mid
21	12	0	73	1.59	28.87544	117	61	NEGATIVE	Mid
23	23	0	57	1.58	22.83288	108	62	NEGATIVE	Mid
26	24	2	60	1.53	25.631	101	84	NEGATIVE	Low

					17				
27	12	0	83	1.71	28.3848	113	60	NEGATIVE	Mid
27	23	0	76	1.52	32.89474	110	79	NEGATIVE	Mid
32	27	2	81	1.62	30.8642	124	86	NEGATIVE	Mid
31	36	0	96	1.68	34.01361	117	61	NEGATIVE	Mid
23	15	0	57	1.66	20.68515	101	59	NEGATIVE	Mid
26	24	2	73	1.6	28.51563	110	72	NEGATIVE	Low
25	37	2	59	1.55	24.55775	116	66	NEGATIVE	Low
32	29	2	64	1.59	25.31545	109	62	NEGATIVE	Low
28	26	2	79	1.65	29.01745	111	56	NEGATIVE	Low
29	31	3	80	1.52	34.62604	139	84	NEGATIVE	Low
32	23	1	79	1.68	27.99036	79	55	NEGATIVE	Low
34	21	1	68	1.52	29.43213	135	89	NEGATIVE	Mid
37	24	1	85	1.67	30.47797	110	74	NEGATIVE	Low
35	22	0	78	1.56	32.05128	111	70	NEGATIVE	Mid
34	33	0	62	1.69	21.70792	170	104	NEGATIVE	Mid
32	37	1	66	1.57	26.77593	101	60	NEGATIVE	Low
28	22	0	83	1.57	33.67277	119	63	NEGATIVE	Mid
28	32	0	82	1.65	30.11938	115	63	NEGATIVE	Mid
36	31	1	63	1.61	24.30462	103	58	NEGATIVE	Mid
28	31	0	60	1.56	24.65483	116	60	NEGATIVE	Mid
31	24	0	90	1.58	36.05191	113	60	NEGATIVE	Mid
27	24	2	76	1.64	28.25699	110	79	NEGATIVE	Low
32	38	0	81	1.47	37.48438	124	86	NEGATIVE	Mid

31	32	1	91	1.66	33.02366	117	61	NEGATIVE	Mid
23	29	3	57	1.59	22.54658	101	59	NEGATIVE	Low
23	23	0	73	1.62	27.81588	110	72	NEGATIVE	Mid
26	12	0	59	1.59	23.33768	116	66	NEGATIVE	Mid
25	37	0	64	1.55	26.63892	109	62	NEGATIVE	Mid
32	24	1	79	1.54	33.31084	111	56	NEGATIVE	Low
28	26	4	80	1.56	32.87311	136	84	NEGATIVE	Mid
29	35	1	79	1.54	33.31084	79	55	NEGATIVE	Low
32	12	2	68	1.63	25.59374	139	89	NEGATIVE	High
34	14	2	85	1.57	34.48416	110	74	NEGATIVE	Low
37	27	0	78	1.6	30.46875	111	70	NEGATIVE	Mid
35	24	2	62	1.62	23.62445	170	104	NEGATIVE	Mid
34	31	2	66	1.61	25.46198	101	64	NEGATIVE	Low
32	24	2	83	1.51	36.40191	119	63	NEGATIVE	Low
28	35	1	82	1.63	30.86304	115	63	NEGATIVE	Low
28	11	0	63	1.68	22.32143	103	58	NEGATIVE	Mid
36	28	3	60	1.73	20.04745	99	49	NEGATIVE	Low
28	14	4	55	1.57	22.31328	116	60	NEGATIVE	High
31	16	0	90	1.68	31.88776	100	52	NEGATIVE	High
28	19	2	80	1.71	27.35885	105	70	NEGATIVE	Low
19	21	0	65	1.65	23.87511	106	63	NEGATIVE	Mid
30	20	0	51	1.69	17.85652	113	70	NEGATIVE	Mid
33	22	4	85	1.67	30.47797	107	61	NEGATIVE	High
41	26	1	72	1.64	26.769	154	91	NEGATIVE	Mid

					78				
25	25	0	85	1.68	30.11621	101	59	NEGATIVE	Mid
23	36	1	57	1.58	22.83288	117	55	NEGATIVE	Low
30	20	0	40	1.66	14.51589	101	51	NEGATIVE	Mid
25	35	0	63	1.61	24.30462	131	74	NEGATIVE	Mid
22	27	1	86	1.59	34.01764	123	60	NEGATIVE	Low
36	33	0	86	1.72	29.06977	122	66	NEGATIVE	Mid
30	24	0	105	1.51	46.05061	112	60	NEGATIVE	Mid
37	24	1	82	1.52	35.49169	82	53	NEGATIVE	Low
22	28	0	61	1.64	22.67995	91	60	NEGATIVE	Mid
32	36	3	76	1.64	28.25699	111	65	NEGATIVE	Low
28	28	1	61	1.53	26.05835	130	77	NEGATIVE	Low
30	30	3	60	1.6	23.4375	137	60	NEGATIVE	Mid
24	33	1	73	1.59	28.87544	119	89	NEGATIVE	Low
29	32	2	92	1.61	35.49246	108	62	NEGATIVE	Low
18	22	2	59	1.6	23.04688	110	71	NEGATIVE	Low
26	31	0	60	1.61	23.14726	120	82	NEGATIVE	Mid
22	12	0	75	1.71	25.64892	123	77	NEGATIVE	Mid
26	29	6	65	1.61	25.07619	125	68	NEGATIVE	High
38	33	1	77	1.62	29.34004	128	68	NEGATIVE	Mid
19	28	2	77	1.57	31.23859	109	68	NEGATIVE	Low
23	28	1	87	1.67	31.19509	90	68	NEGATIVE	Low
30	28	3	87	1.55	36.21228	107	62	NEGATIVE	Low
28	33	0	68	1.69	23.80869	113	61	NEGATIVE	Mid

30	20	0	68	1.65	24.97704	102	58	NEGATIVE	Mid
28	38	0	62	1.59	24.52435	140	80	NEGATIVE	High
41	32	2	83	1.55	34.54735	92	52	NEGATIVE	Mid
28	32	0	65	1.68	23.03005	108	64	NEGATIVE	Mid
30	34	2	60	1.52	25.96953	88	48	NEGATIVE	Low
43	24	1	63	1.55	26.22268	100	80	NEGATIVE	Mid
23	21	0		1.59	0	109	56	NEGATIVE	Mid
36	33	1	63	1.49	28.3771	123	95	NEGATIVE	Mid
34	35	0	59	1.61	22.76147	88	54	NEGATIVE	Mid
28	6	1	63	1.63	23.71184	122	88	NEGATIVE	High
18	30	1	62	1.74	20.47827	123	68	NEGATIVE	Low
20	20	1	59	1.54	24.87772	103	60	NEGATIVE	Low
27	27	0	73	1.61	28.16249	126	67	NEGATIVE	Mid
29	28	2	62	1.58	24.83576	117	74	NEGATIVE	Low
30	27	0	52	1.57	21.09619	103	59	NEGATIVE	Mid
24	29	0	70	1.58	28.04038	120	63	NEGATIVE	Mid
30	26	0	82	1.57	33.26707	191	114	NEGATIVE	High
31	22	0	65	1.66	23.58833	117	74	NEGATIVE	Mid
24	31	2	58	1.68	20.54989	102	62	NEGATIVE	Low
32	26	0	69	1.63	25.97012	104	63	NEGATIVE	Mid
34	27	2	55	1.57	22.31328	119	68	NEGATIVE	Low
36	36	1	55	1.61	21.21832	103	59	NEGATIVE	Low
33	29	1	70	1.62	26.67276	105	56	NEGATIVE	Low
26	18	1	78	1.58	31.24499	110	60	NEGATIVE	Low

34	26	1	59	1.71	20.17715	138	86	NEGATIVE	Low
29	20	0	105	1.54	44.27391	114	69	NEGATIVE	Mid
38	30	0	60	1.65	22.03857	103	44	NEGATIVE	Mid
25	28	0	62	1.68	21.96712	88	44	NEGATIVE	Mid
27	26	1	63	1.65	23.1405	107	70	NEGATIVE	Low
24	25	3	60	1.49	27.02581	115	68	NEGATIVE	Low
29	18	0	73	1.65	26.81359	98	50	NEGATIVE	Mid
19	20	0	52	1.54	21.92613	126	70	NEGATIVE	Mid
18	36	3	62	1.68	21.96712	100	70	NEGATIVE	Mid
31	32	0	70	1.63	26.34649	90	60	NEGATIVE	Mid
27	8	1	64	1.66	23.22543	100	70	NEGATIVE	Low
24	20	0	64	1.64	23.79536	100	70	NEGATIVE	Mid
18	22	1	55	1.71	18.80921	120	60	NEGATIVE	Low
30	24	0	56	1.64	20.82094	100	70	NEGATIVE	Mid
29	22	0	58	1.61	22.37568	110	70	NEGATIVE	Mid
23	33	3	65	1.61	25.07619	120	80	NEGATIVE	Low
28	37	2	120	1.64	44.6163	120	70	NEGATIVE	Low
21	40	3	78	1.59	30.85321	105	70	NEGATIVE	Low
21	26	0	79	1.67	28.32658	100	70	NEGATIVE	Mid
23	36	0	50	1.71	17.09928	100	70	NEGATIVE	Mid
26	43	5	81	1.63	30.48666	105	65	NEGATIVE	High
30	26	0	68	1.47	31.46837	100	60	NEGATIVE	Mid
32	34	1	80	1.56	32.87311	120	80	NEGATIVE	Low
20	36	0	56	1.59	22.151	100	70	NEGATIVE	Mid

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25	38	0	62	1.61	23.918 83	100	60	NEGATIVE	Mid
22	24	4	56	1.53	23.922 42	140	70	NEGATIVE	Mid
28	39	0	73	1.57	29.615 81	110	80	NEGATIVE	Mid
19	36	0	58	1.59	22.942 13	90	60	NEGATIVE	Mid
25	8	3	44	1.57	17.850 62	100	59	NEGATIVE	Low
26	28	0	65	1.58	26.037 49	100	70	NEGATIVE	Mid
38	35	3	58	1.59	22.942 13	150	91	NEGATIVE	Mid
36	22	2	94	1.64	34.949 43	110	60	NEGATIVE	Low
29	41	5	68	1.59	26.897 67	110	80	NEGATIVE	High
21	25	1	74	1.61	28.548 28	100	60	NEGATIVE	Low
34	28	1	60	1.61	23.147 26	110	60	NEGATIVE	Low
30	20	1	80	1.73	26.729 93	100	60	NEGATIVE	Low
32	32	3	58	1.54	24.456 06	120	70	NEGATIVE	Low
25	24	0	65	1.62	24.767 57	100	60	NEGATIVE	Mid
23	36	0	48	1.63	18.066 17	110	70	NEGATIVE	Mid
32	32	1	86	1.58	34.449 61	100	60	NEGATIVE	Low
27	28	0	78	1.59	30.853 21	126	70	NEGATIVE	Mid
31	26	1	62	1.62	23.624 45	109	65	NEGATIVE	Low
30	42	5	60	1.68	21.258 5	126	67	NEGATIVE	High
29	28	5	62	1.61	23.918 83	117	74	NEGATIVE	High
30	30	5	52	1.58	20.83	120	63	NEGATIVE	High
24	35	0	82	1.56	33.694 94	191	114	NEGATIVE	High
30	29	2	65	1.53	27.767 1	117	74	NEGATIVE	Low

31	10	1	38	1.6	14.84375	102	62	NEGATIVE	Low
24	26	0	69	1.76	22.27531	104	63	NEGATIVE	Mid
32	18	0	55	1.51	24.12175	117	68	NEGATIVE	Mid
34	24	1	55	1.62	20.95717	103	59	NEGATIVE	Low
34	16	0	70	1.62	26.67276	105	56	NEGATIVE	Mid
32	30	1	78	1.56	32.05128	112	57	NEGATIVE	Low
26	25	4	50	1.61	19.28938	110	60	NEGATIVE	High
34	34	2	59	1.58	23.63403	110	60	NEGATIVE	Low
29	22	0	59	1.59	23.33768	138	86	NEGATIVE	Mid
38	26	4	105	1.51	46.05061	114	69	NEGATIVE	High
25	26	4	60	1.42	29.756	103	44	NEGATIVE	Mid
27	34	0	52	1.69	18.20665	88	44	NEGATIVE	Mid
24	20	0	62	1.68	21.96712	107	70	NEGATIVE	Mid
27	29	6	60	1.67	21.51386	115	68	NEGATIVE	High
19	26	0	73	1.62	27.81588	98	50	NEGATIVE	Mid
18	23	1	52	1.54	21.92613	113	60	NEGATIVE	Low
27	26	3	76	1.63	28.60476	110	79	NEGATIVE	Low
32	28	0	81	1.69	28.36035	124	86	NEGATIVE	Mid
31	29	3	91	1.65	33.42516	117	61	NEGATIVE	Low
23	30	0	57	1.57	23.12467	101	59	NEGATIVE	Mid
26	11	0	73	1.58	29.24211	110	72	NEGATIVE	Mid
25	15	1	59	1.63	22.20633	116	66	NEGATIVE	Low
32	33	0	64	1.53	27.33991	109	62	NEGATIVE	Mid
28	36	1	79	1.62	30.10212	111	56	NEGATIVE	Low

29	26	0	80	1.52	34.62604	136	84	NEGATIVE	Mid
32	18	0	79	1.61	30.47722	79	55	NEGATIVE	Mid
34	15	0	68	1.52	29.43213	139	89	NEGATIVE	Mid
37	9	1	85	1.65	31.2213	110	74	NEGATIVE	Low
35	22	2	78	1.64	29.00059	117	70	NEGATIVE	Low
34	22	1	62	1.74	20.47827	170	104	NEGATIVE	High
32	24	0	66	1.56	27.12032	101	64	NEGATIVE	Mid
28	12	0	83	1.56	34.10585	119	63	NEGATIVE	Mid
28	23	2	82	1.61	31.63458	115	63	NEGATIVE	Low
36	27	0	63	1.56	25.88757	103	58	NEGATIVE	Mid
28	36	0	66	1.61	25.46198	116	60	NEGATIVE	Mid
31	15	2	90	1.58	36.05191	108	62	NEGATIVE	Mid
18	24	0	65	1.71	22.22906	110	65	NEGATIVE	Mid
26	37	0	60	1.67	21.51386	128	68	NEGATIVE	Mid
22	29	2	77	1.78	24.30249	109	68	NEGATIVE	Low
26	26	2	87	1.65	31.95592	90	68	NEGATIVE	Low
38	31	3	80	1.72	27.04164	108	57	NEGATIVE	Low
19	23	1	50	1.67	17.92822	107	62	NEGATIVE	Low
23	21	1	68	1.62	25.91068	113	61	NEGATIVE	Low
30	24	1	68	1.51	29.82325	101	58	NEGATIVE	Low
28	22	0	62	1.69	21.70792	140	80	NEGATIVE	Mid
41	33	0	83	1.55	34.54735	92	52	NEGATIVE	Mid
28	24	1	65	1.96	16.92003	108	64	NEGATIVE	Low
30	22	0	60	1.64	22.308	88	48	NEGATIVE	Mid

					15				
43	22	0	63	1.57	25.55885	107	65	NEGATIVE	High
23	33	1	60	1.56	24.65483	109	56	NEGATIVE	Low
35	37	1	63	1.52	27.26801	123	95	NEGATIVE	Low
34	22	0	59	1.66	21.41094	88	54	NEGATIVE	Mid
28	32	0	63	1.68	22.32143	122	88	NEGATIVE	Mid
18	31	2	62	1.57	25.15315	125	68	NEGATIVE	Low
20	31	0	59	1.63	22.20633	103	66	NEGATIVE	Mid
27	24	0	73	1.67	26.17519	105	64	NEGATIVE	Mid
29	24	2	75	1.57	30.4272	134	64	NEGATIVE	Low
24	38	0	74	1.58	29.64269	103	60	NEGATIVE	Mid
33	32	1	74	1.57	30.0215	106	69	NEGATIVE	Low
30	29	3	89	1.51	39.03338	143	84	NEGATIVE	Mid
41	23	0	89	1.61	34.3351	116	67	NEGATIVE	Mid
22	12	0	99	1.51	43.41915	98	53	NEGATIVE	Mid
34	37	0	55	1.53	23.49524	109	63	NEGATIVE	Mid
27	24	1	74	1.58	29.64269	105	59	NEGATIVE	Low
25	26	4	75	1.58	30.04326	106	55	NEGATIVE	Mid
29	33	1	89	1.61	34.3351	135	75	NEGATIVE	Low
39	12	2	83	1.57	33.67277	86	56	NEGATIVE	Low
23	14	2	57	1.67	20.43817	123	68	NEGATIVE	Low
29	27	0	71	1.58	28.44095	135	62	NEGATIVE	Mid
30	34	2	65	1.56	26.7094	125	69	NEGATIVE	Low
18	21	2	69	1.62	26.29172	125	75	NEGATIVE	Low

27	27	1	84	1.62	32.00732	99	55	NEGATIVE	Low
43	35	0	64	1.57	25.96454	124	74	NEGATIVE	Mid
27	19	3	75	1.61	28.93407	94	52	NEGATIVE	Low
30	8	4	60	1.63	22.58271	102	67	NEGATIVE	High
39	16	4	82	1.54	34.57581	97	56	NEGATIVE	High
28	17	0	62	1.63	23.33547	91	54	NEGATIVE	Mid
33	23	2	64	1.61	24.69041	117	94	NEGATIVE	Low
31	21	0	82	1.65	30.11938	98	54	NEGATIVE	Mid
31	22	0	53	1.55	22.06035	120	70	NEGATIVE	Mid
26	31	4	68	1.75	22.20408	97	57	NEGATIVE	High
28	26	1	64	1.61	24.69041	123	70	NEGATIVE	Low
36	25	0	100	1.71	34.19856	111	62	NEGATIVE	Mid
25	36	0	85	1.61	32.79194	93	53	NEGATIVE	Mid
30	20	0	67	1.63	25.21736	103	55	NEGATIVE	Mid
29	35	0	67	1.65	24.60973	109	63	NEGATIVE	Mid
27	27	0	72	1.58	28.84153	118	61	NEGATIVE	Mid
30	33	1	59	1.62	22.48133	92	52	NEGATIVE	Mid
28	24	0	65	1.53	27.7671	103	55	NEGATIVE	Mid
19	24	0	49	1.63	18.44255	105	60	NEGATIVE	Mid
20	28	1	59	1.66	21.41094	120	60	NEGATIVE	Low
18	36	0	60	1.54	25.29938	123	64	NEGATIVE	Mid
26	28	3	91	1.55	37.87721	104	64	NEGATIVE	Low
25	30	1	84	1.69	29.41073	130	80	NEGATIVE	Low
39	33	3	80	1.67	28.685	98	59	NEGATIVE	Low

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28	32	1	61	1.58	24.435 19	104	64	NEGATIVE	Low
41	22	2	60	1.65	22.038 57	103	51	NEGATIVE	Mid
23	31	2	70	1.65	25.711 66	103	60	NEGATIVE	Low
33	12	0	64	1.58	25.636 92	106	63	NEGATIVE	Mid
30	29	6	76	1.59	30.062 1	104	69	NEGATIVE	High
24	31	1	68	1.58	27.239 22	104	64	NEGATIVE	Low
39	19	2	69	1.68	24.447 28	130	70	NEGATIVE	Low
27	15	1	82	1.6	32.031 25	136	89	NEGATIVE	Low
30	20	3	67	1.68	23.738 66	140	63	NEGATIVE	Mid
35	28	0	61	1.61	23.533 04	125	63	NEGATIVE	Mid
19	28	0	48	1.63	18.066 17	110	74	NEGATIVE	Mid
41	33	0	80	1.53	34.174 89	138	89	NEGATIVE	High
22	20	2	62	1.51	27.191 79	113	76	NEGATIVE	Low
26	38	2	88	1.63	33.121 31	89	44	NEGATIVE	Low
34	32	0	55	1.47	25.452 36	123	60	NEGATIVE	Mid
24	32	2	69	1.63	25.970 12	110	58	NEGATIVE	Low
29	34	1	63	1.57	25.558 85	124	70	NEGATIVE	Low
22	24	0	55	1.59	21.755 47	88	47	NEGATIVE	Mid
30	24	1	75	1.63	28.228 39	106	70	NEGATIVE	Low
25	38	0	50	1.61	19.289 38	151	70	NEGATIVE	Mid
41	36	1	82	1.61	31.634 58	126	66	NEGATIVE	Mid
22	6	1	84	1.59	33.226 53	150	77	NEGATIVE	Mid
26	30	0	96	1.61	37.035 61	104	67	NEGATIVE	Mid

38	20	2	60	1.61	23.14726	126	75	NEGATIVE	Low
25	27	0	62	1.53	26.48554	107	69	NEGATIVE	Mid
23	28	2	75	1.65	27.54821	91	54	NEGATIVE	Low
37	27	0	70	1.66	25.40282	95	59	NEGATIVE	Mid
27	29	0	60	1.58	24.03461	117	67	NEGATIVE	Mid
30	25	0	70	1.64	26.02617	102	87	NEGATIVE	Mid
27	21	0	82	1.57	33.26707	106	63	NEGATIVE	Mid
29	22	2	75	1.61	28.93407	103	65	NEGATIVE	Low
27	31	0	74	1.65	27.1809	127	71	NEGATIVE	Mid
27	26	2	80	1.55	33.29865	106	64	NEGATIVE	Low
27	27	2	63	1.62	24.00549	92	55	NEGATIVE	Low
28	36	2	60	1.66	21.77384	117	68	NEGATIVE	Low
30	29	1	90	1.71	30.7787	134	71	NEGATIVE	Low
20	18	1	63	1.58	25.23634	144	103	NEGATIVE	Mid
29	31	1	81	1.62	30.8642	128	70	NEGATIVE	Low
26	26	1	87	1.68	30.82483	122	77	NEGATIVE	Low
38	20	0	67	1.72	22.64738	103	59	NEGATIVE	Mid
27	30	0	90	1.53	38.44675	110	63	NEGATIVE	Mid
28	28	0	57	1.72	19.26717	112	71	NEGATIVE	Mid
30	26	1	88	1.63	33.12131	100	60	NEGATIVE	Low
19	25	3	68	1.56	27.94214	106	61	NEGATIVE	Low
25	18	0	72	1.78	22.7244	163	110	NEGATIVE	Mid
24	20	0	77	1.54	32.46753	118	68	NEGATIVE	Mid
29	21	3	70	1.67	25.099	112	64	NEGATIVE	Low

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27	27	0	78	1.64	29.00059	108	85	NEGATIVE	Mid
30	36	1	62	1.62	23.62445	89	53	NEGATIVE	Low
35	32	0	68	1.65	24.97704	91	54	NEGATIVE	Mid
41	8	1	65	1.55	27.05515	96	52	NEGATIVE	Mid
22	20	0	53	1.34	29.5166	96	52	NEGATIVE	Mid
26	22	0	84	1.46	39.40702	121	52	NEGATIVE	Mid
28	24	3	60	1.62	22.86237	108	63	NEGATIVE	Low
24	22	3	60	1.65	22.03857	121	62	NEGATIVE	Low
26	33	3	57	1.78	17.99015	134	71	NEGATIVE	Low
28	37	3	65	1.43	31.7864	132	70	NEGATIVE	Low
25	40	0	76	1.65	27.91552	100	53	NEGATIVE	Mid
27	26	0	65	1.62	24.76757	134	89	NEGATIVE	Mid
29	36	5	61	1.52	26.40235	136	79	NEGATIVE	High
25	43	0	55	1.56	22.60026	112	65	NEGATIVE	High
22	26	0	72	1.63	27.09925	112	65	NEGATIVE	Mid
27	34	1	67	1.65	24.60973	132	71	NEGATIVE	Low
29	36	0	99	1.53	42.29143	132	69	NEGATIVE	Mid
41	38	0	73	1.65	26.81359	100	53	NEGATIVE	Mid
28	24	4	65	1.45	30.91558	87	46	NEGATIVE	Mid
28	39	0	67	1.67	24.02381	124	61	NEGATIVE	Mid
18	36	0	63	1.56	25.88757	92	52	NEGATIVE	Mid
30	28	3	71	1.62	27.0538	101	64	NEGATIVE	Low
19	28	0	67	1.65	24.60973	136	83	NEGATIVE	Mid

34	35	3	64	1.42	31.739 73	101	53	NEGATIVE	Low
29	22	2	64	1.65	23.507 81	109	59	NEGATIVE	Low
33	41	5	73	1.56	29.996 71	116	75	NEGATIVE	High
23	25	1	69	1.62	26.291 72	118	64	NEGATIVE	Low
29	28	1	71	1.46	33.308 31	100	56	NEGATIVE	Low
28	20	1	75	1.65	27.548 21	124	71	NEGATIVE	Low
41	32	3	81	1.76	26.149 28	91	53	NEGATIVE	Mid
31	24	0	83	1.72	28.055 71	115	75	NEGATIVE	Mid
23	36	0	54	1.47	24.989 59	113	69	NEGATIVE	Mid
26	32	1	80	1.73	26.729 93	115	57	NEGATIVE	Low
23	28	0	81	1.46	37.999 62	105	65	NEGATIVE	Mid
35	26	1	61	1.45	29.013 08	115	59	NEGATIVE	Low
26	42	5	63	1.71	21.545 09	130	70	NEGATIVE	High
35	28	5	65	1.61	25.076 19	125	60	NEGATIVE	High
22	30	5	61	1.65	22.405 88	119	62	NEGATIVE	High
22	35	0	55	1.33	31.092 77	131	63	NEGATIVE	Mid
28	29	2	57	1.61	21.989 89	109	66	NEGATIVE	Low
43	16	1	60	1.6	23.437 5	114	62	NEGATIVE	Mid
41	19	0	55	1.66	19.959 36	120	67	NEGATIVE	High
27	22	0	62	1.69	21.707 92	111	58	NEGATIVE	Mid
30	26	1	60	1.62	22.862 37	123	61	NEGATIVE	Low
25	14	0	68	1.72	22.985 4	127	59	NEGATIVE	Low
27	15	4	63	1.75	20.571 43	114	65	NEGATIVE	High
41	9	0	78	1.73	26.061	110	71	NEGATIVE	High

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34	25	1	64	1.5	28.44444	100	54	NEGATIVE	Low
18	36	3	60	1.5	26.66667	105	63	NEGATIVE	Low
29	22	0	68	1.75	22.20408	113	67	NEGATIVE	Mid
30	22	0	92	163.5	0.003442	103	52	NEGATIVE	Mid
23	8	0	65	1.54	27.40766	108	58	NEGATIVE	Mid
27	34	3	74	1.62	28.19692	100	55	NEGATIVE	Low
31	13	1	80	1.63	30.11028	103	51	NEGATIVE	Low
33	14	1	70	1.68	24.80159	98	52	NEGATIVE	Low
28	29	0	58	1.63	21.82995	109	60	NEGATIVE	Mid
31	23	3	87	1.63	32.74493	127	89	NEGATIVE	Low
22	12	2	82	1.71	28.04282	112	60	NEGATIVE	Low
29	36	0	60	1.6	23.4375	103	49	NEGATIVE	Mid
27	23	0	63	1.55	26.22268	98	55	NEGATIVE	Mid
28	18	0	68	1.65	24.97704	75	44	NEGATIVE	Mid
30	34	0	52	160	0.002031	112	67	NEGATIVE	Mid
30	30	1	88	1.63	33.12131	110	53	NEGATIVE	Low
24	34	2	59	1.6	23.04688	105	56	NEGATIVE	Low
19	27	2	77	1.61	29.70564	115	63	NEGATIVE	Low
39	27	3	80	1.5	35.55556	104	46	NEGATIVE	Low
30	26	2	51	1.74	16.84503	116	55	NEGATIVE	Low
30	32	0	58	1.69	20.30741	129	86	NEGATIVE	Mid
22	27	0	59	1.6	23.04688	109	68	NEGATIVE	Mid
30	32	0	80	1.64	29.7442	110	58	NEGATIVE	Mid

30	33	0	49	1.64	18.21832	120	61	NEGATIVE	Mid
27	26	1	83	1.67	29.76084	133	65	NEGATIVE	Low
31	20	1	58	1.6	22.65625	110	53	NEGATIVE	Low
24	25	2	56	1.6	21.875	118	63	NEGATIVE	Low
29	30	1	68	163	0.002559	115	70	NEGATIVE	Low
30	33	1	90	1.69	31.5115	121	71	NEGATIVE	Low
36	32	0	100	173	0.003341	109	68	NEGATIVE	Mid
20	32	3	80	1.65	29.38476	105	64	NEGATIVE	Low
27	37	0	55	1.8011	16.95458	108	69	NEGATIVE	Mid
23	36	0	64	1.69	22.40818	100	54	NEGATIVE	Mid
27	28	0	61	1.45	29.01308	110	59	NEGATIVE	Mid
28	14	0	73	1.62	27.81588	117	68	NEGATIVE	Mid
23	18	1	70	1.52	30.29778	99	49	NEGATIVE	Low
30	29	1	75	1.59	29.66655	85	53	NEGATIVE	Low
28	20	3	59	1.69	20.65754	98	59	NEGATIVE	Low
30	38	1	62	1.59	24.52435	150	72	NEGATIVE	Low
18	42	3	56	1.31	32.63213	134	71	NEGATIVE	Low
23	37	1	78	1.32	44.76584	108	57	NEGATIVE	Low
30	30	0	67	1.56	27.53123	150	67	NEGATIVE	High
30	20	0	59	1.58	23.63403	100	59	NEGATIVE	Mid
28	16	0	85	1.32	48.78329	97	61	NEGATIVE	Mid
31	20	1	80	1.57	32.45568	77	39	NEGATIVE	Low
34	40	2	45	1.56	18.49112	94	60	NEGATIVE	Low
19	36	3	69	1.55	28.72008	121	74	NEGATIVE	Low

22	28	3	60	1.62	22.86237	106	62	NEGATIVE	Low
29	42	1	71	1.58	28.44095	130	76	NEGATIVE	Low
31	20	2	81	1.68	28.69898	111	54	NEGATIVE	Low
29	40	0	65	1.5	28.88889	115	63	NEGATIVE	Mid
30	36	1	84	1.32	48.20937	127	56	NEGATIVE	Low
28	36	1	59	1.31	34.38028	124	72	NEGATIVE	Low
26	32	3	91	1.62	34.67459	100	55	NEGATIVE	Low
23	32	1	56	1.66	20.32225	116	69	NEGATIVE	Low
32	13	2	89	168	0.003153	118	66	NEGATIVE	Low
29	24	1	64	1.57	25.96454	108	52	NEGATIVE	Low
31	34	0	62	1.34	34.52885	110	57	NEGATIVE	Mid
33	34	0	67	1.7	23.18339	94	50	NEGATIVE	Mid
34	28	1	54	1.69	18.9069	111	57	NEGATIVE	Low
23	34	2	71	162	0.002705	88	75	NEGATIVE	Low
28	40	1	59	1.44	28.45293	95	52	NEGATIVE	Low
28	30	2	66	1.57	26.77593	125	70	NEGATIVE	Low
26	16	0	85	1.61	32.79194	120	65	NEGATIVE	Mid
32	29	2	91	1.58	36.45249	122	72	NEGATIVE	Low
27	36	2	76	1.38	39.90758	109	61	NEGATIVE	Low
20	32	2	62	1.46	29.08613	155	91	NEGATIVE	Mid
42	32	0	94	154.5	0.003938	127	65	NEGATIVE	High
27	20	3	84	1.63	31.61579	66	33	NEGATIVE	Low
27	34	1	57	1.7	19.72318	121	67	NEGATIVE	Low
25	22	1	70	1.63	26.346	104	52	NEGATIVE	Low

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20	34	0	62	1.52	26.835 18	128	76	NEGATIVE	Mid
41	36	1	75	1.76	24.212 29	110	63	NEGATIVE	Mid
25	20	3	70	1.68	24.801 59	105	68	NEGATIVE	Low
28	36	3	70	1.67	25.099 5	90	70	NEGATIVE	Low
28	36	3	66	1.31	38.459 3	108	58	NEGATIVE	Low
20	38	1	59	1.64	21.936 35	120	77	NEGATIVE	Low
32	23	0	89	1.62	33.912 51	124	88	NEGATIVE	Mid
39	31	0	94	162.5	0.0035 6	152	87	NEGATIVE	High
42	12	2	91	1.59	35.995 41	96	56	NEGATIVE	Mid
27	34	2	60	1.74	19.817 68	130	87	NEGATIVE	Low
32	13	2	61	1.65	22.405 88	117	68	NEGATIVE	Low
36	8	2	101	1.4	51.530 61	106	62	NEGATIVE	Low
39	28	2	81	1.7	28.027 68	110	60	NEGATIVE	Mid
20	28	2	50	167	0.0017 93	114	67	NEGATIVE	Low
25	37	2	64	1.72	21.633 32	105	58	NEGATIVE	Low
30	30	0	59	1.64	21.936 35	110	61	NEGATIVE	Mid
29	40	0	63	1.65	23.140 5	101	60	NEGATIVE	Mid
31	38	1	79	161	0.0030 48	146	90	NEGATIVE	Mid
42	16	1	92	1.63	34.626 82	89	44	NEGATIVE	Mid
30	20	0	50	1.38	26.254 99	111	74	NEGATIVE	Mid
24	38	4	58	1.72	19.605 19	126	78	NEGATIVE	High
20	30	0	64	1.72	21.633 32	109	67	NEGATIVE	Mid
32	36	0	57	1.66	20.685 15	112	54	NEGATIVE	Mid

25	31	3	70	1.66	25.40282	94	51	NEGATIVE	Low
28	39	1	55	1.61	21.21832	111	58	NEGATIVE	Low
22	30	2	48	1.65	17.63085	111	63	NEGATIVE	Low
31	28	2	67	1.58	26.83865	112	85	NEGATIVE	Low
18	36	3	56	1.59	22.15102	120	73	NEGATIVE	Low
41	33	2	72	1.6	28.125	116	81	NEGATIVE	Mid
30	34	1	85	1.61	32.79194	108	84	NEGATIVE	Low
35	32	0	50	1.5	22.222	108	83	NEGATIVE	Mid
41	30	0	67	1.32	38.45271	142	72	NEGATIVE	High
27	34	3	80	1.59	31.64432	94	48	NEGATIVE	Low
31	30	1	48	1.7	16.609	82	45	NEGATIVE	Low
28	34	1	53	1.51	23.24459	110	61	NEGATIVE	Low
32	33	2	88	1.53	37.59238	103	57	NEGATIVE	Low
29	20	0	80	1.63	30.11028	110	70	NEGATIVE	Mid
31	27	0	67	1.71	22.91303	127	75	NEGATIVE	Mid
22	9	2	95	1.69	33.26214	119	68	NEGATIVE	Low
29	18	1	51	1.67	18.28678	102	62	NEGATIVE	Low
30	31	1	56	1.67	20.0796	110	57	NEGATIVE	Low
25	24	1	64	1.31	37.29386	112	70	NEGATIVE	Low
30	26	2	57	1.62	21.71925	101	70	NEGATIVE	Low
26	30	0	84	1.63	31.61579	96	59	NEGATIVE	Mid
22	29	3	47	1.59	18.59104	105	58	NEGATIVE	Low
35	32	1	58	1.59	22.94213	118	63	NEGATIVE	Low
28	20	1	88	150	0.003911	116	67	NEGATIVE	Low

28	18	0	90	1.64	33.46222	124	75	NEGATIVE	Mid
32	7	0	89	1.66	32.29787	107	56	NEGATIVE	Mid
20	32	2	56	1.64	20.82094	119	66	NEGATIVE	Low
29	34	1	64	1.64	23.79536	99	62	NEGATIVE	Low
27	29	2	57	1.69	19.95728	118	64	NEGATIVE	Low
29	29	1	65	1.64	24.16716	102	63	NEGATIVE	Low
19	32	0	53	1.71	18.12524	108	67	NEGATIVE	Mid
28	32	1	69	1.61	26.61934	102	64	NEGATIVE	Low
24	32	1	51	1.49	22.97194	116	67	NEGATIVE	Low
26	32	0	71	1.57	28.80441	122	65	NEGATIVE	Mid
23	24	3	53	1.68	18.77834	117	59	NEGATIVE	Low
27	32	1	67	1.67	24.02381	102	59	NEGATIVE	Low
29	28	5	59	1.61	22.76147	110	66	NEGATIVE	High
28	27	3	60	1.66	21.77384	156	82	NEGATIVE	Mid
41	17	0	65	1.48	29.67495	124	71	NEGATIVE	High
30	34	1	63	1.7	21.79931	115	67	NEGATIVE	Low
29	31	3	62	1.3	36.68639	114	73	NEGATIVE	Low
27	29	2	74	1.6	28.90625	107	68	NEGATIVE	Low
26	32	0	78	1.49	35.13355	129	60	NEGATIVE	Mid
34	29	2	60	1.62	22.86237	91	47	NEGATIVE	Low
27	25	1	57	1.65	20.93664	113	63	NEGATIVE	Low
32	28	1	87	1.65	31.95592	126	92	NEGATIVE	Low
34	32	1	74	1.64	27.51338	129	94	NEGATIVE	Low
31	26	1	69	1.5	30.666	101	64	NEGATIVE	Low

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19	35	2	52	1.62	19.81405	91	60	NEGATIVE	Low
31	30	2	81	1.53	34.60208	110	78	NEGATIVE	Low
31	40	1	81	1.57	32.86137	129	78	NEGATIVE	Low
30	28	0	89	1.63	33.49769	140	80	NEGATIVE	High
42	40	1	90	1.65	33.05785	140	80	NEGATIVE	High
41	26	0	66	1.62	25.14861	110	60	NEGATIVE	High
28	18	1	60	1.63	22.58271	120	80	NEGATIVE	Low
32	26	0	70	1.64	26.02617	113	53	NEGATIVE	Mid
29	34	0	89	1.62	33.91251	79	45	NEGATIVE	Mid
28	37	2	58	1.3	34.31953	106	69	NEGATIVE	Low
32	30	3	69	1.59	27.29322	118	65	NEGATIVE	Low
26	28	0	62	1.65	22.77319	100	78	NEGATIVE	Mid
41	31	3	68	1.61	26.23356	108	52	NEGATIVE	Mid
27	23	3	48	1.62	18.28989	126	64	NEGATIVE	Low
27	28	2	78	1.63	29.35752	120	66	NEGATIVE	Low
27	32	3	50	1.68	17.71542	77	45	NEGATIVE	Low
30	26	3	50	1.72	16.90103	120	70	NEGATIVE	Low
23	28	1	91	1.67	32.62935	126	91	NEGATIVE	Low
30	29	3	60	1.63	22.58271	104	56	NEGATIVE	Low
42	12	1	56	1.65	20.56933	113	83	NEGATIVE	Mid
27	10	0	89	1.6	34.76563	126	70	NEGATIVE	Mid
34	15	0	79	1.58	31.64557	109	86	NEGATIVE	Mid
26	30	2	88	1.62	33.53147	110	70	NEGATIVE	Low

28	36	3	51	1.64	18.961 93	109	69	NEGATIVE	Low
28	34	2	90	1.52	38.954 29	111	60	NEGATIVE	Low
29	30	1	63	1.64	23.423 56	116	78	NEGATIVE	Low
32	34	1	62	1.54	26.142 69	105	81	NEGATIVE	Low
34	30	1	60	1.59	23.733 24	136	73	NEGATIVE	Low
41	34	0	68	1.52	29.432 13	112	61	NEGATIVE	High
35	30	0	59	17.2	0.1994 32	120	80	NEGATIVE	Mid
24	34	5	59	1.56	24.243 92	128	81	NEGATIVE	High
31	22	1	71	1.65	26.078 97	104	57	NEGATIVE	Low
32	38	1	66	1.59	26.106 56	121	66	NEGATIVE	Low
34	34	2	88	1.63	33.121 31	143	78	NEGATIVE	Mid
25	15	0	80	1.57	32.455 68	124	61	NEGATIVE	Mid
27	39	3	100	1.53	42.718 61	112	67	NEGATIVE	Low
28	33	3	60	1.49	27.025 81	104	58	NEGATIVE	Low
39	25	1	67	1.57	27.181 63	118	50	NEGATIVE	Low
27	26	0	91	1.57	36.918 33	110	70	NEGATIVE	Mid
29	33	2	78	1.59	30.853 21	110	70	NEGATIVE	Low
29	25	5	77	1.6	30.078 13	110	70	NEGATIVE	High
28	26	0	53	1.62	20.195 09	100	56	NEGATIVE	Mid
39	33	2	58	1.58	23.233 46	90	58	NEGATIVE	Low
29	24	5	60	1.6	23.437 5	140	80	NEGATIVE	High
26	27	0	68	1.8	20.987 65	129	78	NEGATIVE	Mid
23	34	2	71	1.6	27.734 38	129	60	NEGATIVE	Low
26	33	5	60	1.62	22.862	119	68	NEGATIVE	High

					37				
32	24	0	69	1.67	24.740 94	115	60	NEGATIVE	Mid
22	27	2	45	1.54	18.974 53	119	77	NEGATIVE	Low
30	34	1	55	1.67	19.721 04	110	75	NEGATIVE	Low
31	33	0	78	94	0.0088 28	110	70	NEGATIVE	Mid
23	35	3	75	1.6	29.296 88	123	59	NEGATIVE	Low
31	20	0	65	1.57	26.370 24	111	54	NEGATIVE	Mid
27	32	3	55	1.7	19.031 14	110	63	NEGATIVE	Low
26	20	0	55	1.58	22.031 73	120	66	NEGATIVE	Mid
28	29	3	84	1.66	30.483 38	115	68	NEGATIVE	Low
28	32	1	61	1.58	24.435 19	97	61	NEGATIVE	Low
32	26	0	66	1.55	27.471 38	115	73	NEGATIVE	Mid
29	35	2	57	1.56	23.422 09	120	90	NEGATIVE	Low
29	33	1	72	1.58	28.841 53	108	70	NEGATIVE	Low
30	32	0	63	1.73	21.049 82	107	80	NEGATIVE	Mid
26	26	2	61	1.58	24.435 19	100	80	NEGATIVE	Low
30	35	5	80	1.62	30.483 16	110	60	NEGATIVE	High
34	15	0	52	1.67	18.645 34	100	70	NEGATIVE	Mid
29	39	2	85	1.64	31.603 21	110	70	NEGATIVE	Low
23	33	1	68	1.52	29.432 13	125	80	NEGATIVE	Low
26	25	3	81	1.56	33.284 02	110	80	NEGATIVE	Low
35	26	0	68	1.66	24.677 02	100	60	NEGATIVE	Mid
41	33	3	69	1.62	26.291 72	120	70	NEGATIVE	Mid
24	24	0	76	1.67	27.250 89	110	80	NEGATIVE	Mid

34	27	3	67	1.66	24.31412	106	60	NEGATIVE	Low
31	34	0	75	1.57	30.4272	109	43	NEGATIVE	Mid
29	33	3	72	1.59	28.47989	105	53	NEGATIVE	Low
21	35	0	80	1.54	33.7325	130	60	NEGATIVE	Mid
30	20	2	90	1.66	32.66076	109	68	NEGATIVE	Low
27	22	2	61	1.61	23.53304	111	69	NEGATIVE	Low
31	92	0	64	1.52	27.70083	123	68	NEGATIVE	Mid
32	32	2	61	1.51	26.75321	115	67	NEGATIVE	Low
30	33	2	60	1.55	24.97399	142	90	NEGATIVE	Mid
21	33	0	58	1.57	23.53037	110	60	NEGATIVE	Mid
31	25	3	68	1.64	25.28257	105	57	NEGATIVE	Low
21	29	0	66	1.68	23.38435	100	80	NEGATIVE	Mid
35	33	2	60	1.6	23.4375	110	82	NEGATIVE	Low
26	34	0	85	1.6	33.20313	110	80	NEGATIVE	Mid
23	29	2	65	1.61	25.07619	120	80	NEGATIVE	Low
32	23	0	60	1.6	23.4375	98	60	NEGATIVE	Mid
29	34	3	58	1.56	23.833	109	66	NEGATIVE	Low
35	27	1	54	1.82	16.30238	145	89	NEGATIVE	Mid
25	27	1	96	1.61	37.03561	134	82	NEGATIVE	Low
24	28	0	82	1.66	29.75758	120	62	NEGATIVE	Mid
26	32	5	65	1.7	22.49135	112	59	NEGATIVE	High
34	24	1	45	1.65	16.52893	109	56	NEGATIVE	Low
27	24	2	48	1.56	19.72387	136	82	NEGATIVE	Low
30	35	2	79	1.67	28.32658	108	70	NEGATIVE	Low

30	20	1	64	1.71	21.887 08	107	67	NEGATIVE	Low
30	30	1	64	1.48	29.218 41	120	70	NEGATIVE	Low
29	20	0	90	1.56	36.982 25	106	60	NEGATIVE	Mid
29	30	0	69	1.54	29.094 28	102	60	NEGATIVE	Mid
31	32	0	60	1.66	21.773 84	100	60	NEGATIVE	Mid
24	26	0	59	1.64	21.936 35	105	80	NEGATIVE	Mid
21	32	3	65	1.63	24.464 6	100	80	NEGATIVE	Low
30	32	3	71	1.59	28.084 33	110	60	NEGATIVE	Low
28	32	1	60	1.58	24.034 61	102	80	NEGATIVE	Low
24	33	0	61	1.57	24.747 45	100	70	NEGATIVE	Mid
29	19	2	58	1.61	22.375 68	90	60	NEGATIVE	Low
30	33	3	59	1.62	22.481 33	110	70	NEGATIVE	Low
26	27	5	81	1.61	31.248 79	100	50	NEGATIVE	High
32	31	2	75	1.65	27.548 21	105	70	NEGATIVE	Low
35	28	1	66	1.56	27.120 32	100	60	NEGATIVE	Low
34	27	1	48	1.66	17.419 07	100	60	NEGATIVE	Low
31	32	0	68	1.58	27.239 22	120	80	NEGATIVE	Mid
29	24	0	64	1.55	26.638 92	110	80	NEGATIVE	Mid
30	29	0	59	1.59	23.337 68	90	60	NEGATIVE	Mid
26	33	1	58	1.71	19.835 16	105	70	NEGATIVE	Low
30	28	3	66	1.65	24.242 42	100	60	NEGATIVE	Low
24	31	5	48	1.56	19.723 87	120	80	NEGATIVE	High
31	24	1	67	1.56	27.531 23	110	70	NEGATIVE	Low
26	32	2	65	1.58	26.037	100	50	NEGATIVE	Low

					49				
28	38	1	67	1.64	24.91077	119	73	NEGATIVE	Low
35	37	0	62	1.69	21.70792	119	78	NEGATIVE	Mid
25	35	1	58	1.72	19.60519	130	68	NEGATIVE	Low
31	38	1	68	1.68	24.09297	101	62	NEGATIVE	Low
26	33	1	79	1.5	35.11111	127	77	NEGATIVE	Low
22	32	2	52	1.61	20.06095	117	68	NEGATIVE	Low
23	38	1	63	1.62	24.00549	141	76	NEGATIVE	Mid
40	34	8	77	1.65	28.28283	99	67	NEGATIVE	High
19	39	2	78	1.55	32.46618	111	72	NEGATIVE	Low
28	38	1	75	1.66	27.2173	123	74	NEGATIVE	Low
27	34	1	60	1.71	20.51913	107	64	NEGATIVE	Low
27	39	1	67	1.63	25.21736	120	70	NEGATIVE	Low
30	37	1	65	1.59	25.71101	142	82	NEGATIVE	Mid
23	38	1	106	1.76	34.22004	110	60	NEGATIVE	Low
29	36	1	56	1.51	24.56033	100	70	NEGATIVE	Low
30	38	1	62	1.52	26.83518	97	57	NEGATIVE	Low
31	38	2	80	1.61	30.86301	110	70	NEGATIVE	Low
36	38	1	76	1.62	28.959	120	80	NEGATIVE	Low
26	39	1	68	1.63	25.59374	116	80	NEGATIVE	Low
19	35	2	82	1.75	26.77551	115	57	NEGATIVE	Low
27	38	2	80	1.56	32.87311	150	90	NEGATIVE	Low
36	40	3	76	1.57	30.83289	110	70	NEGATIVE	Low
37	35	3	71	1.54	29.93759	160	50	NEGATIVE	High

27	40	2	110	1.6	42.96875	160	140	NEGATIVE	Low
23	37	2	70	1.48	31.95763	118	70	NEGATIVE	Low
23	37	2	78	1.66	28.306	100	60	NEGATIVE	Low
35	40	2	61	1.54	25.72103	90	60	NEGATIVE	Low
34	39	3	59	1.57	23.93606	132	75	NEGATIVE	Low
35	39	1	83	1.66	30.12048	100	60	NEGATIVE	Low
31	40	2	96	1.67	34.42217	150	80	NEGATIVE	Low
40	38	6	83	1.68	29.4076	127	81	NEGATIVE	High
40	38	4	64	1.81	19.53542	107	58	NEGATIVE	High
38	38	4	59	1.67	21.15529	103	57	NEGATIVE	High
32	38	1	70	1.6	27.34375	114	71	NEGATIVE	Low
35	39	3	61	1.67	21.87242	100	60	NEGATIVE	Low
39	32	4	67	1.56	27.53123	106	62	NEGATIVE	High
41	39	3	77	1.53	32.89333	90	60	NEGATIVE	Mid
28	37	3	50	1.58	20.02884	100	54	NEGATIVE	Low
37	35	4	71	1.56	29.17488	130	80	NEGATIVE	High
34	38	2	112	1.67	40.1592	110	60	NEGATIVE	Low
34	38	8	68	1.52	29.43213	100	60	NEGATIVE	High
35	36	2	67	1.68	23.73866	90	60	NEGATIVE	Low
34	36	4	67	1.52	28.99931	102	56	NEGATIVE	High
26	37	1	86	1.65	31.58861	130	60	NEGATIVE	Low
20	33	6	72	1.59	28.47989	116	70	NEGATIVE	High
30	40	2	92	1.55	38.29344	101	65	NEGATIVE	Low
28	38	2	78	1.66	28.306	112	66	NEGATIVE	Low

33	36	3	65	1.68	23.03005	113	71	NEGATIVE	Low
20	35	0	56	1.66	20.32225	60	55	NEGATIVE	Mid
34	37	2	65	1.6	25.39063	123	77	NEGATIVE	Low
37	38	4	81	1.69	28.36035	80	50	NEGATIVE	High
20	36	0	49	1.57	19.8791	113	94	NEGATIVE	Mid
28	37	3	60	1.56	24.65483	115	67	NEGATIVE	Low
25	39	1	74	1.67	26.53376	159	90	NEGATIVE	Mid
27	35	1	38	1.52	16.44737	90	55	NEGATIVE	Low
31	35	1	57	1.68	20.19558	100	50	NEGATIVE	Low
35	40	1	70	1.52	30.29778	106	58	NEGATIVE	Low
22	38	1	58	1.65	21.30395	100	60	NEGATIVE	Low
36	38	2	63	1.59	24.9199	90	50	NEGATIVE	Low
29	38	2	71	1.55	29.55255	122	75	NEGATIVE	Low
19	37	1	75	1.66	27.2173	110	60	NEGATIVE	Low
32	38	2	96	1.68	34.01361	110	70	NEGATIVE	Low
27	38	2	66	1.66	23.95123	100	50	NEGATIVE	Low
33	38	6	76	1.6	29.6875	120	70	NEGATIVE	High
28	36	3	67	1.69	23.45856	110	69	NEGATIVE	Low
35	35	2	78	1.57	31.64429	132	76	NEGATIVE	Low
23	37	1	67	1.58	26.83865	108	63	NEGATIVE	Low
33	39	1	62	1.68	21.96712	116	76	NEGATIVE	Low
31	39	1	73	1.68	25.86451	106	60	NEGATIVE	Low
30	40	3	63	1.63	23.71184	140	79	NEGATIVE	Mid
26	34	1	62	1.58	24.835	130	60	NEGATIVE	Low

					76				
28	38	2	67	1.67	24.02381	100	50	NEGATIVE	Low
38	40	4	72	1.65	26.44628	145	80	NEGATIVE	High
28	38	3	100	1.63	37.63785	130	65	NEGATIVE	Low
21	38	1	88	1.61	33.94931	120	80	NEGATIVE	Low
32	39	2	188	1.65	69.05418	140	70	NEGATIVE	Mid
29	38	3	81	1.63	30.48666	121	62	NEGATIVE	Low
37	39	2	74	1.68	26.21882	113	67	NEGATIVE	Mid
25	37	1	70	1.65	25.71166	110	60	NEGATIVE	Low
31	38	1	75	1.63	28.22839	108	58	NEGATIVE	Low
34	38	4	66	1.69	23.10843	102	55	NEGATIVE	High
31	37	3	100	1.57	40.5696	130	90	NEGATIVE	Low
43	37	3	82	1.68	29.05329	120	70	NEGATIVE	Mid
26	38	2	63	1.69	22.05805	107	59	NEGATIVE	Low
21	38	1	83	1.53	35.45645	130	60	NEGATIVE	Low
24	39	2	66	1.6	25.78125	110	60	NEGATIVE	Low
38	38	1	73	1.57	29.61581	115	67	NEGATIVE	Low
38	40	3	81	1.62	30.8642	101	69	NEGATIVE	Low
23	39	2	70	1.64	26.02617	100	50	NEGATIVE	Low
21	38	2	50	1.58	20.02884	100	71	NEGATIVE	Low
32	37	2	70	1.57	28.39872	160	90	NEGATIVE	Low
23	39	2	69	1.71	23.597	110	60	NEGATIVE	Low
35	39	1	67	1.66	24.31412	100	60	NEGATIVE	Low
26	37	2	66	1.56	27.12032	117	64	NEGATIVE	Low

31	39	1	150	1.57	60.8544	120	80	NEGATIVE	Low
35	35	1	56	1.59	22.15102	111	60	NEGATIVE	Low
36	40	2	76	1.58	30.44384	110	65	NEGATIVE	Low
29	35	3	61	1.53	26.05835	130	70	NEGATIVE	Low
25	36	2	63	1.56	25.88757	90	60	NEGATIVE	Low
35	38	3	71	1.53	30.33021	104	60	NEGATIVE	Low
34	37	2	86	1.56	35.33859	110	65	NEGATIVE	Low
28	36	2	64	1.64	23.79536	114	64	NEGATIVE	Low
38	38	2	55	1.61	21.21832	120	60	NEGATIVE	Low
34	39	4	89	1.64	33.09042	130	70	NEGATIVE	Low
23	38	1	105	1.59	41.53317	140	60	NEGATIVE	Mid
32	37	2	110	1.68	38.97392	132	86	NEGATIVE	Low
27	38	1	78	1.64	29.00059	106	64	NEGATIVE	Low
34	29	2	68	1.61	26.23356	125	77	NEGATIVE	Low
21	39	1	75	1.62	28.57796	90	60	NEGATIVE	Low
35	39	5	74	1.65	27.1809	100	60	NEGATIVE	Low
28	39	2	104	1.62	39.62811	120	70	NEGATIVE	Low
32	41	2	81	1.61	31.24879	108	65	NEGATIVE	Low
40	36	2	64	1.71	21.88708	130	80	NEGATIVE	Mid
45	39	5	90	1.52	38.95429	95	50	NEGATIVE	High
36	41	3	109	1.66	39.55581	120	80	NEGATIVE	Low
33	32	2	97	1.59	38.36874	140	80	NEGATIVE	Mid
30	41	2	123	1.64	45.73171	120	80	NEGATIVE	Low
30	39	3	73	1.54	30.780	104	63	NEGATIVE	Low

					91				
32	39	2	81	1.52	35.05886	110	60	NEGATIVE	Low
22	38	1	63	1.62	24.00549	102	54	NEGATIVE	Low
33	37	2	57	1.66	20.68515	150	95	NEGATIVE	Mid
37	39	3	56	1.61	21.6041	105	69	NEGATIVE	Low
24	37	1	72	1.64	26.76978	100	60	NEGATIVE	Low
25	39	1	64	1.59	25.31545	111	70	NEGATIVE	Low
26	37	2	79	1.51	34.6476	139	70	NEGATIVE	Mid
32	40	1	71	1.5	31.55556	120	74	NEGATIVE	Low
37	39	5	84	1.61	32.40616	120	85	NEGATIVE	High
31	39	3	71	1.51	31.13899	119	65	NEGATIVE	Low
33	37	3	90	1.65	33.05785	110	60	NEGATIVE	Low
29	38	0	75	1.63	28.22839	112	65	NEGATIVE	Mid
29	35	2	77	1.53	32.89333	113	75	NEGATIVE	Low
23	39	0	78	1.65	28.65014	132	81	NEGATIVE	Mid
31	35	2	76	1.64	28.25699	100	50	NEGATIVE	Low
27	37	1	47	1.66	17.05618	103	67	NEGATIVE	Low
37	38	2	61	1.55	25.39022	127	76	NEGATIVE	Low
34	38	1	73	1.57	29.61581	104	61	NEGATIVE	Low
32	40	2	75	1.54	31.62422	130	70	NEGATIVE	Low
32	38	2	77	1.6	30.07813	155	70	NEGATIVE	Mid
18	39	2	97	1.72	32.78799	120	70	NEGATIVE	Low
38	37	3	82	1.62	31.24524	150	80	NEGATIVE	Mid
32	40	2	87	1.61	33.56352	132	76	NEGATIVE	Low

20	37	1	64	1.63	24.08822	110	56	NEGATIVE	Low
29	39	2	67	1.6	26.17188	120	69	NEGATIVE	Low
29	36	2	78	1.7	26.98962	115	57	NEGATIVE	Low
33	37	1	82	1.56	33.69494	118	76	NEGATIVE	Low
23	37	1	77	1.68	27.28175	131	65	NEGATIVE	Low
20	38	1	85	1.51	37.27907	121	80	NEGATIVE	Low
35	36	2	118	1.67	42.31059	120	70	NEGATIVE	Low
39	36	4	71	1.68	25.1559	110	70	NEGATIVE	High
34	38	1	73	1.68	25.86451	104	61	NEGATIVE	Low
32	40	2	75	1.67	26.89232	130	70	NEGATIVE	Low
32	38	2	77	1.58	30.84442	160	69	NEGATIVE	Mid
18	39	2	97	1.66	35.20105	120	70	NEGATIVE	Low
38	37	3	82	1.62	31.24524	150	80	NEGATIVE	Mid
32	40	2	87	1.66	31.57207	132	76	NEGATIVE	Low
20	37	1	64	1.62	24.38653	110	56	NEGATIVE	Low
29	39	2	67	1.58	26.83865	120	69	NEGATIVE	Low
29	36	2	78	1.64	29.00059	115	57	NEGATIVE	Low
33	37	1	82	1.63	30.86304	118	76	NEGATIVE	Low
23	37	1	77	1.67	27.60945	131	65	NEGATIVE	Low
20	38	1	85	1.68	30.11621	121	80	NEGATIVE	Low
35	36	2	118	1.63	44.41266	120	70	NEGATIVE	Low
39	36	4	71	1.69	24.85907	110	70	NEGATIVE	High
25	40	1	72	1.66	26.12861	110	60	NEGATIVE	Low
36	37	3	101	1.61	38.964	170	110	NEGATIVE	High

					55				
38	38	2	68	1.67	24.38237	110	70	NEGATIVE	Low
36	39	0	78	1.55	32.46618	125	78	NEGATIVE	Mid
39	38	4	83	1.57	33.67277	120	70	NEGATIVE	High
28	39	3	69	1.66	25.03992	107	58	NEGATIVE	Low
26	37	2	69	1.58	27.6398	100	60	NEGATIVE	Low
30	38	3	85	1.56	34.92768	110	60	NEGATIVE	Low
26	37	1	70	1.6	27.34375	98	65	NEGATIVE	Low
22	36	0	67	1.59	26.50212	97	58	NEGATIVE	High
40	39	6	76	1.58	30.44384	125	77	NEGATIVE	High
29	40	3	80	1.53	34.17489	120	71	NEGATIVE	Low
30	39	2	69	1.71	23.597	107	73	NEGATIVE	Low
26	39	2	98	1.52	42.4169	127	75	NEGATIVE	Low
24	37	0	74	1.62	28.19692	142	73	NEGATIVE	mid
39	36	4	71	1.68	25.1559	110	70	NEGATIVE	High
32	37	2	90	1.66	32.66076	155	95	NEGATIVE	Mid
17	20	0	83	1.6	32.42188	128	76	NEGATIVE	High
37	40	3	60	1.55	24.97399	125	28	NEGATIVE	Mid
33	40	3	71	1.59	28.08433	110	60	NEGATIVE	Low
21	37	0	67	1.65	24.60973	128	68	NEGATIVE	High
28	39	0	93	1.52	40.25277	100	70	NEGATIVE	High
24	40	2	60	1.68	21.2585	124	74	NEGATIVE	Low
23	39	0	85	1.52	36.79017	120	70	NEGATIVE	High
30	38	1	66	1.67	23.66524	118	68	NEGATIVE	mid

19	35	0	72	1.56	29.5858	118	64	NEGATIVE	High
36	38	2	93	1.69	32.56189	100	60	NEGATIVE	Low
27	39	3	61	1.57	24.74745	129	75	NEGATIVE	Low
40	39	2	73	1.57	29.61581	140	80	NEGATIVE	High
23	39	3	98	1.65	35.99633	180	80	NEGATIVE	High
35	38	3	63	1.61	24.30462	110	80	NEGATIVE	Low
27	36	0	68	1.56	27.94214	119	73	NEGATIVE	High
19	37	0	70	1.58	28.04038	128	61	NEGATIVE	High
27	36	0	68	1.64	25.28257	119	73	NEGATIVE	High
19	39	1	70	1.47	32.39391	128	61	NEGATIVE	Low
26	37	0	71	1.66	25.76571	120	60	NEGATIVE	Mid
29	38	2	66	1.59	26.10656	120	50	NEGATIVE	Low
28	40	0	74	1.62	28.19692	111	60	NEGATIVE	High
30	39	2	64	1.59	25.31545	110	58	NEGATIVE	Low
21	35	1	71	1.55	29.55255	120	60	NEGATIVE	Low
33	37	3	103	1.54	43.4306	110	60	NEGATIVE	Low
29	40	3	69	1.56	28.35306	124	67	NEGATIVE	Low
22	38	0	62	1.54	26.14269	100	60	NEGATIVE	High
34	37	0	99	1.63	37.26147	130	80	NEGATIVE	High
33	38	3	84	1.57	34.07846	121	72	NEGATIVE	Low
37	39	2	64	1.6	25	140	80	NEGATIVE	Mid
19	37	1	78	1.62	29.72108	111	72	NEGATIVE	Low
40	36	8	77	1.61	29.70564	114	72	NEGATIVE	High
33	38	1	74	1.51	32.45472	119	70	NEGATIVE	Low

23	35	0	65	1.63	24.4646	148	93	NEGATIVE	High
26	40	4	77	1.68	27.28175	120	70	NEGATIVE	High
22	32	1	52	1.73	17.37445	117	68	NEGATIVE	Low
31	40	2	68	1.57	27.58733	110	55	NEGATIVE	Low
35	38	0	62	1.68	21.96712	119	78	NEGATIVE	High
25	37	2	60	1.71	20.51913	120	70	NEGATIVE	Low
28	38	1	52	1.65	19.10009	119	73	NEGATIVE	Low
42	37	4	72	1.69	25.2092	168	94	NEGATIVE	High
25	37	0	72	1.67	25.81663	105	62	NEGATIVE	High
34	35	2	63	1.64	23.42356	104	61	NEGATIVE	Low
33	40	3	65	1.68	23.03005	100	68	NEGATIVE	Low
30	37	2	71	1.58	28.44095	102	60	NEGATIVE	Low
41	39	3	72	1.66	26.12861	120	70	NEGATIVE	Mid
28	35	1	66	1.61	25.46198	112	70	NEGATIVE	Low
25	37	2	70	1.59	27.68878	130	70	NEGATIVE	Low
26	35	0	65	1.72	21.97134	100	60	NEGATIVE	High
34	38	1	80	1.51	35.08618	150	29	NEGATIVE	Mid
27	40	2	70	1.52	30.29778	100	56	NEGATIVE	Low
29	39	2	75	1.64	27.88519	121	62	NEGATIVE	Low
27	38	1	70	1.64	26.02617	120	80	NEGATIVE	Low
33	38	3	70	1.53	29.90303	140	66	NEGATIVE	Low
22	38	1	63	1.6	24.60938	102	54	NEGATIVE	Low
33	37	2	69	1.59	27.29322	100	60	NEGATIVE	Low
23	36	0	81	1.61	31.248	130	70	NEGATIVE	High

					79				
33	39	1	76	1.6	29.6875	120	70	NEGATIVE	Low
33	35	3	74	1.61	28.54828	130	64	NEGATIVE	Low
30	40	2	94	1.71	32.14664	107	59	NEGATIVE	Low
20	38	2	64	1.61	24.69041	112	77	NEGATIVE	Low
38	35	3	83	1.62	31.62628	110	70	NEGATIVE	Low
34	39	2	72	1.57	29.21011	122	63	NEGATIVE	Low
37	39	2	75	1.67	26.89232	150	80	NEGATIVE	Mid
36	37	1	45	1.55	18.73049	121	75	NEGATIVE	Low
38	38	3	80	1.69	28.01022	100	60	NEGATIVE	Low
36	38	2	71	1.65	26.07897	111	53	NEGATIVE	Low
30	36	1	73	1.59	28.87544	110	70	NEGATIVE	Low
28	38	3	66	1.55	27.47138	107	58	NEGATIVE	Low
39	36	4	80	1.68	28.34467	120	70	NEGATIVE	mid
38	39	2	75	1.52	32.46191	125	78	NEGATIVE	Low
38	38	2	68	1.55	28.30385	110	70	NEGATIVE	Low
36	39	3	75	1.59	29.66655	125	78	NEGATIVE	Low
38	37	2	86	1.49	38.73699	110	70	NEGATIVE	Low
25	40	1	72	1.61	27.77671	103	56	NEGATIVE	Low
36	39	3	101	1.63	38.01423	170	110	NEGATIVE	High
26	37	1	84	1.74	27.74475	127	75	NEGATIVE	Low
30	39	2	65	1.54	27.40766	107	73	NEGATIVE	Low
29	40	5	80	1.61	30.86301	120	71	NEGATIVE	High
40	35	6	76	1.58	30.44384	120	77	NEGATIVE	High

35	36	2	118	1.57	47.872 12	102	66	NEGATIVE	Low
23	37	1	77	1.58	30.844 42	131	69	NEGATIVE	Low
39	38	4	84	1.57	34.078 46	133	72	NEGATIVE	Mid
32	37	1	55	1.66	19.959 36	110	57	NEGATIVE	Low
20	38	1	49	1.68	17.361 11	96	62	NEGATIVE	Low
25	39	0	96	1.63	36.132 33	128	80	NEGATIVE	Mid
38	36	3	73	1.57	29.615 81	107	61	NEGATIVE	Low
32	40	1	68	1.61	26.233 56	104	64	NEGATIVE	Low
27	39	2	62	1.62	23.624 45	109	64	NEGATIVE	Low
29	38	2	71	1.58	28.440 95	96	59	NEGATIVE	Low
21	35	1	77	1.71	26.332 89	101	56	NEGATIVE	Low
20	38	1	75	1.54	31.624 22	138	72	NEGATIVE	Low
22	38	1	67	1.65	24.609 73	100	90	NEGATIVE	Low
23	37	2	85	1.68	30.116 21	124	64	NEGATIVE	Low
32	37	5	54	1.65	19.834 71	100	60	NEGATIVE	High
23	36	3	72	1.49	32.430 97	117	71	NEGATIVE	Low
33	35	2	82	1.65	30.119 38	118	76	NEGATIVE	Low
27	38	2	78	1.54	32.889 19	115	57	NEGATIVE	Low
29	37	1	72	1.68	25.510 2	110	70	NEGATIVE	Low
29	39	2	65	1.63	24.464 6	120	69	NEGATIVE	Low
20	37	1	64	1.66	23.225 43	110	56	NEGATIVE	Low
32	39	3	87	1.64	32.346 82	130	70	NEGATIVE	Low
38	37	3	79	1.71	27.016 86	121	77	NEGATIVE	Low
18	39	3	97	1.64	36.064	120	70	NEGATIVE	Low

					84				
32	38	2	68	1.61	26.23356	85	50	NEGATIVE	Low
32	40	3	75	1.61	28.93407	130	70	NEGATIVE	Low
34	38	3	73	1.64	27.14158	104	61	NEGATIVE	Low
24	37	0	75	1.59	29.66655	142	73	NEGATIVE	High
29	38	2	95	1.67	34.06361	150	80	NEGATIVE	Mid
26	39	0	67	1.71	22.91303	114	60	NEGATIVE	Mid
37	41	4	135	1.63	50.8111	150	80	NEGATIVE	High
37	37	1	67	1.47	31.0056	104	58	NEGATIVE	Low
27	35	0	70	1.56	28.76397	100	65	NEGATIVE	Mid
40	39	2	95	1.59	37.57763	129	76	NEGATIVE	Mid
34	39	2	72	1.61	27.77671	100	60	NEGATIVE	Low
31	38	2	68	1.53	29.04866	110	73	NEGATIVE	Low
33	38	1	72	1.57	29.21011	100	50	NEGATIVE	Low
34	39	1	84	1.59	33.22653	100	70	NEGATIVE	Low
15	38	0	75	1.57	30.4272	120	60	NEGATIVE	Mid
31	39	1	73	1.58	29.24211	110	60	NEGATIVE	Low
30	35	1	65	1.59	25.71101	130	70	NEGATIVE	Low
29	38	1	88	1.64	32.71862	110	60	NEGATIVE	Low
37	39	8	67	1.59	26.50212	130	90	NEGATIVE	High
37	37	2	79	1.61	30.47722	110	60	NEGATIVE	Low
30	37	3	103	1.61	39.73612	130	70	NEGATIVE	Low
27	37	3	67	1.73	22.38631	112	60	NEGATIVE	Low
32	40	0	78	1.54	32.88919	102	70	NEGATIVE	Mid

37	38	2	65	1.62	24.76757	100	60	NEGATIVE	Low
23	40	1	83	1.63	31.23941	110	60	NEGATIVE	Low
27	37	2	86	1.58	34.44961	131	77	NEGATIVE	Low
22	36	0	79	1.59	31.24876	100	60	NEGATIVE	Mid
36	38	4	72	1.62	27.43484	102	58	NEGATIVE	High
21	41	0	69	1.68	24.44728	110	60	NEGATIVE	Mid
32	38	5	74	1.61	28.54828	90	65	NEGATIVE	High
28	37	1	64	1.58	25.63692	95	60	NEGATIVE	Low
28	40	2	102	1.56	41.91321	130	74	NEGATIVE	Low
29	39	3	79	1.53	33.7477	110	63	NEGATIVE	Low
40	37	2	110	1.6	42.96875	140	90	NEGATIVE	High
22	38	1	63	1.76	20.33833	210	60	NEGATIVE	High
36	38	2	69	1.51	30.26183	99	58	NEGATIVE	Low
32	39	1	61	1.62	23.24341	117	64	NEGATIVE	Low
29	39	1	77	1.62	29.34004	122	70	NEGATIVE	Low
22	37	0	75	1.56	30.81854	109	9	NEGATIVE	Mid
25	37	2	103	1.61	39.73612	160	80	NEGATIVE	High
33	38	1	63	1.58	25.23634	108	71	NEGATIVE	Low
23	40	1	105	1.59	41.53317	105	80	NEGATIVE	Low
20	36	0	65	1.51	28.50752	110	60	NEGATIVE	Mid
34	38	5	63	1.42	31.2438	140	80	NEGATIVE	High
30	38	1	65	1.69	22.75831	124	72	NEGATIVE	Low
24	37	2	76	1.68	26.92744	105	63	NEGATIVE	Low
31	39	3	91	1.67	32.629	154	90	NEGATIVE	Mid

					35				
35	38	3	62	1.62	23.624 45	109	60	NEGATIVE	Low
23	37	1	85	1.54	35.840 78	90	57	NEGATIVE	Low
27	37	3	66	1.63	24.840 98	120	70	NEGATIVE	Low
37	27	5	80	1.69	28.010 22	120	67	NEGATIVE	High
27	38	3	72	1.65	26.446 28	110	60	NEGATIVE	Low
21	39	2	80	1.57	32.455 68	106	68	NEGATIVE	Low
27	35	0	74	1.58	29.642 69	110	60	NEGATIVE	Mid
27	40	3	85	1.63	31.992 17	110	70	NEGATIVE	Low
26	38	2	78	1.53	33.320 52	92	61	NEGATIVE	Low
30	37	2	65	1.62	24.767 57	120	60	NEGATIVE	Low
18	35	0	58	1.52	25.103 88	110	60	NEGATIVE	Mid
34	39	3	74	1.61	28.548 28	110	80	NEGATIVE	Low
33	39	4	96	1.52	41.551 25	118	72	NEGATIVE	High
34	35	5	72	1.65	26.446 28	126	74	NEGATIVE	High
39	37	2	61	1.64	22.679 95	132	81	NEGATIVE	Low
23	38	2	72	1.74	23.781 21	100	65	NEGATIVE	Low
21	40	1	70	1.56	28.763 97	149	89	NEGATIVE	Mid
24	35	1	63	1.56	25.887 57	118	65	NEGATIVE	Low
32	35	2	61	1.61	23.533 04	119	57	NEGATIVE	Low
38	37	3	55	1.56	22.600 26	90	56	NEGATIVE	Low
32	39	4	75	1.61	28.934 07	107	65	NEGATIVE	High
31	26	2	74	1.58	29.642 69	140	97	NEGATIVE	Mid
26	39	3	69	1.71	23.597	128	68	NEGATIVE	Low

38	37	8	76	1.67	27.25089	138	68	NEGATIVE	High
20	37	1	56	1.78	17.67454	111	58	NEGATIVE	Low
23	34	1	58	1.65	21.30395	105	60	NEGATIVE	Low
34	40	2	61	1.72	20.61925	112	67	NEGATIVE	Low
22	38	2	60	1.67	21.51386	127	71	NEGATIVE	Low
39	34	2	76	1.62	28.959	110	57	GLUCOSE TRACE	Low
35	36	2	83	1.51	36.40191	100	60	TRACE OF PROTEIN	Low
38	38	2	56	1.69	19.60716	103	65	TRACE OF PROTEIN	Low
33	39	5	104	1.55	43.28824	140	78	GLUCOSE TRACE	High
30	38	2	66	1.96	17.18034	100	50	NEGATIVE	Low
29	41	1	64	1.64	23.79536	151	87	NEGATIVE	Mid
20	37	1	81	1.57	32.86137	122	68	NEGATIVE	Low
28	36	4	61	1.56	25.06575	120	80	NEGATIVE	High
25	37	3	84	1.52	36.35734	110	64	NEGATIVE	Low
23	41	1	55	1.66	19.95936	122	83	NEGATIVE	Low
32	35	3	106	1.68	37.55669	133	76	NEGATIVE	Low
19	37	1	84	1.57	34.07846	128	62	NEGATIVE	Low
29	35	1	63	1.63	23.71184	110	60	NEGATIVE	Low
38	37	3	62	1.67	22.23099	99	64	NEGATIVE	Low
32	24	3	72	1.57	29.21011	119	77	PROTEIN TRACE	Low
29	27	3	58	1.58	23.23346	129	77	PROTEIN TRACE	Low
26	24	1	95	1.57	38.54112	130	78	PR0TEIN TRACE	Low
25	35	2	55	1.51	24.12175	101	59	NEGATIVE	Low
41	36	3	93	1.61	35.878	152	74	NEGATIVE	High

					25				
29	39	1	82	1.51	35.96333	120	70	GLUCOSE TRACE	Low
23	40	1	89	1.53	38.01957	130	80	NEGATIVE	Low
27	28	3	71	1.58	28.44095	114	70	NEGATIVE	Low
49	26	3	69	1.58	27.6398	150	93	NEGATIVE	Low
20	36	2	61	1.61	23.53304	111	60	NEGATIVE	Low
22	37	1	67	1.57	27.18163	100	50	NEGATIVE	Low
36	35	3	99	1.67	35.49787	90	50	NEGATIVE	Low
42	38	4	67	1.58	26.83865	93	61	NEGATIVE	High
32	39	2	68	1.56	27.94214	112	67	GLUCOSE TRACE	Low
29	41	3	53	1.62	20.19509	110	70	NEGATIVE	Low
21	36	1	57	1.62	21.71925	109	58	NEGATIVE	Low
31	39	1	67	1.57	27.18163	122	74	NEGATIVE	Low
33	38	3	74	1.61	28.54828	60	64	NEGATIVE	Low
28	39	3	72	1.63	27.09925	117	71	NEGATIVE	Low
27	37	1	58	1.54	24.45606	100	60	TRACE OF PROTEIN	Low
34	40	0	80	1.63	30.11028	90	50	NEGATIVE	Mid
38	37	1	77	1.61	29.70564	118	73	NEGATIVE	Low
37	40	4	75	1.65	27.54821	100	60	NEGATIVE	High
26	38	3	60	1.55	24.97399	103	60	NEGATIVE	Low
22	37	0	65	1.75	21.22449	100	60	NEGATIVE	Mid
35	39	3	110	1.61	42.43663	121	75	NEGATIVE	Low
18	36	1	50	1.71	17.09928	103	53	NEGATIVE	Low
22	36	1	70	1.61	27.00513	110	68	NEGATIVE	Low

23	35	0	61	1.63	22.959 09	92	80	NEGATIVE	Mid
35	37	2	72	1.65	26.446 28	94	53	NEGATIVE	Low
29	35	2	51	1.58	20.429 42	130	87	NEGATIVE	Low
32	36	4	96	1.62	36.579 79	129	72	NEGATIVE	High
26	35	2	67	1.53	28.621 47	124	79	NEGATIVE	Low
25	37	5	81	1.63	30.486 66	92	66	NEGATIVE	High
37	39	6	71	1.66	25.765 71	112	70	NEGATIVE	High
29	29	4	56	1.54	23.612 75	91	43	NEGATIVE	High
24	35	2	64	1.55	26.638 92	113	47	NEGATIVE	Low
20	38	1	75	1.69	26.259 58	120	60	NEGATIVE	Low
31	35	1	67	1.67	24.023 81	133	72	NEGATIVE	Low
33	30	2	62	1.58	24.835 76	107	58	NEGATIVE	Low
36	37	3	75	1.65	27.548 21	123	68	PROTEIN TRACE	Low
29	35	6	82	1.65	30.119 38	111	57	NEGATIVE	High
36	38	4	72	1.58	28.841 53	110	66	NEGATIVE	High
37	35	5	55	1.59	21.755 47	86	58	NEGATIVE	High
21	28	3	73	1.58	29.242 11	103	56	NEGATIVE	Low
35	37	5	75	1.68	26.573 13	114	68	NEGATIVE	High
19	38	1	59	1.6	23.046 88	109	64	NEGATIVE	Low
31	39	3	56	1.68	19.841 27	103	56	NEGATIVE	Low
32	38	2	60	1.61	23.147 26	98	63	NEGATIVE	Low
35	39	0	64	1.63	24.088 22	183	85	NEGATIVE	Mid
32	39	3	65	1.53	27.767 1	90	60	NEGATIVE	Low
28	37	3	60	1.51	26.314	107	63	NEGATIVE	Low

					64				
32	39	2	84	1.63	31.61579	101	50	NEGATIVE	Low
33	35	4	68	1.47	31.46837	95	60	NEGATIVE	High
38	35	4	93	1.63	35.0032	131	88	PROTEIN TRACE	High
25	40	2	75	1.57	30.4272	107	63	NEGATIVE	Low
38	35	4	56	1.59	22.15102	114	68	NEGATIVE	High
36	37	3	61	1.63	22.95909	155	86	NEGATIVE	Mid
31	38	3	77	1.61	29.70564	107	59	PROTEIN TRACE	Low
22	39	1	74	1.61	28.54828	136	76	NEGATIVE	Low
25	35	1	77	1.59	30.45766	138	58	GLUCOSE TRACE	Low
34	30	2	96	1.61	37.03561	133	80	PROTEIN TRACE	Low
29	29	1	81	1.61	31.24879	135	86	PROTEIN TRACE	Low
30	28	3	57	1.53	24.34961	92	65	NEGATIVE	Low
38	35	4	57	1.65	20.93664	125	71	NEGATIVE	High
30	35	2	69	1.66	25.03992	120	80	NEGATIVE	Low
37	38	4	77	1.58	30.84442	127	70	NEGATIVE	High
33	41	4	72	1.64	26.76978	90	60	NEGATIVE	High
27	38	4	73	1.57	29.61581	100	60	NEGATIVE	High
46	30	3	79	1.61	30.47722	140	83	NEGATIVE	High
30	38	2	107	1.65	39.30211	110	58	NEGATIVE	Low
35	36	3	79	1.55	32.88241	140	70	GLUCOSE TRACE	Mid
21	35	1	53	1.62	20.19509	160	60	NEGATIVE	High
24	35	2	75	1.66	27.2173	112	67	NEGATIVE	Low
37	38	3	76	1.71	25.9909	110	60	NEGATIVE	Low

36	32	2	102	1.58	40.85884	110	70	NEGATIVE	Low
31	40	2	78	1.58	31.24499	101	66	NEGATIVE	Low
36	32	1	98	1.62	37.34187	150	90	PROTEIN TRACE	Mid
24	33	2	98	1.64	36.43664	127	76	NEGATIVE	Low
33	32	2	130	1.52	56.26731	130	70	GLUCOSE TRACE	Low
19	33	1	70	1.64	26.02617	119	53	NEGATIVE	Low
32	30	3	72	1.54	30.35925	128	82	NEGATIVE	Low
26	38	0	75	1.59	29.66655	100	50	NEGATIVE	Mid
27	38	0	85	1.52	36.79017	126	70	NEGATIVE	Mid
33	39	2	75	17.2	0.253515	110	60	NEGATIVE	Low
25	40	1	90	1.56	36.98225	109	60	NEGATIVE	Low
35	38	6	70	1.65	25.71166	100	50	NEGATIVE	High
36	39	7	89	1.59	35.2043	100	60	NEGATIVE	High
31	37	1	80	1.63	30.11028	117	75	NEGATIVE	Low
31	35	0	56	1.57	22.71897	109	68	NEGATIVE	Mid
29	41	3	88	1.53	37.59238	100	460	NEGATIVE	Low
28	35	1	59	1.49	26.57538	103	64	NEGATIVE	Low
36	37	0	83	1.57	33.67277	128	75	NEGATIVE	Mid
40	38	5	79	1.57	32.04998	110	73	NEGATIVE	Mid
38	39	2	72	1.59	28.47989	100	60	NEGATIVE	Low
28	38	1	74	1.6	28.90625	98	50	NEGATIVE	Low
17	37	0	81	1.62	30.8642	100	60	NEGATIVE	Mid
26	39	1	59	1.58	23.63403	102	56	NEGATIVE	Low
30	38	4	61	1.6	23.828	125	78	NEGATIVE	High

					13				
27	40	3	65	1.8	20.06173	130	85	NEGATIVE	Low
34	38	2	71	1.6	27.73438	139	71	NEGATIVE	Low
31	38	2	83	1.62	31.62628	124	69	NEGATIVE	Low
38	37	3	85	1.67	30.47797	125	34	NEGATIVE	Low
30	38	2	95	1.54	40.05735	106	62	NEGATIVE	Low
36	40	1	82	1.67	29.40227	136	88	NEGATIVE	Low
23	37	2	73	94	0.008262	118	73	NEGATIVE	Low
29	39	1	60	1.6	23.4375	90	60	NEGATIVE	Low
34	38	1	52	1.57	21.09619	120	80	NEGATIVE	Low
30	40	3	62	1.7	21.45329	104	51	NEGATIVE	Low
25	36	2	72	1.58	28.84153	1o5	65	NEGATIVE	Low
26	38	2	68	1.66	24.67702	130	90	NEGATIVE	Low
20	39	2	68	1.58	27.23922	110	60	NEGATIVE	Low
22	37	0	80	1.55	33.29865	127	70	NEGATIVE	Mid
19	38	0	63	1.56	25.88757	100	60	NEGATIVE	Mid
35	39	1	66	1.58	26.43807	114	63	NEGATIVE	Low
23	37	4	75	1.73	25.05931	130	86	NEGATIVE	High
28	37	2	63	1.58	25.23634	139	88	NEGATIVE	Low
23	39	2	70	1.62	26.67276	109	65	NEGATIVE	Low
36	38	4	77	1.67	27.60945	100	60	NEGATIVE	High
27	35	1	59	1.64	21.93635	120	90	NEGATIVE	Low
23	37	0	60	1.52	25.96953	137	81	NEGATIVE	Mid
38	38	3	106	1.56	43.55687	114	63	NEGATIVE	Low

22	36	1	67	1.66	24.31412	97	58	NEGATIVE	Low
26	37	1	75	1.62	28.57796	117	64	NEGATIVE	Low
26	38	2	70	1.67	25.0995	106	60	NEGATIVE	Low
30	38	3	83	1.66	30.12048	110	60	NEGATIVE	Low
26	39	3	67	1.57	27.18163	100	60	NEGATIVE	Low
32	38	3	77	1.59	30.45766	116	75	NEGATIVE	Low
31	40	1	76	1.54	32.04588	100	60	NEGATIVE	Low
28	37	1	77	1.66	27.9431	123	71	NEGATIVE	Low
24	37	4	69	1.61	26.61934	170	100	NEGATIVE	High
32	38	3	81	1.52	35.05886	150	89	NEGATIVE	Mid
41	37	4	67	1.51	29.38468	120	70	NEGATIVE	High
19	32	0	59	1.55	24.55775	110	70	NEGATIVE	High
34	36	2	76	1.57	30.83289	100	60	NEGATIVE	Low
30	39	2	75	1.64	27.88519	114	69	NEGATIVE	Low
36	37	2	60	1.68	21.2585	100	50	NEGATIVE	Low
38	39	4	80	1.6	31.25	90	60	NEGATIVE	High
30	39	3	85	1.6	33.20313	110	70	NEGATIVE	Low
35	38	2	105	1.61	40.5077	150	80	NEGATIVE	Low
30	36	4	58	1.6	22.65625	102	59	NEGATIVE	High
31	39	2	93	1.56	38.21499	120	85	NEGATIVE	Low
34	27	0	85	1.82	25.66115	110	70	NEGATIVE	Mid
20	35	1	73	1.61	28.16249	130	70	NEGATIVE	Low
23	37	0	105	1.66	38.10422	160	90	NEGATIVE	High
39	38	3	74	1.7	25.60554	150	80	NEGATIVE	High

19	36	0	75	1.65	27.54821	120	70	NEGATIVE	High
25	36	1	69	1.56	28.35306	103	62	NEGATIVE	Low
25	37	3	62	1.67	22.23099	113	67	NEGATIVE	Low
20	39	0	59	1.71	20.17715	100	67	NEGATIVE	Mid
25	40	2	56	1.48	25.56611	90	50	NEGATIVE	Low
36	39	2	89	1.56	36.57133	136	71	NEGATIVE	Low
27	37	1	64	1.54	26.986	129	70	NEGATIVE	Low
37	37	2	70	1.66	25.40282	90	60	NEGATIVE	Low
37	37	4	65	1.64	24.16716	141	87	NEGATIVE	High
32	36	5	59	1.63	22.20633	119	17	NEGATIVE	High
26	40	2	67	1.59	26.50212	100	60	NEGATIVE	Low
30	39	3	71	1.58	28.44095	9	60	NEGATIVE	Low
38	40	4	60	1.57	24.34176	119	70	NEGATIVE	High
30	36	2	70	1.61	27.00513	100	70	NEGATIVE	Low
27	39	1	77	1.62	29.34004	110	80	NEGATIVE	Low
31	37	2	89	1.61	34.3351	110	6	NEGATIVE	Low
18	39	1	69	1.65	25.34435	120	60	NEGATIVE	Low
32	37	2	92	1.56	37.80408	158	84	NEGATIVE	Mid
29	35	2	76	1.66	27.5802	110	70	NEGATIVE	Low
35	37	4	61	1.58	24.43519	139	80	NEGATIVE	Mid
23	35	1	65	1.55	27.05515	105	50	NEGATIVE	Low
40	36	2	68	1.59	26.89767	100	60	NEGATIVE	Mid
25	38	1	69	1.71	23.597	90	60	NEGATIVE	Low
30	35	3	63	1.65	23.1405	114	76	NEGATIVE	Low

32	37	3	90	1.56	36.98225	110	80	NEGATIVE	Low
29	37	0	69	1.56	28.35306	120	70	NEGATIVE	Mid
30	38	4	64	1.58	25.63692	138	82	NEGATIVE	Mid

Appendix B: Sample Source Codes for Model Development

```
from warnings import filterwarnings
filterwarnings(action="ignore")

import numpy as np
import pandas as pd
from tqdm import tqdm
from io import StringIO
from tabulate import tabulate

import keras
from keras import layers
from keras import optimizers
from keras import callbacks
from keras import Sequential
from keras import regularizers
from keras.utils import to_categorical

from sklearn import metrics
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split, StratifiedKFold
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassif
ier

from xgboost import XGBClassifier
from catboost import CatBoostClassifier
from lightgbm import LGBMClassifier

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use("ggplot")
```