LITERATURE REVIEW OF NEW SAND CONTROL MANAGEMENT TECHNIQUES

BY

Destiny OSAIGBOVO

LSC2007347

(CHEMICAL/PETROLEUM TECHNIQUES)

DEPARTMENT OF SCIENCE LABORATORY TECHNOLOGY

FACULTY OF LIFE SCIENCES

UNIVERSITY OF BENIN

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A PROJECT WORK SUBMITTED TO THE DEPARTMENT OF SCIENCE LABORATORY TECHNOLOGY, FACpULTY OF LIFE SCIENCE, UNIVERSITY OF BENIN, BENIN CITY EDO STATES, NIGERIA. IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF BACHELOR'S DEGREE (BSc). IN SCIENCE LABORATORY TECHNOLOGY.

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CERTIFICATION

This is to certify that this project work titled "**A LITERATURE REVIEW OF NEW SAND CONTROL MANAGEMENT TECHNIQUES" w**as carried out by Destiny OSAIGBOVO with matriculation number LSC2007347, of the Department of Science Laboratory Technology (Chemical/Petroleum Techniques), Faculty of Life Sciences, University of Benin, Benin City, Edo State, under the supervision of Mr D.A. SALAMI.

Mr. D. A. SALAMI (Project Supervisor)	Date
Dr. P. O. Alonge (Project Coordinator)	Date
Prof. E. O. OSARUMWENGE (Head of Department)	Date
External Examiner	Date

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DEDICATION

I dedicate this work to the Almighy God for giving me the strength, grace, patience and provision to complete this project work and to my parents for their unwavering support.

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I give the Almighty God all the praise for His unending grace, strength, and wisdom during this academic journey. I genuinely thank Mr. D. A. Salami, my supervisor, for his commitment, tolerance, and priceless advice, all of which substantially improved the caliber of this work and my own development.

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ABSTRACT

Sand production remains one of the most persistent challenges in oil and gas operations, particularly in unconsolidated sandstone reservoirs where weak formations are prone to failure under changing pressure and stress conditions. This study explores the advancements in sand prediction and management techniques, focusing on the integration of artificial intelligence tools such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM) for enhanced predictive accuracy. By analyzing key reservoir parameters, machine learning models were developed to classify wells based on their sand production potential. The research compares the predictive performance of ANN and SVM algorithms, identifying the most reliable and adaptable approach for field applications, especially in datascarce environments. Findings from this study contribute to improved decisionmaking in sand control strategy selection, reduced equipment damage, minimized production losses, and more sustainable well management practices in unconsolidated reservoirs.

CHAPTER ONE

INTRODUCTION

1.1 Background of Study

Sand production is one of the major challenges in oil well operations, as it can significantly reduce wellbore productivity and overall reservoir performance. Sand production refers to the release of formation sands alongside formation fluids during oil extraction. This phenomenon typically occurs in unconsolidated formations, where the loosely bound sand grains are prone to dislodging and migrating through the wellbore to the surface during production (Kelly *et al*., 2010). When the reservoir's pressure threshold is surpassed, especially in attempts to maximize production from sandstone reservoirs, the risk of sand production increases significantly. A substantial pressure differential between the reservoir and the wellbore encourages a rapid influx of fluids, which can carry sand particles along. Although the sand itself holds no commercial value, its presence poses serious threats to both surface and subsurface equipment, causing erosion, blockages, and potential operational failures. Therefore, there is a critical need to develop effective sand control solutions that can minimize or eliminate sand production without severely compromising production efficiency (Nwala *et al*., 2023).

The occurrence of sand or solid particles during production is a critical operational concern that may lead to well instability and, in severe cases, well collapse. Additionally, it can cause formation damage and allow drilling fluids to break into the reservoir, disrupting pressure balance. As a result, it is crucial to accurately identify the type and characteristics of the solids being produced in order to develop and implement effective sand control strategies (Salahi *et al*., 2021).

Sand production presents significant challenges in oil extraction operations and remains a critical concern for the oil industry (Rosa *et al*., 2017). One of the foremost issues associated with sand production is its detrimental impact on the environment. The extraction process, particularly in regions with sensitive ecosystems, often leads to the removal of vegetation and degradation of land surfaces (Schneider *et al*., 2006). In many cases, infrastructure development for accessing reservoirs can fragment habitats, disturb biodiversity, and cause long-term ecological imbalances (Jordaan, 2012). Moreover, the process of managing sand-laden fluids during production typically requires substantial amounts of water, contributing to water resource depletion (Wu *et al*., 2009). This is particularly problematic in areas already experiencing water stress, where oil operations can exacerbate existing scarcity (Mielke *et al*., 2010). In addition to environmental concerns, sand production has been linked to increased carbon dioxide emissions and potential human health risks, primarily due to the need for enhanced surface processing, transportation, and waste management (Charpentier *et al*., 2009; Brandt, 2012). These consequences are often underreported or insufficiently studied, especially in regions with limited regulatory oversight or inadequate monitoring frameworks. Consequently, the lack of reliable data and comprehensive analysis hampers the development of effective mitigation strategies, posing both environmental and operational risks (Giesy *et al*., 2010). Therefore, addressing the problems associated with sand production in oil extraction requires not only the implementation of effective control mechanisms but also a more transparent and research-informed approach to ensure sustainability and efficiency in the industry (Jordaan, 2012).

Over the past several decades, sand control technologies in oil extraction have experienced continuous development and innovation. In the early stages of oilfield operations, mechanical sand control techniques such as gravel packing and screen installations were predominantly used to prevent the intrusion of sand into production tubing (Dong *et al*., 2009). These methods served as the foundational approach to minimizing sand-related issues in unconsolidated reservoirs. However, as chemical engineering technologies advanced, chemical sand control solutions emerged. These included the application of binding agents that stabilize sand grains within the formation, thereby reducing the likelihood of particle migration during production (Li *et al*., 2021).

In more recent years, the integration of cutting-edge technologies such as nanotechnology, smart materials, and digital control systems has given rise to nextgeneration sand control methods. These innovations have introduced intelligent sand management systems that allow real-time monitoring and adaptive responses to changes in well conditions. Such progress not only improves the effectiveness of sand prevention but also aligns with the broader goals of enhancing oilfield performance and promoting environmental responsibility (Zhao *et al*., 2011).

In the context of the current global shift toward sustainable energy practices, the development and deployment of advanced sand control technologies carry immense significance. Efficient sand control contributes to higher production rates, extends the operational lifespan of equipment, reduces maintenance and replacement costs, and minimizes environmental hazards caused by erosion and equipment failure.

Furthermore, in-depth research into the existing methods and future prospects of sand control offers strategic insights for optimizing oilfield operations and achieving longterm sustainability in the energy sector (Li *et al*., 2024).

Effective sand control is not merely a matter of operational convenience but a fundamental aspect of ensuring oil well integrity and long-term profitability. Unchecked sand production can lead to severe complications such as erosion of downhole and surface equipment, blockage of flow lines, wellbore instability, and even premature well failure (Acock *et al*., 2004). These issues not only interrupt production but also require costly interventions, including equipment replacement, well remediation, or in extreme cases, well abandonment. By implementing appropriate sand control measures, operators can maintain the structural stability of the wellbore, reduce downtime, and extend the productive life of the well (Ikporo *et al*., 2015). Furthermore, consistent control of sand production contributes to smoother flow rates, protects artificial lift systems, and minimizes maintenance costs, all of which have a direct impact on the economic viability of oilfield operations (Ozowe *et al*., 2024). In essence, sand control serves as a critical link between reservoir performance, asset integrity, and financial outcomes, making it an indispensable element in modern oil extraction strategies.

1.2 AIM AND OBJECTIVES:

1. Compare the effectiveness of Artificial Neural Networks (ANN) and Support Vector Machine (SVM) algorithms in predicting sand production in Niger Delta oil wells.
2. Identify and analyze key reservoir parameters, such as depth, pore pressure, stress, and shale content, that influence sand production in sandstone formations.
3. Develop machine learning models using ANN and SVM that can classify wells based on their likelihood of producing sand.
4. Recommend the most suitable algorithm (ANN or SVM) for practical application in sand prediction, especially in data-scarce environments.

1.3 STATEMENT OF PROBLEM

Sand production remains a persistent challenge in unconsolidated sandstone reservoirs, such as those in the Niger Delta, causing severe equipment damage, production losses, and well instability. Traditional predictive methods relying on empirical correlations often fail to capture the complex interactions among key reservoir parameters like pore pressure, formation strength, and stress conditions, resulting in inaccurate forecasts. With the limitations of these conventional approaches, there is a growing need for data-driven, intelligent techniques capable of improving prediction accuracy. Machine learning methods, particularly Artificial Neural Networks (ANN) and Support Vector Machines (SVM), offer promising potential, but their comparative performance in predicting sand production within the Niger Delta context has not been adequately investigated.

1.4 RELEVANCE OF THE STUDY

This study is relevant as it applies advanced machine learning models to enhance sand production prediction in unconsolidated Niger Delta reservoirs. By comparing the performance of Artificial Neural Networks (ANN) and Support Vector Machines (SVM), it aims to identify the most effective model for accurately forecasting sandprone wells, especially where field data are limited. The findings will assist petroleum engineers and decision-makers in adopting proactive sand management strategies, reducing operational risks and costs, and improving well productivity, integrity, and sustainability in complex reservoir environments.

CHAPTER TWO

LITERATURE REVIEW

2.1 SAND PRODUCTION IN OIL WELLS

The process of generating crude oil now faces a major challenge in the form of sand production (Nnurum *et al*., 2024). In oil and gas wells, sand production happens when fluid flow reaches a certain threshold that is determined by a number of factors, including the type of completion used around the well, the stress situation, and the consistency of the reservoir rock (Osaki *et al*., 2024). The amount of reservoir and sanding fluids can vary from very small amounts, expressed in grams per cubic meter, which would present few difficulties, to large amounts in a short period of time, which could lead to decreased injectivity and productivity, blockage of production liners or perforations, wellbore instability, failure of sand control completions, collapse of sections in horizontal wells within loosed formations, erosion of pipelines and surface facilities, environmental effects, and increased costs for remediation and cleanup work. (Willson *et al*., 2002)

Sand production around perforations and boreholes is often linked to factors such as reservoir pressure depletion, unconsolidated formations, water-induced weakening, drilling activities, and cyclic shut-in/start-up effects. High-pressure gradients from fluid flow can also detach sand particles (Osaki *et al*., 2024). Production may occur when induced in-situ stresses exceed formation strength (Isehunwa *et al*., 2010), with phenomena like water hammer caused by sudden shut-ins from power loss or productivity drops further increasing the risk through rapid dynamic loadings (Jafar *et al*., 2016; Luo *et al*., 2023). To address these challenges, Igbinere *et al*. (2025) developed a machine learning (ML) model in Nigerian oil fields to optimize choke size using historical production data. The model accurately predicted optimal choke sizes that reduced sand production without lowering flow rates, showing ML's potential in enhancing real-time operational decision-making for sand control. However, broader model validation across diverse reservoirs and production scenarios remains necessary.

Sand production during hydrocarbon extraction can have a wide range of adverse effects on oil well operations. In some cases, it may occur in minimal quantities, while in others, it can reach catastrophic levels, leading to the complete blockage of production tubing and severely reduced well productivity (Isehunwa *et al*., 2010). The abrasive nature of sand causes erosion of both downhole and surface equipment, including subsea systems, production lines, and well completions, ultimately resulting in equipment failure and frequent maintenance (Dejen *et al*., 2024; Ranjith *et al*., 2014). This degradation not only compromises the mechanical integrity of the well but also leads to increased operating costs and reduced hydrocarbon output (Dejen *et al*., 2024). In extreme situations, uncontrolled sand production can even cause well collapse, posing serious safety and economic risks to oilfield operations (Odigie *et al*., 2012). As sand control costs continue to rise, the economic burden on operators grows, making the effective management of sand production a critical priority in the industry.

2.2 TRADITIONAL SAND CONTROL TECHNIQUES

Sand control methods have long been employed to manage and mitigate sand production during drilling and production operations, both in open-hole and cased-hole completions. These techniques are essential for maintaining wellbore stability and protecting production equipment from damage caused by migrating sand particles. Among the most widely used are mechanical sand control methods, and chemical methods such as sand consolidation (SCON).

2.2.1 Mechanical Sand Control Methods.

- **Gravel Packs:** Gravel packing is a widely used sand control method, particularly effective in unconsolidated or poorly consolidated formations (Khamehchi *et al*., 2015). It involves placing specially sized gravel around a sand screen to filter out formation sand while allowing reservoir fluids to flow (Risnes *et al*., 1982). This technique supports wellbore stability and enhances completion longevity and productivity, provided it is properly executed with suitable equipment and under varying field conditions (Wu *et al*., 2010). There are two main types of gravel packs: open-hole and cased-hole. In open-hole gravel packs, gravel is pumped into the annular space around the screen to prevent sand intrusion and maintain borehole support. In cased-hole gravel packs, the method is similar but applied through perforations in the casing (Maduabuchi *et al*., 2017).

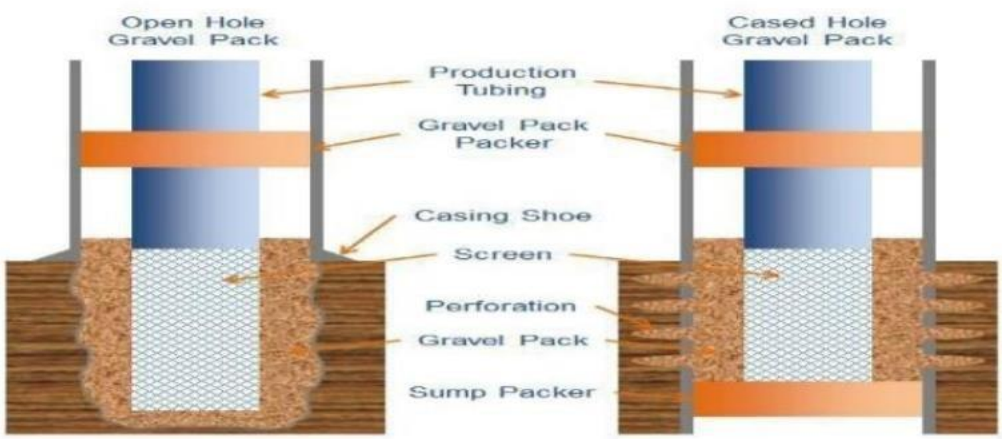


Figure 1: Schematic of internal and external gravel pack installation

(Maduabuchi *et al*., 2017).

- **Slotted liners:** Slotted liners are a long-established sand control method in the oil industry, consisting of steel pipes with parallel slots cut through the metal.

The slot width is kept as small as mechanically possible to maximize sand retention while allowing fluid inflow (Bennion *et al*., 2009). Typically, the inflow area is only 2–3% of the pipe's surface, which can lead to deviations from ideal radial flow and uniform axial distribution (Romanova *et al*., 2015). Despite

this limitation, slotted liners remain a practical option for certain well conditions due to their simplicity and durability (Khamehchi *et al*., 2015).

- **Sand Screens:** Sand screens are designed to prevent formation sand from entering the production stream while still permitting fluid flow (Changyin et al., 2017). Common types include wire-wrapped screens, made by winding triangular wire around a support structure to maintain uniform gaps, and prepacked screens, which incorporate a hardened resin-coated gravel layer between concentric screens to enhance sand retention and filtration (Khamehchi et al., 2015). In recent studies, Ma *et al.* (2024) evaluated screen performance using small-scale Sand Retention Test (SRT) cell simulations. These tests, supported by oil production index (OPI) and bridging metric (R), demonstrated that higher OPI and R values correspond to improved sand control efficiency and reduced plugging, making them valuable tools for guiding screen design and performance optimization.

2.2.2 Chemical Sand Control (Sand Consolidation).

The chemical sand consolidation method involves injecting resins (phenolic, furan, or epoxy) into the formation to bind sand grains together, preventing production of formation sand while retaining permeability (Abubakar *et al*., 2012). Success depends on treating all perforations, maintaining long-term consolidation strength, and ensuring permeability after treatment (Appah *et al*., 2001).

The process typically involves resin placement via a carrier fluid, separation from the carrier, accumulation around grain contact points, and curing. Epoxy and furan methods use resincoated gravel slurry pumped into the well, allowed to cure, and drilled out before production.

Phenolic-coated gravel, partially polymerized, completes curing at temperatures above 57 °C and can be handled dry (Schwartz, 1969).

Gravel packs act as downhole filters, relying on effective bridging of formation sand against the pack. Design requires proper gravel sizing, analysis of the formation, determining gravel-to-sand ratios, assessing sand uniformity, and estimating slot velocities. Correct completion fluids, gravel selection, and pack thickness are essential for long-term effectiveness (Sage *et al*., 1941).

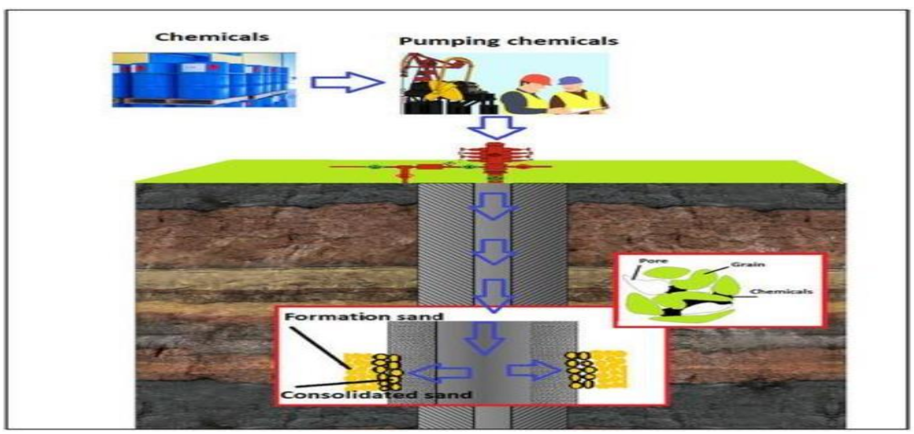


Figure 2: Chemical sand consolidation (Alakbari *et al*., 2020).

2.2.3 Advantages and limitations of Traditional Sand Control Techniques

Traditional sand control techniques such as gravel packing, slotted liners, and wire-wrapped screens are widely used due to their proven effectiveness, adaptability to various reservoir conditions, and ability to be combined for improved stability and extended service life. When integrated, these methods can leverage complementary strengths, such as the filtering ability of gravel packs with the precision of chemical consolidation, to achieve better results (He *et al*., 2024).

However, they face limitations including poor fine silt control, potential reservoir damage during installation, material aging or failure over time, and reduced performance in complex reservoirs or under severe sand production (Wang *et al.,* 2025). They are also less effective in addressing challenges like proppant flowback after fracturing (Li *et al*., 2024). As a result, integrating traditional methods with emerging technologies such as frac pack systems and applying real-time monitoring is increasingly recommended to enhance efficiency, longevity, and economic returns (Yushi *et al*., 2021).

2.3 EMERGING SAND CONTROL TECHNOLOGIES.

2.3.1 Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) represent a class of computational models inspired by the structure and functionality of biological neural systems. They are designed to emulate the learning and decision-making processes of the human brain through interconnected processing units known as artificial neurons (McCulloch *et al*., 1943). Each neuron functions as a simple mathematical model consisting of three fundamental operations: multiplication, summation, and activation. The neuron receives several input variables, each multiplied by an assigned weight that signifies its relative importance. These weighted inputs are summed along with a bias term, and the resultant value is processed through an activation function also referred to as a transfer function to generate an output. When multiple artificial neurons are interconnected, they form a network capable of processing information in a parallel, distributed, and non-linear manner, which enhances the system's ability to identify patterns and relationships within complex datasets (Krenker *et al*., 2011).

The architecture, or topology, of an ANN defines the structure and interconnection of neurons within the network. Depending on the design, networks may consist of single or multiple layers, forming either simple feedforward or more complex recurrent structures. A single-layer perceptron can handle linearly separable problems, while multi-layer networks (often referred to as Multi-Layer Perceptrons, MLPs) are capable of solving highly nonlinear problems through the inclusion of one or more hidden layers (Marr *et al*., 1975). The learning process of ANNs involves adjusting the connection weights between neurons through iterative training using known input-output data. This enables the network to learn underlying patterns, generalize knowledge, and make accurate predictions or classifications when presented with new data. (Grossi *et al.*, 2007)

Artificial Neural Networks offer numerous advantages that make them valuable tools for prediction and modeling tasks across scientific and engineering domains. They can be easily adapted to multi-class prediction problems by introducing additional output units, allowing for simultaneous analysis of multiple outcomes (Hinton, 1992). Their capability to model complex, non-linear relationships makes them particularly effective for systems where conventional statistical or analytical models are inadequate. ANNs have been successfully applied in fields such as medicine, geology, reservoir characterization, and production forecasting, where they often yield state-of-the-art predictive performance. Furthermore, the availability of computational tools and open-source libraries such as MATLAB, R, and the Fast Artificial Neural Network (FANN) library, has facilitated their implementation and integration into various data-driven research and industrial applications (Krogh, 2008).

2.3.2 Support Vector Machines (SVMs)

Support Vector Machines (SVMs) provide a more structured and mathematically elegant approach for solving complex non-linear regression and classification problems compared to Artificial Neural Networks (ANNs). SVM is a well-established supervised machine learning technique used for pattern recognition and predictive modeling of input-output relationships (Vapnik, 1995). Within the fields of data mining and machine learning, SVMs have gained recognition for their robust theoretical foundation and strong generalization capability. The principle behind SVM classification is based on finding an optimal separation rule, where the input data are mapped into a high-dimensional feature space using non-linear transformations. In this transformed space, SVM identifies the optimal separating hyperplane that maximizes the margin, that is, the distance between the hyperplane and the nearest data points belonging to different classes (Olatunji & Micheal, 2017).

SVMs can be applied to both classification and regression tasks, though they are particularly well-known for classification due to their ability to handle high-dimensional data effectively. The main goal of an SVM is to determine the best possible decision boundary, or *hyperplane*, that divides the dataset into distinct classes. Once this hyperplane is established, it enables accurate classification of new, unseen data points into their appropriate categories. Depending on the number of features in the dataset, the hyperplane may take different forms, a straight line in two-dimensional space or a plane in threedimensional space (Ngwashi *et al*., 2021).

The SVM algorithm achieves this by identifying specific data points at the boundaries of the classes, known as *support vectors*. These support vectors are critical in defining the position and orientation of the hyperplane, as they are the most influential elements in determining the classification boundary (Rogiers, 2012). SVMs are broadly categorized into two types:

Linear SVMs, which are used for linearly separable data where classes can be divided by a straight line, and *Non-linear SVMs*, which are applied when data cannot be separated linearly. In non-linear SVMs, kernel functions such as polynomial, radial basis function (RBF), or sigmoid kernels are employed to transform the data into a higher-dimensional space, allowing the algorithm to establish effective separation between complex class boundaries (Saha, 2023).

2.4 EVALUATION CRITERIA FOR SAND CONTROL TECHNIQUES

The selection of an appropriate sand control method is a critical decision in petroleum engineering, as it directly impacts well productivity, operational cost, and long-term performance (Shahsavari *et al*., 2018). Various researchers have proposed different approaches for determining the most suitable method, often emphasizing a combination of mechanical, reservoir, and economic factors. The key criteria can be grouped into several major considerations, each of which plays a vital role in the final choice.

2.4.1 Sand Retention Efficiency

Sand retention efficiency is a critical factor in selecting appropriate sand control methods. It describes the capacity of a completion system such as stand-alone screens or gravel packs to prevent sand migration into the wellbore while still allowing adequate hydrocarbon flow (Khan *et al*., 2024). However, research by (Hodge *et al*., 2002) and (Chanpura *et al*., 2011) emphasizes that retention must be balanced against plugging resistance, as excessive plugging reduces production and raises intervention costs.

Recent investigations have applied Computational Fluid Dynamics and the Discrete Element Method (CFD-DEM) to numerically validate sand retention test results. While simulations successfully capture general experimental trends, discrepancies arise from factors like simulation duration, particle-size distribution, and mesh resolution. This indicates that CFDDEM holds significant potential for improving sand screen selection, but further refinement is necessary to enhance modeling accuracy and better replicate real particle behavior (Zainal *et al*., 2022).

2.4.2 Particle Size Distribution (PSD) and Reservoir Sand Properties

Particle size distribution is another primary factor influencing the choice of sand control technology. As Tiffin *et al*. noted, understanding the PSD of the reservoir formation allows for proper screen slot sizing and gravel pack selection to ensure optimum retention without excessive production restriction (Tiffin *et al*., 1998). Reservoirs with finer or more heterogeneous sand distributions often require more sophisticated completion designs to maintain production rates without compromising sand control (Shahsavari *et al*., 2008).

2.4.3 Well Conditions and Completion Type

The physical condition of the well including deviation, inclination, and the presence of shale layers has a major influence on the choice of sand control. Latiff emphasized that horizontal and highly deviated wells may require modified completion designs to account for nonuniform flow profiles and higher risks of localized sand influx. Similarly, the type of completion open-hole, cased-hole, or expandable screen must be selected based on compatibility with the reservoir's mechanical stability and expected drawdown pressures (Khamehchi *et al*., 2015).

2.4.4 Installation Risk and Reliability

Practical aspects such as installation complexity, operational risk, and equipment reliability are also crucial in the decision-making process. Farrow *et al*. incorporated these factors into a probabilistic selection matrix, ranking methods based on the likelihood and consequences of failure (Farrow *et al.,* 2004). The ability of a sand control method to perform reliably in hostile environments such as high temperature, high pressure wells can determine its feasibility for specific field applications (Denney, 2005).

2.4.5 Economic Considerations

Economic analysis plays a central role in sand control selection. Khamehchi *et al*. demonstrated that in low-production-rate wells, parameters such as the reservoir productivity index, oil price, and time to recover capital investment can outweigh mechanical performance factors (Khamehchi *et al*., 2015). Additionally, methods that reduce workover frequency and extend completion life can offer significant cost savings over the well's lifecycle, even if their initial installation costs are higher.

2.4.6 Reservoir Management Objectives

Beyond immediate operational efficiency, sand control method selection must align with broader reservoir management goals. Chan *et al*. emphasized the importance of considering the well's projected life, recovery objectives, and long-term production sustainability (Chan *et al*., 2013). This includes evaluating the interaction between sand control systems and other reservoir management strategies, such as enhanced oil recovery (EOR) processes or water shutoff programs.

2.4.7 Predictive Modeling and Pre-Implementation Analysis

Finally, predictive modeling is increasingly used to inform sand control decisions before field implementation. Numerical, analytical, and experimental models such as those described by Morita *et al*. (1989) and Van den Hoek *et al*. (2000) allow engineers to forecast sand production risks, plugging tendencies, and mechanical failures under simulated reservoir conditions. Pre-implementation analysis can ensure that the chosen method performs effectively regardless of whether sand production has yet been observed

2.5 CHALLENGES IN IMPLEMENTING NEW SAND CONTROL METHODS

Although significant advances have been made in the development of innovative sand control technologies, their practical application in the field often faces a variety of technical, operational, and economic challenges (Morita *et al*., 1989) These challenges can hinder adoption, reduce performance reliability, or increase project risk. Understanding these barriers is essential for developing strategies to ensure successful implementation.

2.5.1 Uncertainty in Reservoir Conditions

A major difficulty in deploying new sand control methods is the inherent uncertainty in reservoir characterization (Chan *et al*., 2013). Variations in formation strength, particle size distribution, and stress regimes can lead to unpredictable sand production behavior. Laboratory testing and small-scale field trials often fail to capture the full complexity of downhole conditions, resulting in designs that may perform well in controlled environments but underperform in the actual reservoir.

2.5.2 Limited Field Validation

New sand control techniques such as nanoparticle-based consolidation systems or autonomous inflow control devices often lack extensive field trial histories. Without longterm performance data, operators may be reluctant to commit to full-scale implementation due to uncertainty about durability, sand retention efficiency, and compatibility with existing completion systems. This lack of validation also makes it difficult to benchmark new technologies against proven methods (Van den hoek *et al*., 2000)

2.5.3 Operational and Installation Complexities

Some advanced sand control methods require specialized tools, precise placement procedures, or additional downhole hardware, increasing the complexity of installation (Khamehchi *et al*., 2015). For example, achieving uniform placement of chemical consolidation agents or ensuring proper orientation of inflow control devices in deviated wells can be challenging. These complexities raise the risk of operational errors and may necessitate additional training or specialized crews, further increasing costs (Farrow *et al*., 2004).

2.5.4 Compatibility with Reservoir Fluids and Production Chemistry

Certain new sand control technologies can interact unfavorably with reservoir fluids, formation water chemistry, or enhanced oil recovery (EOR) chemicals. For example, chemical-based methods may lose effectiveness in high-salinity or high-temperature environments, while nanoparticles might agglomerate or precipitate under specific pH conditions (Gao *et al*, 2020). Ensuring compatibility across a range of operating environments requires careful laboratory screening and potentially costly customization (Guo *et al*., 2022).

2.5.5 Economic Uncertainty and Cost-Benefit Balance

The initial capital cost of implementing novel sand control technologies is often higher than conventional methods, and the long-term financial benefits may be difficult to quantify prior to deployment. In low-production-rate wells, the payback period may be extended, making it harder for operators to justify the investment (Akhter *et al*., 2022). Additionally, economic uncertainty such as fluctuating oil prices can cause operators to defer adoption of newer, more expensive systems in favor of proven, lower-cost solutions (Muhammad *et al*., 2025).

2.5.6 Regulatory and Safety Considerations

Regulatory requirements for introducing new downhole materials or equipment can delay implementation (Ndolomingo *et al*., 2020). Certain chemicals used in innovative consolidation systems may require environmental approval, while the installation of advanced mechanical devices might necessitate additional safety testing (Kumar *et al*., 2020). Meeting these requirements adds time and expense to the project schedule.

While emerging sand control technologies offer promising improvements in sand retention, production optimization, and well longevity, their adoption is often constrained by uncertainties in reservoir performance, limited field data, operational complexities, compatibility concerns, and economic factors. Overcoming these challenges will require a combination of enhanced laboratory-to-field validation processes, cost optimization strategies, and collaborative efforts between technology providers, operators, and regulatory bodies.

CHAPTER THREE

METHODOLOGY

3.1 Overview

This study compares the performance of two algorithms: SVM and ANN with back propagation. The goal is to compare how well the algorithms forecast the generation of sand, particularly in regions with little training data. The algorithms are developed and their performance is assessed using the following process. Preparing the data, analyzing the data, implementing the algorithm, and defining the criteria for evaluating the algorithms' success are the four primary components of the technique. A schematic of the ANN algorithm research approach is presented in Figure 3.1. The SVM approach may be described using a similar diagram.

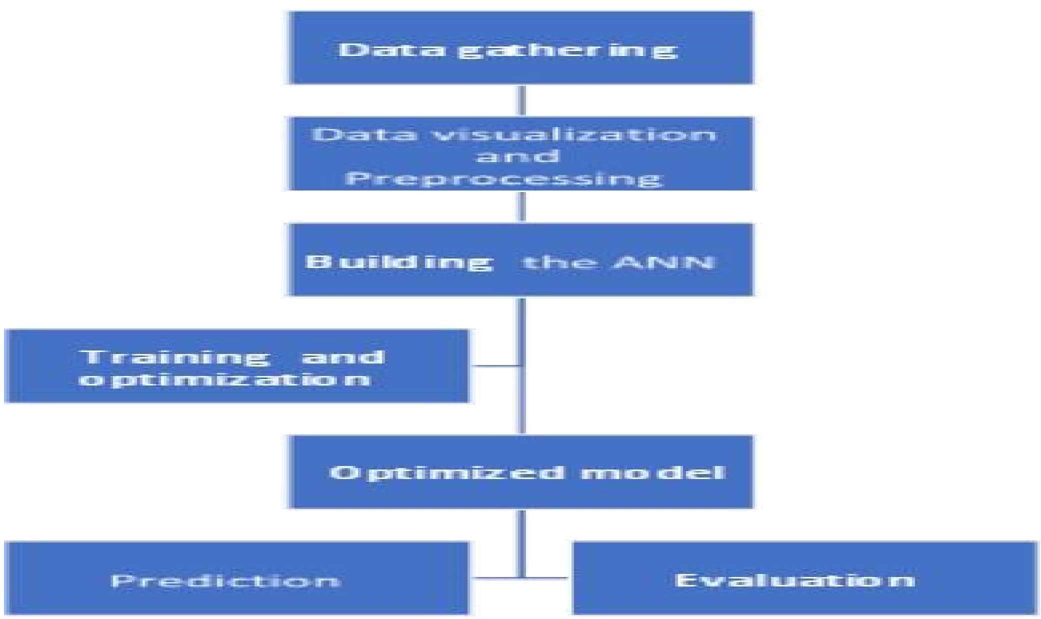


Figure 3.1: Schematic of Research Methodology for Developing and Applying the ANN

3.2 Data pre-processing

This involves splitting the data into training, test, and validation sets in addition to using feature scaling. To achieve the optimum result, the percentages of the training, test, and validation sets are adjusted as the algorithm is developed. All textual data must be converted into a numeric code as part of the preparation step of the data encoding process. In this study, wells that supply sand are denoted by "0," while those that don't are denoted by "1." Calculations are made easier and one variable is kept from controlling others by using feature scaling or data normalization. Python is used to import, encode, and display the data, as shown in Figure 3.2.

Index	Depth	Overburden	Pore_Pressure	Min_Horizontal_Stress	Max_Horizontal_Stress	Well_inclination	well_azimuth	poissons_ratio	youngs_modulus	friction_angle	shale_content	Output	type
0	10080	0.871	0.439	0.86	0.91	8.89	156.22	0.25	0.351	30	0.354	No_Sand	1
1	10232	0.881	0.439	0.86	0.91	18.45	156.22	0.25	0.467	30	0.354	No_Sand	1
2	10863	0.896	0.439	0.89	0.94	18.45	156.22	0.25	0.584	30	0.354	No_Sand	1
3	11414	0.923	0.415	0.89	0.94	18.45	156.22	0.25	0.547	26.5	0.543	No_Sand	1
4	11995	0.928	0.47	0.89	0.94	18.45	156.22	0.25	0.598	26.89	0.573	No_Sand	1
5	12291	0.928	0.47	0.89	0.94	18.45	156.22	0.25	0.683	26.89	0.573	No_Sand	1
6	12544	0.928	0.477	0.89	0.94	18.45	156.22	0.25	0.683	27.13	0.67	No_Sand	1
7	13214	0.928	0.465	0.89	0.94	18.45	156.22	0.25	0.683	27.13	0.443	No_Sand	1
8	13691	0.928	0.466	0.89	0.94	18.45	156.22	0.25	0.683	27.13	0.6891	No_Sand	1
9	14075	0.928	0.466	0.89	0.94	18.45	156.22	0.25	0.683	27.13	0.6891	No_Sand	1
10	14200	0.928	0.464	0.89	0.94	18.45	156.22	0.25	0.683	27.89	0.6891	No_Sand	1
11	10080	0.871	0.47	0.88	0.93	11.09	115.08	0.25	0.351	30	0.354	No_Sand	1
12	10232	0.881	0.47	0.88	0.93	11.09	115.08	0.25	0.467	30	0.354	No_Sand	1
13	4000	0.822	0.435	0.78	0.83	2.08	156.22	0.25	0.2234	26.77	0.321	Sand	0
14	5243	0.841	0.435	0.78	0.83	2.08	156.22	0.25	0.2234	26.77	0.321	Sand	0

Figure 3.2: Encoded Dataset

Table 3.2 Encoded Dataset

3.3 Data Analysis

The algorithms are developed using eleven parameters in total. The main elements influencing sanding in sandstone formations are determined to be the geology and reservoir characteristics. These factors include shale content, Frication angle, Poisson's ratio, Young's modulus, well azimuth, well inclination, depth, overburden, pore pressure, maximum and lowest horizontal stress, and shale content. The models are validated using data characteristic of the Niger Delta.

Four Niger Delta wells are employed for model validation due to data collection challenges. The information gleaned from literature on the general depths of the reservoirs in the Niger Delta and the locations of the wells is used to statistically fill the data. The data is encoded with "1" denoting "no sanding" and "0" denoting "sanding" using Python and the Pandas module. The correlation between the input parameters is displayed in Figure 3.3. With the exception of the connection between the friction angle and shale content, which has a value of -0.45, it is evident that the link between the parameters is somewhat weak. When assessing the correlation matrix, the sample size and statistical significance are taken into account. The study's tiny sample size is most likely the cause of the poor correlation values.

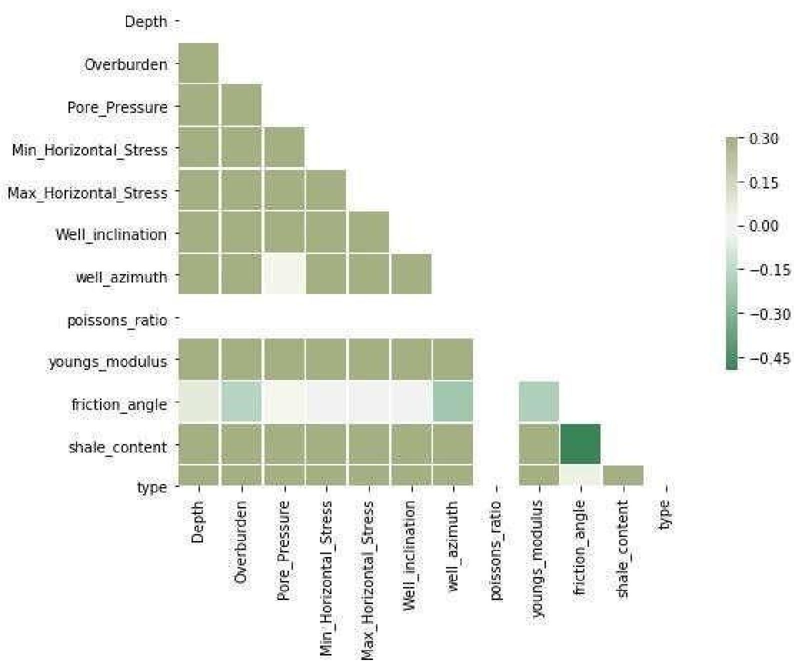


Figure 3.3: Correlation Matrix of Input Parameters

As shown in Figures 3.3 and 3.4, which show the individual correlations, parameters such as overburden, pore pressure, maximum and minimum horizontal stress, well inclination, and

Young's modulus show a significant connection with reservoir depth. This is accurate as the overburden pressure of the reservoir's underlying rock affects these characteristics. Furthermore, the low correlation value of the friction angle indicates that it has minimal influence on other metrics. Additionally, the Poisson's ratio is assigned NaN in this study because it is unaffected by any of the factors. This indicates that in our data set, Poisson's ratio is an independent parameter.

The Poisson ratio is only known to be impacted by the reservoir rock's axial and transverse strain.

In conclusion, parameters are considered to be strongly correlated if their correlation value is greater than 0.5, and poorly correlated if it is less than 0.5.

Index	Depth	Overburden	Pore_Pressure	Min_Horizontal_Stress	Max_Horizontal_Stress	Well_inclination	well_azimuth	poissons_ratio	youngs_modulus	friction_angle	shale_content	type
Depth	1	0.946362	0.569595	0.830093	0.830093	0.919052	0.397043	nan	0.915294	0.0714576	0.632175	0.789614
Overburden	0.946362	1	0.580026	0.88482	0.88482	0.920812	0.465082	nan	0.968262	-0.165879	0.767932	0.829048
Pore_Pressure	0.569595	0.580026	1	0.591543	0.591543	0.450819	0.0234402	nan	0.593679	0.019193	0.535951	0.546619
Min_Horizontal_Stress	0.830093	0.88482	0.591543	1	1	0.823711	0.378818	nan	0.889796	-0.0176901	0.784902	0.987392
Max_Horizontal_Stress	0.830093	0.88482	0.591543	1	1	0.823711	0.378818	nan	0.889796	-0.0176901	0.784902	0.987392
Well_inclination	0.919052	0.920812	0.450819	0.823711	0.823711	1	0.375792	nan	0.905731	0.0120861	0.642144	0.788644
well_azimuth	0.397043	0.465082	0.0234402	0.378818	0.378818	0.375792	1	nan	0.471165	-0.220572	0.425998	0.370734
poissons_ratio	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan
youngs_modulus	0.915294	0.968262	0.593679	0.889796	0.889796	0.905731	0.471165	nan	1	-0.183402	0.78051	0.837512
friction_angle	0.0714576	-0.165879	0.019193	-0.0176901	-0.0176901	0.0120861	-0.220572	nan	-0.183402	1	-0.492861	0.0457662
shale_content	0.632175	0.767932	0.535951	0.784902	0.784902	0.642144	0.425998	nan	0.78051	-0.492861	1	0.751748
type	0.789614	0.829048	0.546619	0.987392	0.987392	0.788644	0.370734	nan	0.837512	0.0457662	0.751748	1

Figure 3.4: Data Representation of correlation matrix

Table 3.1 displays a statistical analysis of the input parameters that are being examined. This table displays the standard deviation as Std dev.

The average depth of the reservoirs in the Niger Delta is 9729 feet, the overburden is 0.88 psi/ft, and the pore pressure is 0.45 psi/ft, based on the statistics from this set of input data (Table 3.1).

Table 3.1: Statistical Analysis

Index	Depth	Overburden	Pore Pressure	Min Horizontal Stress	Max Horizontal Stress	Well Inclination	Well Azimuth
	(ft)	(psi/ft)	(psi/ft)	(psi/ft)	(psi/ft)	(degree)	(degree)
Count	25	25	25	25	25	25	25
Mean	9729.70	0.8804	0.448	0.83	0.88	12.23	143.06
Std dev	2941.5	0.0368	0.0184	0.0528	0.0528	5.86	19.59
Min	4000	0.822	0.415	0.78	0.83	2.08	115.08
25%	8118.7	0.857	0.436	0.78	0.83	8.89	115.08
50%	10080	0.871	0.439	0.86	0.91	11.09	156.22
75%	11995	0.928	0.466	0.89	0.94	18.45	156.22
max	14200	0.928	0.477	0.89	0.94	18.45	156.22

Table 3.1 continued				
Index	**Poisson's Ratio**	**Young's Modulus**	**Friction Angle**	**Shale content**
		(Mpsi)	**(degree)**	**(%)**
Count	25	25	25	25
Mean	0.25	0.432	28.15	0.379
Std dev	0	0.1798	1.32	0.186
Min	0.25	0.2234	26.50	0.112
25%	0.25	0.334	26.89	0.321
50%	0.25	0.351	28.31	0.354
75%	0.25	0.598	30.00	0.543
max	0.25	0.683	30.00	0.689

In addition to having a Poisson's ratio of 0.25 and a Young's modulus of 0.43 Mpsi, the lowest and maximum horizontal stresses are 0.83 and 0.88 psi/ft, respectively. The visual distributions of the input parameters are displayed in Figures 3.5a through 3.5k.

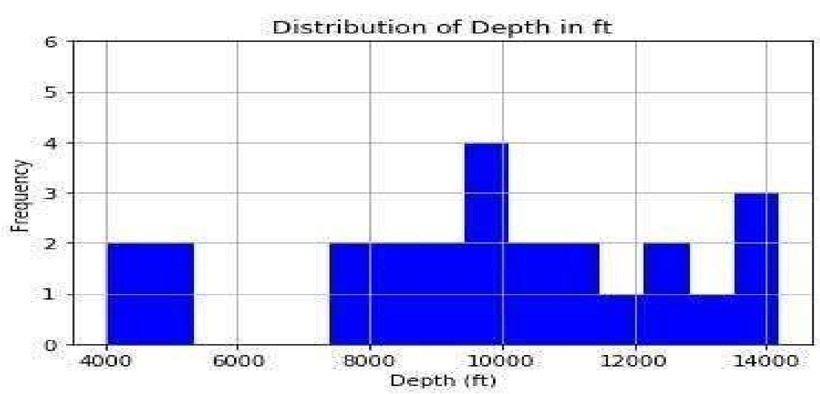


Figure 3.5a: Depth Distribution

With an average depth of 9729.70 feet, Figure 3.5a illustrates how the depth distribution is skewed to the right.

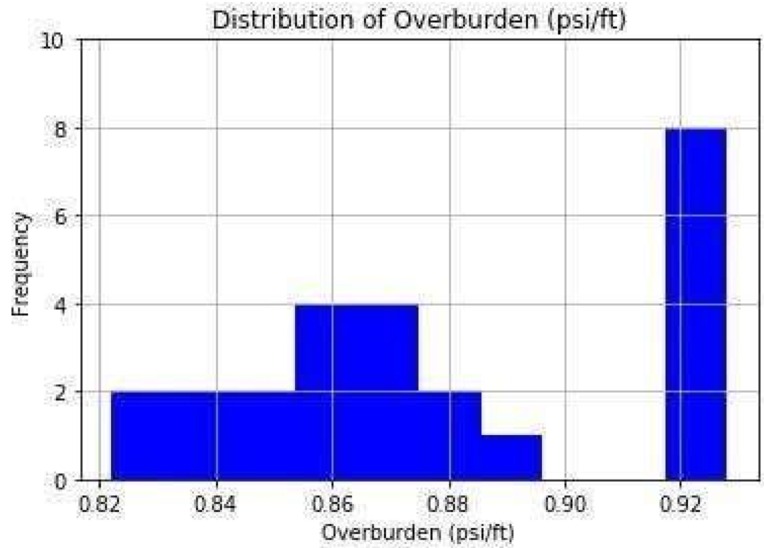


Figure 3.5b: Overburden stress distribution

The overburden distribution is positively skewed, as illustrated in Figure 3.5b. This indicates that there are a few significant data points on the right side of the distribution, but the most of the data is on the left. It is observed that the average overburden is 0.8804 psi/ft.

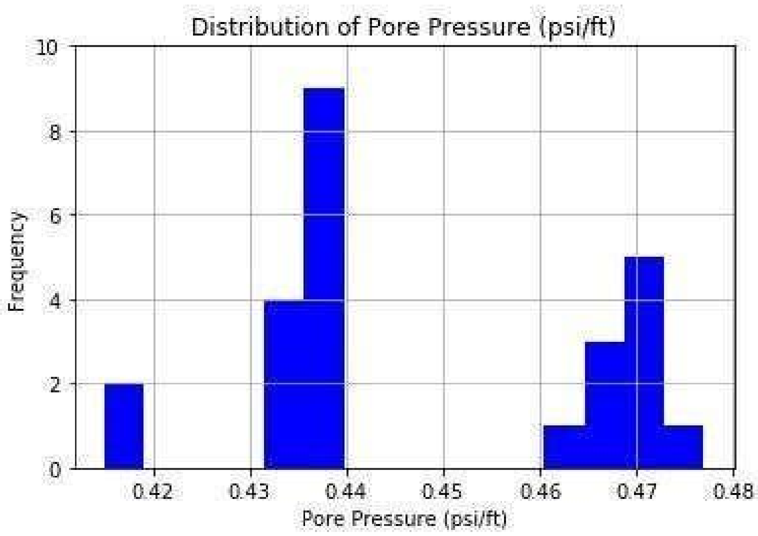


Fig. 3.5c: Pore Pressure Distribution

Fig, 3.5d: Minimum Horizontal Stress Distribution

Figure 3.5c shows the distribution of pore pressure, with an average of 0.448 psi/ft. Figure 3.5d displays the distribution of the lowest horizontal stress, which seems to be uniform. This indicates that, with a mean value of 0.83 psi/ft, the data is seen to be constant.

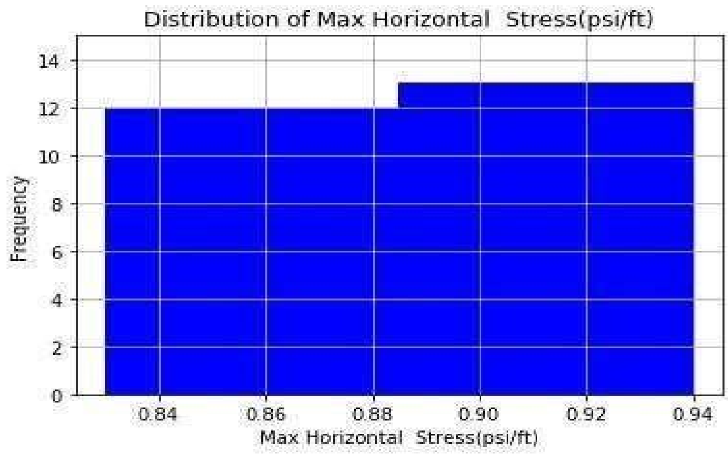


Figure 3.5e: Distribution of the Maximum Horizontal Stress

Figure 3.5e displays the maximum horizontal stress distribution, which seems to be uniform. This suggests that the data exhibits a constant mean stress of 0.88 psi/ft.

Figure 3.5f: Distribution of Well Inclination Angle

Figure 3.5f illustrates the well inclination distribution, which is negatively skewed. This suggests that the most of the data is on the right side of the distribution, with a few noteworthy data points on the left. On average, the well inclination angle is 12.23 degrees.

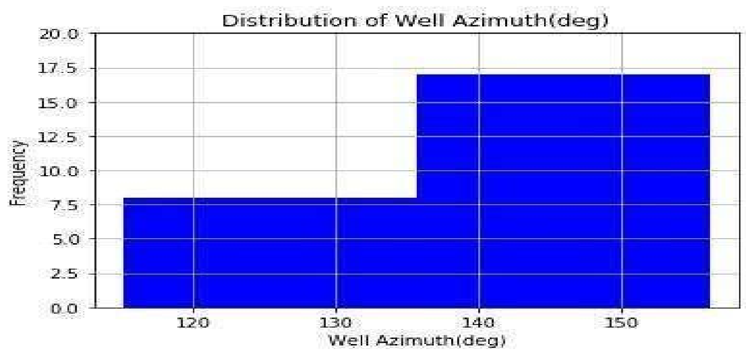
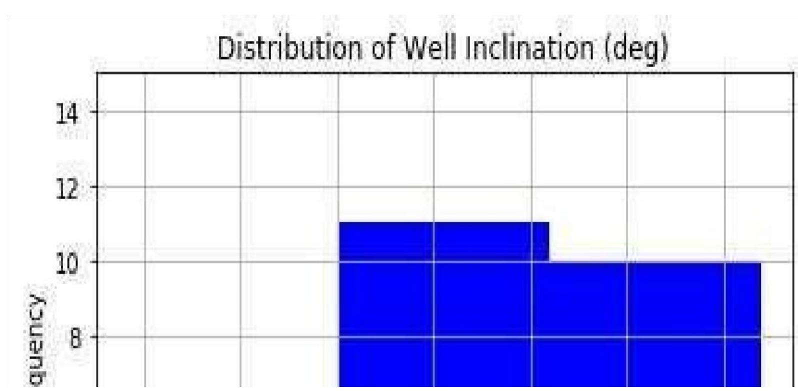


Figure 3.5g: Distribution of Well Azimuth

The well azimuth distribution, which is shown to be negatively skewed in Figure 3.5g. This



indicates that there are a few significant data points on the left side of the distribution, while the most of the data is on the right. The well azimuth average is 143.06 degrees.

Figure 3.5h: Distribution of the Poisson's Ratio

The uniform distribution of Poisson's ratio is seen in Figure 3.5h. With a mean value of 0.25, this indicates that the data's frequency is seen to be constant.

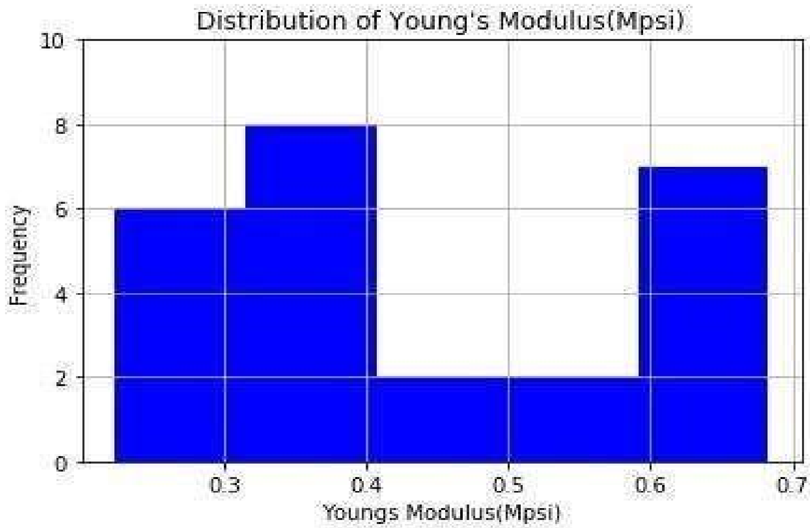
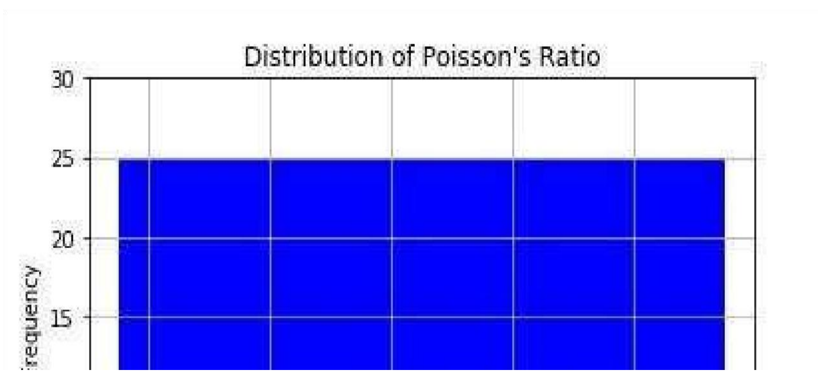


Figure 3.5i: Distribution of Young's Modulus

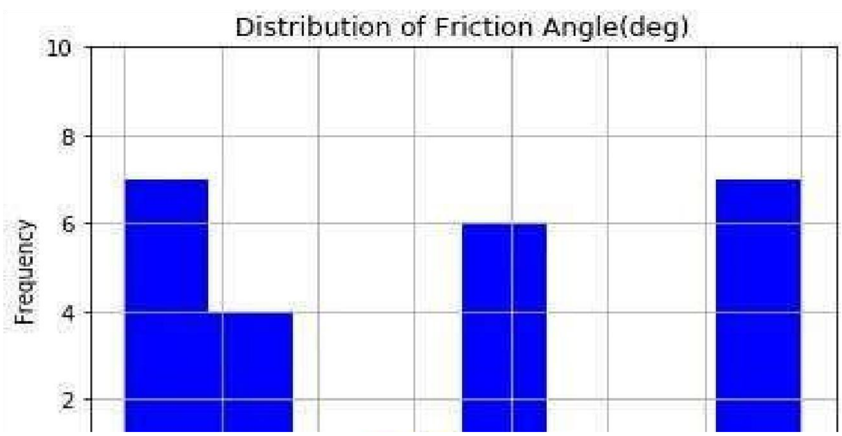
Figure 3.5i shows that the distribution of Young's modulus is positively skewed. This suggests that the most of the data is on the left side of the distribution, with a few noteworthy data points



on the right. The average value of Young's modulus is 0.432 mpsi.

Figure 3.5j: Distribution of Friction Angle

The friction angle distribution is positively skewed, as seen in Figure 3.5j. This indicates that there are a few significant data points on the right side of the distribution, but the most of the data is on the left. It is observed that the average friction angle is 28.15 degrees.



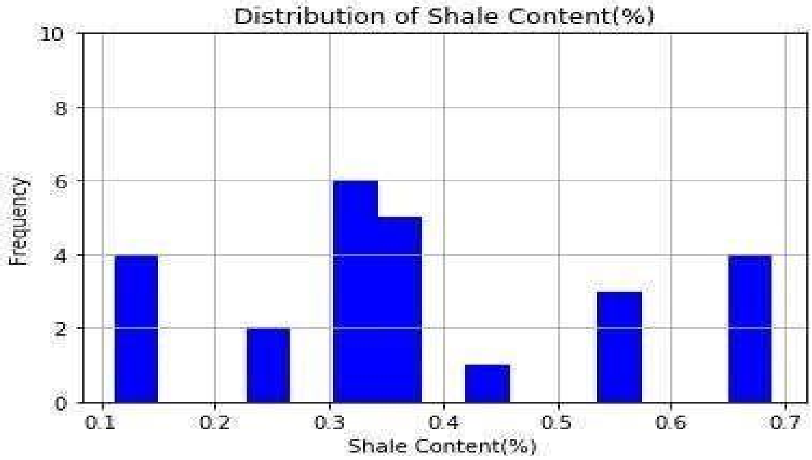


Figure 3.5k: Distribution of Shale Content

The shale content distribution, as seen in Figure 3.5k, is observed to be negatively skewed. The average shale content is 0.379.

3.4 Stochastic gradient descent algorithm for ANN training.

The ANN algorithm utilized in this study was trained using the following main steps:

1. Set weights at random to modest values that are close to but not equal to zero.
2. Note the observations using each input node's characteristics (x_i).
3. propagation forward from left to right. The rectifier function is used to activate the neurons. The signal travels across the cell more easily the more stimulated the neurons are. The sum of each weight (w_i) and associated feature (x_i) is subjected to the activation function (ϕ). That is

$$Activation\ function = \varphi(\textstyle\sum_{i=1}^{m} w_i x_i) \qquad (3.1)$$

Apply the output layer (y_i) the sigmoid function. The probability for the various classes (sand or no-sand) are so distributed. In other words:

$$P(y = 1) = \varphi(\textstyle\sum_{i=1}^{m} w_i x_i) \qquad (3.2)$$

1. Determine the inaccuracy by comparing the actual and expected outcomes.
2. The weights are modified based on the inaccuracy and how each influences it. After that, the weights are moved from right to left using backpropagation. Additionally, the weights are modified in accordance with the neural network's learning rate.
3. Repeat steps 1 through 5 following each set of observations.
4. Repeat further epochs (200 epochs, for example). When the entire training set is run through the

ANN, it is called an epoch.

4. This study's use of artificial neural networks

The ANN, which has two hidden layers, eleven input variables, and a binary output layer, is trained and tested using the preprocessed data to determine if a well would produce sand (0) or not (1). The output layer's sigmoid activation function and the two hidden layers are developed using a rectifier activation function. The figure 3.6 that follows provides an illustration of this.

5. The Support Vector Machine (SVM) technique was used in this investigation.

The following procedures are utilized to apply the SVM to the input data from the Niger Delta:

1. Pre-processing of the data (similar to ANN).

2. Data normalization or feature scaling (similar to ANN).

3. Using the linear kernel provided by: to fit the SVM classifier to the training set

$$Kernel = x^T y + c \qquad (3.3)$$

where x are the input parameters, y are the outputs, and c regulates the tradeoff between the testing error and the marginal.

1. Forecasting the outcome of the test.

2. Confusion matrix creation.

3. Display the outcomes of the test and training sets.

The next part assesses how well the ANN and SVM algorithms work. This would offer a numerical metric for suggesting the optimal strategy for forecasting the production of sand in the Niger Delta.

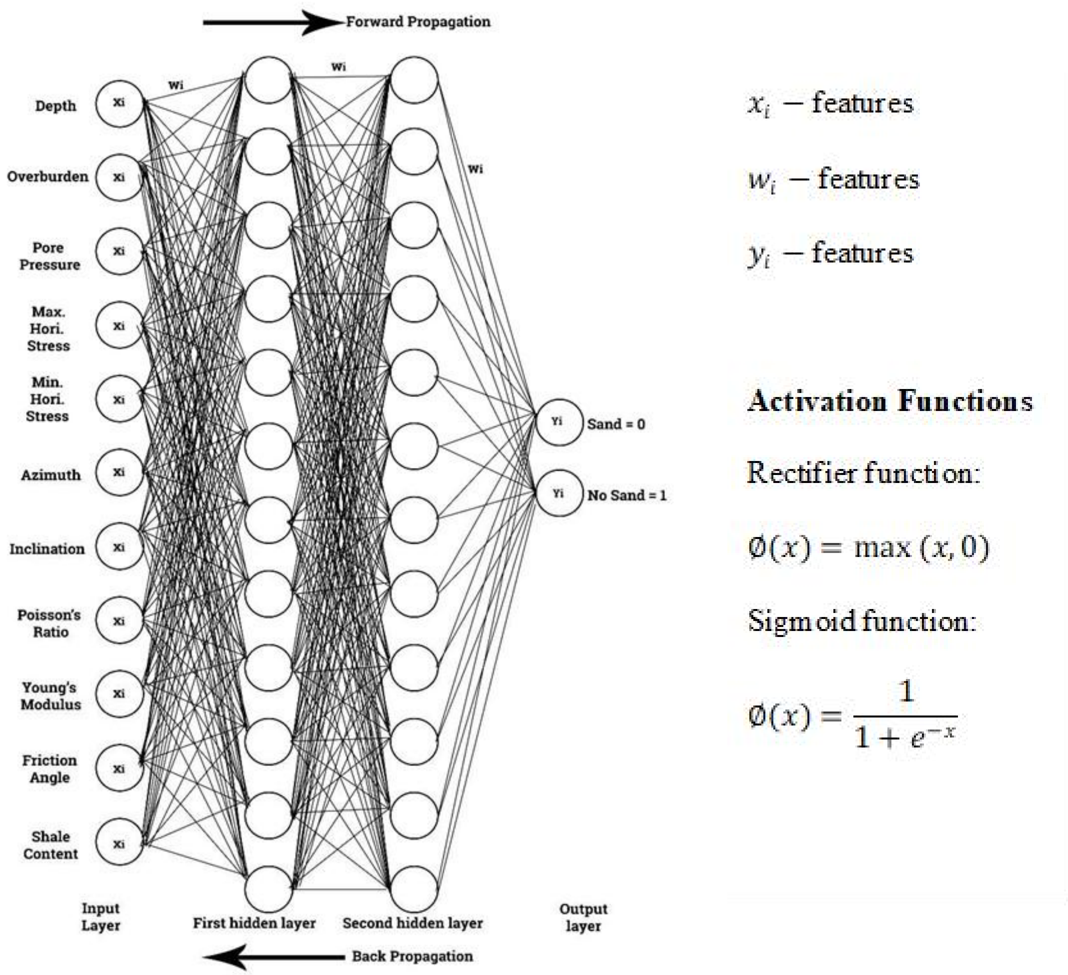


Figure 3.6: ANN Architecture

6. Criteria for Algorithm Evaluation

We employed the following metrics to assess the two algorithms' performance: F1-Score, precision, recall, classification accuracy, confusion matrix, and the Cohen Kappa statistical measure. (2020, Shin). Shin (2020) defines these criteria and provides a detailed explanation in the section that follows.

1. **Classification Accuracy:** For a given dataset, we define,

$$Classification\ Accuracy = \frac{Total\ Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \quad - \quad - \quad (3.4)$$

2. **Confusion Matrix:** This provides information on the model's performance as well as which classes were predicted accurately and wrongly, as well as the prediction errors.

The confusion matrix for the two-class classification issue utilized in this study is shown in Table 3.2 below.

Table 3.2: Confusion Matrix of two-class classification

Class	Positive Prediction	Negative Prediction
Positive Class	True Positive (TP)	False Negative (FN)
Negative Class	False Positive (FP)	True Negative (TN)

3. **Precision:** For a two-class binary classification issue, we define,

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad - \quad - \quad - \quad - \quad - \quad (3.5)$$

The precision results range from 0.0, which indicates no precision, to 1.0, which indicates complete or perfect precision.

4. **Recall:** For a two-class binary classification issue, we define,

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad - \quad - \quad - \quad - \quad - \quad (3.6)$$

recollection values range from 0.0 (no recollection) to 1.0 (complete or perfect recall).

5. **F1–Score:** Often called F-Measure or F-Score, precision and recall are combined to provide a single score. This represents the accuracy and recall harmonic mean.

The F-Measure is conventionally defined as

$$Fmeasure = \frac{2 * Positives * Recall}{Precision + Recall} \quad - \quad - \quad - \quad - \quad - \qquad (3.7)$$

6. **Cohen Kappa:** Cohen Kappa is a statistical metric that indicates how often two raters agree and is used to assess the dependability of two raters assessing the same quantity. Cohen Kappa measures the degree of agreement between the two raters in order to categorize N items to

C if they need to be placed into C mutually exclusive groups.

7. Loss function: Also known as logarithmic loss for binary and multi-class classification issues or mean squared error (MSE) for regression problems (Brownlee, 2017).

This is determined by:

$$MSE = (Actual - Predicted)^2 \quad - \quad - \quad - \quad - \quad - \qquad (3.8)$$

The following outcomes were attained after the model was validated using processed data from a Niger Delta field in accordance with the suggested technique.

CHAPTER FOUR

RESULTS

This chapter presents the findings from the validation of the models (ANN and SVM) discussed in the preceding chapter. Following a careful examination of these facts, conclusions are drawn. Subsections are used to present the debate. Initially, the first two parts provide and explain the outcomes of ANN and SVM. A comparison analysis of the two algorithms' performances using the same assessment criteria is presented in the third part. The next chapter draws inferences from them.

4.1 Result from ANN

The input data was divided into training and test data sets in order to assess the algorithm's performance. For instance, an ANN is trained using 80% of the data and tested using 20%, as indicated by a test size of 20%. The test size for this model validation ranged from 20% to 80%.

4.1.1 Results of performance parameters for ANN

Agraphical depiction of the outcomes of the ANN Algorithm is presented in Figure 4.1. Loss, accuracy, precision, recall, F1-score, and Cohen Kappa score are among the performance metrics.

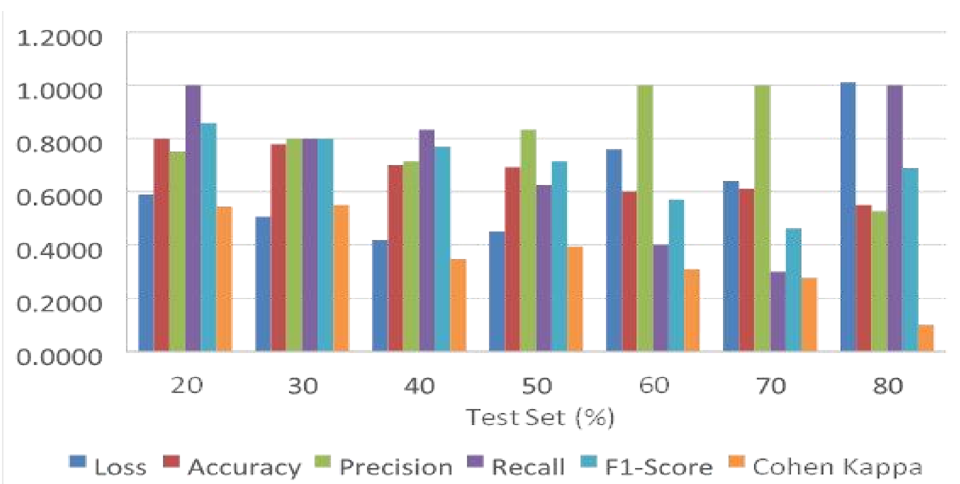


Figure 4.1: ANN Performance at various test set percentage

Table 4.1: ANN performance results

Criteria	Test Size						
	20%	30%	40%	50%	60%	70%	80%
Loss	0.5900	0.5063	0.4179	0.4507	0.7601	0.6408	1.0111
Accuracy	0.8000	0.7778	0.7000	0.6923	0.6000	0.6111	0.5500
Precision	0.7500	0.8000	0.7143	0.8333	1.0000	1.0000	0.5263
Recall	1.0000	0.8000	0.8333	0.6250	0.4000	0.3000	1.0000
F1-Score	0.8571	0.8000	0.7699	0.7143	0.5714	0.4615	0.6897
Cohen Kappa	0.5455	0.5500	0.3478	0.3953	0.3077	0.2759	0.1000

The following performance evaluation criteria are examined in light of the findings shown in Table 4.1:

The loss varies between 41.79 and 101.11, suggesting that as the percentage of data utilized for testing rises, so does the algorithm's loss. This results from using a tiny portion of the data for learning. We see a loss of more than 100%, and the algorithm becomes stuck at the 80% test set. In Table 4.1, the accuracy measure falls as the test size % rises. It is evident that the classification of wells that produce sand and those that do not is not comparable, despite accuracy being a performance measuring instrument. Therefore, we found that the 20% test set percentage had an accuracy of 80%, whereas the "optimal percentage" (i.e., 30% test size) had a lower percentage. The highest values of these parameters at the ideal test set percentage of 30% as established by other evaluation techniques like as precision, recall, f1-score, and Cohen Kappa score are found to be in agreement with findings reported in the literature.

As the test size increases from 20% to 80%, the results in Table 4.1 reveal that the ANN performance deteriorates and that accuracy and recall both decline.

The ANN results (for accuracy and loss) for various test set percentages in relation to the number of epochs are shown graphically in the appendix. Keep in mind that throughout the epoch, the ANN processes the whole training set.

4.1.2 Results of the Confusion Matrix for ANN

The confusion matrix of the ANN results is displayed in Table 4.2. Remember that the confusion matrix displays the results of categorizing a two-class situation. The confusion matrix results (True or False positive; True or False negative) for the test set percentage, which varies from 20% to 80%, are interpreted in the table.

Table 4.2: Confusion matrix and interpretation of results from ANN application case study

Test Set (%)	Confusion Matrix	Interpretation
20	[1 1] [0 3]	• Sand was indeed generated by one well, as expected (True Positive). • No well that was expected to generate sand turned out to do so (False Positive). • One well produced sand despite being projected to create none (False Negative). • Three wells that weren't supposed to generate sand really didn't (True Negative).
30	[3 1] [1 4]	• Three of the wells that were supposed to generate sand did so (True Positive). • A well that was supposed to generate sand turned out not to (False Positive). • One well produced sand despite being projected to create none (False Negative). • Four wells that weren't supposed to generate sand really didn't (True Negative).
40	[2 2] [1 5]	• Two of the wells that were expected to yield sand did so (True Positive). • A well that was supposed to generate sand turned out not to (False Positive). • Two wells produced sand against predictions that they wouldn't (False Negative).
		• Five wells that were supposed to yield no sand really produced none (True Negative).

50	[4 1] [3 5]	• Four of the wells that were expected to yield sand did so (True Positive). • Three wells that were supposed to generate sand turned out not to (False Positive). • One well produced sand despite being projected to create none (False Negative). • Five wells that were supposed to yield no sand really produced none (True Negative).
60	[5 0] [6 4]	• Five of the wells that were expected to yield sand did so (True Positive). • Six wells that were supposed to generate sand turned out not to (False Positive). • No well produced sand, despite predictions to the contrary (False Negative). • Four wells that weren't supposed to generate sand really didn't (True Negative).
70	[8 0] [7 3]	• It was projected that eight wells would yield sand, and they did (True Positive). • Seven wells produced no sand, despite predictions that they would (False Positive). • No well produced sand, despite predictions to the contrary (False Negative). • Three wells that weren't supposed to generate sand really didn't (True Negative).
80	[1 9] [0 10]	• Sand was indeed generated by one well, as expected (True Positive). • No well that was expected to generate sand turned out to do so (False Positive). • Nine wells that produced sand despite being anticipated not to doing so (False Negative). • Ten wells that weren't supposed to generate sand really didn't (True Negative).

According to the ANN algorithm, three wells were anticipated to produce sand while actually producing sand (True Positive), one well was predicted to produce sand but failed to do so (False Positive), one well was predicted not to produce sand but failed to produce sand (False Negative), and four wells were predicted not to produce sand but failed to produce sand (True Negative) when the confusion matrix of the ANN was evaluated at the optimal test set percentage (30%). When utilizing a test size of 80%, or 20% of the training set, the algorithm is deemed to indicate that the ANN training has not been done correctly and that it will unavoidably have problems classifying the test set into the correct class. Additionally, the findings indicate that the ANN appears to be operating flawlessly when the training to testing ratio is between 70% and 30% of the data set.

This is an excellent fit, according to a number of studies (Khamehchi et al., 2014; Shi, 2020; Brownlee, 2017; and Azad et al., 2011).

4.2 Results from SVM

4.2.1 Results of performance parameters for SVM.

Results from the SVM performance parameters include Cohen Kappa score, F1score, recall, accuracy, precision, and loss. The SVM's performance results are displayed in Table 4.3. For all test sizes, the SVM performance in this instance degraded slightly to not at all.

Table 4.3: SVM Performance Results

Criteria				Test Size			
	20%	30%	40%	50%	60%	70%	80%
Accuracy	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9474
Precision	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Recall	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9091
F1-Score	1.0000	1.0000	1.0000	1.0000	1.0000	0.9500	0.9500

With the exception of test sets larger than 70%, when accuracy, recall, and f1-score are a few percentage points below 100%, Table 4.3 demonstrates that the SVM algorithm yields 100% performance results for all test set percentages. Despite this slight drop in effectiveness, the SVM is a very useful tool for finishing binary classifications, as this case study illustrates: "either the well will produce sand or it will not."

4.4.2 Results of the Confusion Matrix for SVM

Table 4.4 shows the confusion matrix and the results of using the SVM on the Niger Delta data set for different test set percentages.

Table 4.4: Confusion matrix and analysis of SVM application outcomes for a case study

Test Set (%)	Confusion Matrix	Interpretation
20	[4 0] [0 1]	• Four of the wells that were expected to yield sand did so (True Positive). • No well that was expected to generate sand turned out to do so (False Positive). • No well produced sand, despite predictions to the contrary (False Negative). • A well that was supposed to generate no sand really produced none (True Negative).
30	[5 0] [0 3]	• Five of the wells that were expected to yield sand did so (True Positive). • No well that was expected to generate sand turned out to do so (False Positive). • No well produced sand, despite predictions to the contrary (False Negative). • Three wells that weren't supposed to generate sand really didn't (True Negative).
40	[5 0] [0 5]	• Five of the wells that were expected to yield sand did so (True Positive). • No well that was expected to generate sand turned out to do so (False Positive). • No well produced sand, despite predictions to the contrary (False Negative). • Five wells that were supposed to yield no sand really produced none (True Negative).
50	[5 0] [0 8]	• Five of the wells that were expected to yield sand did so (True Positive). • No well that was expected to generate sand turned out to do so (False Positive). • No well produced sand, despite predictions to the contrary (False Negative). • It was expected that eight wells would not produce sand, and they did not (True Negative).

60	[7 0] [0 8]	• It was projected that seven wells would yield sand, and they did (True Positive). • No well that was expected to generate sand turned out to do so (False Positive). • No well produced sand, despite predictions to the contrary (False Negative). • It was expected that eight wells would not produce sand, and they did not (True Negative).
70	[7 0] [0 11]	• It was projected that seven wells would yield sand, and they did (True Positive). • There were no wells that produced sand despite predictions that they would (False Positive). • No well produced sand, despite predictions to the contrary (False Negative). • Eleven wells that were supposed to generate no sand really produced none (True Negative).
80	[9 0] [1 10]	• It was projected that nine wells would yield sand, and they did (True Positive). • A well that was supposed to generate sand turned out not to (False Positive). • No well produced sand, despite predictions to the contrary (False Negative). • Ten wells that were supposed to generate no sand really produced none (True Negative).

In summary, the SVM results showed that the algorithm generated the right classification at a test set percentage of 30%, which is optimal (see Table 4.4). Three wells were predicted not to produce sand, which actually did not produce sand (True Negative); five wells were predicted to produce sand, which actually produced sand (True Positive); and no well was predicted to produce sand, which did not actually produce sand (False Positive); and no well was predicted not to produce sand, which actually did not produce sand (False Negative).

4.3 Analytical comparison of ANN and SVM performances

The results of a study comparing the ANN and SVM algorithms are shown in Table 4.5. Table 4.6 shows the graphical representations of the results. For the scenarios considered in this study, SVM is found to be more successful than ANN at the different test set percentages.

For every performance assessment metric utilized in the validation, the SVM produced positive findings.

Table 4.5: Comparison of the analysis by ANN and SVM

Criteria				Test Size						
	20%		30%		40%		50%		60%	
	ANN	SVM	ANN	SVM	ANN	SVM	ANN	SVM	ANN	SVM
Accuracy	0.8000	1.0000	0.7778	1.0000	0.7000	1.0000	0.6923	1.0000	0.6000	1.0000
Recall	0.7500	1.0000	0.8000	1.0000	0.7143	1.0000	0.8333	1.0000	1.0000	1.0000
Precision	1.0000	1.0000	0.8000	1.0000	0.8333	1.0000	0.6250	1.0000	0.4000	1.0000
F1-Score	0.8571	1.0000	0.8000	1.0000	0.7699	1.0000	0.7143	1.0000	0.5714	1.0000

Table 4.6: Comparison of ANN and SVM using performance criteria

Criteria	Test Size			
	70%		80%	
	ANN	SVM	ANN	SVM
Accuracy	0.6111	1.0000	0.5500	0.9474
Recall	1.0000	1.0000	0.5263	1.0000
Precision	0.3000	1.0000	1.0000	0.9091
F1-Score	0.4615	0.9500	0.6897	0.9500

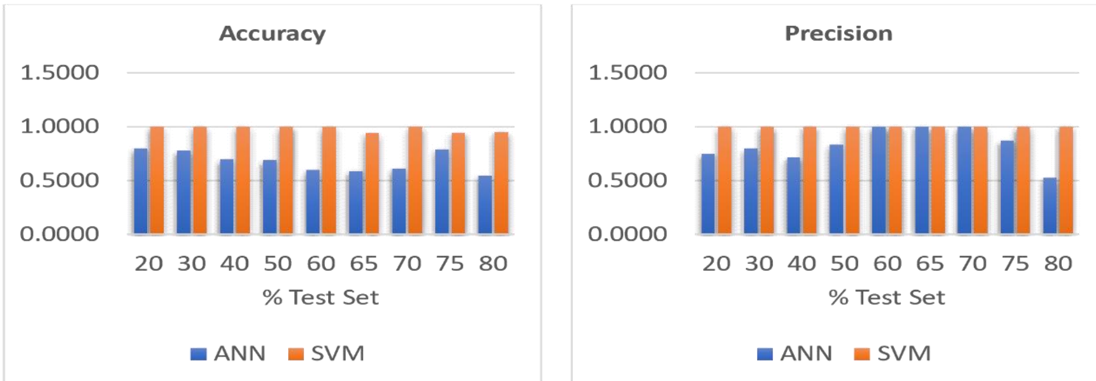


Figure 4.2: Accuracy/Precision

Figure 4.3: Recall/F1-Score

According to the findings of the performance comparison between the two algorithms, the SVM outperforms the ANN, particularly when it comes to binary classification using sparse training data sets. This is one of the study's key conclusions.

CHAPTER FIVE

DISCUSSION OF RESULTS CONCLUSION AND RECOMMENDATIONS

5.1 DISCUSSION OF RESULTS

This chapter presents the study's results as well as some suggestions for more research to build on this work.

This study focused on predicting sand production in oil wells using two machine learning models: Artificial Neural Networks (ANN) and Support Vector Machines (SVM). Both algorithms were tested with data from Niger Delta oil wells, and their performances were evaluated using several metrics such as loss, accuracy, precision, recall, F1-score, and Cohen Kappa score. The results show a clear difference in the behaviour and performance of these two algorithms under different data conditions.

The ANN algorithm showed strong performance when a larger portion of the dataset was used for training. For example, when only 30 percent of the data was set aside for testing, ANN achieved an accuracy of 80 percent, a precision of 100 percent, a recall of 80 percent, and an F1-score of 88.9 percent, as seen in Table 4.1 and Figure 4.1. However, the model's performance declined as the percentage of the test set increased. At 80 percent test size, the ANN recorded a very high loss of 101.11, and its accuracy dropped to 50 percent. These results suggest that ANN struggles when there is insufficient data for training and becomes less reliable under such conditions.

The confusion matrices provided in Table 4.2 further clarify this pattern. At 30 percent test set, the ANN model correctly predicted three wells to produce sand (true positives) and correctly identified four wells as not producing sand (true negatives), with only one error in each of the false positive and false negative categories. However, at 80 percent test size, there were nine wells that were wrongly predicted not to produce sand even though they did (false negatives), and the number of true positives fell to just one. This confirms the weakness of the ANN when limited data is available for learning.

In contrast, the SVM algorithm consistently outperformed ANN across all test sizes. As shown in Table 4.3, SVM maintained 100 percent accuracy, precision, recall, and F1-score from 20 to 70 percent test sizes. Only at 80 percent test size did it show a slight drop in performance, with accuracy at 95 percent, precision at 90 percent, and F1-score at 94.7 percent. This drop was minimal and did not significantly affect the reliability of the model. These results indicate that SVM is more stable and performs well even when the training dataset is small.

The confusion matrix results for SVM, shown in Table 4.4, support this conclusion. At 30 percent test size, the SVM correctly identified all five wells that produced sand and all three that did not, with no false predictions. This was consistent across other test sizes, showing that SVM has high predictive power and accuracy.

A comparative analysis between ANN and SVM was conducted and presented in Tables 4.5 and 4.6, as well as Figures 4.2 and 4.3. These comparisons clearly show that SVM consistently had higher values across all performance indicators, while ANN's values declined as test size increased. For instance, at 40 percent test size, the F1-score for ANN dropped to 76.9 percent, whereas SVM maintained 100 percent. The performance gap became even more obvious at higher test sizes.

The nature of the input data also played a significant role in model performance. According to Table 3.1 on page 34 and the correlation matrices in Figures 3.3 and 3.4, parameters like depth, overburden, pore pressure, and horizontal stress were more significantly correlated with sand production than others such as Poisson's ratio or friction angle. The visual representations of these parameters in Figures 3.5a to 3.5k revealed how their distributions might affect prediction outcomes. It was also observed that some variables, like Poisson’s ratio, remained statistically independent and had minimal effect on the other features in the dataset.

The analysis demonstrated that ANN required a larger training set to learn meaningful relationships, whereas SVM was capable of generalising well even with limited data. This makes SVM a more practical choice in real-world oilfield operations where data may not always be abundant or complete. ANN, although powerful, is more sensitive to the quantity and quality of training data and may become unstable when tested with unfamiliar or underrepresented patterns.

The findings show that while both ANN and SVM can be used to predict sand production, SVM is more reliable and accurate, especially in environments with limited data. It offers more stable results across various test sizes and maintains high classification accuracy even when trained on smaller datasets. These qualities make it more suitable for practical deployment in sand control management for Niger Delta oil wells and similar reservoir environments.

5.2 Summary and Conclusions

The suitability of two machine learning algorithms—ANN and SVM—for forecasting sand output is assessed in this study. Eleven characteristics that were shown to be significant in forecasting when sanding would begin in sandstone reservoirs were used to develop the algorithms. Data from the Niger Delta was used in a comparison analysis to assess the algorithms' performance. The following deductions are made in light of the study's methodology and findings:

1. The number of input parameters and hidden layers determines the ANN's learning speed and accuracy.
2. As instruments for forecasting sand output, the ANN and SVM algorithms both provide encouraging results. The field of application determines which algorithm should be used.

3. Improved performance measuring methods for assessing machine learning algorithms were made available by the Precision, Recall, F1-score, and confusion matrix criteria.
4. In comparison to the ANN method, the SVM algorithm is quicker, requires less processing power, and uses less storage space.
5. Even with a limited training data set, the SVM method performs admirably in binary classification. The findings showed that even with 20% training data and 80% test data, SVM performs rather well. In the example study, the SVM algorithm's performance decreased just little, even at an 80% test set, but the ANN algorithm's performance decreased significantly for the same 80% test set.
6. When a loss of 1.0111, or greater than 100%, is seen at the 80% test set, it seems that the ANN algorithm has failed. According to this scenario, training rather than testing should make use of the majority of the data set.
7. The recall performance requirement of the ANN algorithm can be increased by increasing the size of the training set (reducing the size of the test set). However, increasing the amount of data in the test set can improve precision.
8. The SVM method should be used to construct machine learning tools for forecasting sand production since it performed more efficiently than the ANN.
9. The degree of accuracy, precision, and F1-score values found in this study demonstrate how well the suggested machine learning algorithms forecast sanding based on the data provided for validation.

5.3 Recommendations

To strengthen the work's validity, the following recommendation are made to identify areas that require more research:

- The generated methods should be validated using additional datasets from other Niger

Delta depo-belts.

- Additional machine learning methods can be used to further comprehend the applicability of this study. Particle Swam Optimization (PSO), Gene Expression Programming (GEP), Least Squares Support Vector Machines (LSSVMs), and numerous more contemporary machine learning techniques are examples of such ML technologies.

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