AN INTELLIGENT MACHINE LEARNING FRAMEWORK FOR FISHRIES FOR-CASTING AND SECURITY SURVIELANCE

BY

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A PROJECT SUBMITTED TO THE DEPARTMENT OF COMPUTER SCIENCE, FACULTY OF COMPUTING, UNIVERSITY OF BENIN, IN PARTIAL FULFILMENT FOR THE REQUIREMENTS FOR THE AWARD OF THE MASTER IN COMPUTER SCIENCE (M.Sc.) DEGREEE IN COMPUTER SCIENCES

FEBUARY, 2026

DECLARATION

I, Abigail Mojibola OMORODION with the matriculation number PG/PSC2215998, by this means, declare that this research project on ‘’An Intelligent Machine Learning Framework for Fisheries Forecasting and Security Surveillance’’ which is being submitted by me. In partial fulfilment for the award of the Masters of Science Degree in Computer Science, is an authentic report carried out by me during the 2022/2023 academic session. I further undertake the work embodied in the report has not been submitted previously for the award of degree or diploma by me to any other university or institution.

______________________________ ______________________________

Abigail Mojibola Omorodion **DATE**
PG/PSC2215998

CERTIFICATION

This is to certify that this project work was carried out by Abigail Mojibola OMORODION with the matriculation number PG/PSC2215998 of the department of computer science, University of Benin, under my supervision and it is adequate in scope and content for the award of Master in Computer Science (M.Sc.) Degree in Computer Science of the University of Benin.

Prof. Mrs. Susan Konyeha **Project Supervisor**	**Date**

APPROVAL

This project is hereby approved by the Department of Computer Science in partial fulfilment of the requirements for the award of Master in Computer Science (M.Sc.) Degree in Computer Science of the University of Benin, Benin City, Nigeria.

______________________	______________________
Dr. Mrs. Rosemary Usiobiafo	**Date**
Head of Department	

DEDICATION

This project is dedicated to God Almighty for His love and mercies throughout my study period, also to my dear parents for their great support and to my beloved husband, close friends and associates for your immense contributions during the course of this project work.

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Firstly, I want to use this opportunity to thank God almighty who gave life and made all things possible. Then I wish to thank my project supervisor **Prof. (Mrs.) Susan Konyeha** for her endurance and kindness in guiding me through this project work. In that regard, I also wish to appreciate other project supervisors in the department and my special thanks goes to the University of Benin and all members of staff in the Department of Computer Science (listed below) who provided the platform for my education and labored hard to train me well in knowledge and service. God bless you all.

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ABSTRACT

Fisheries and aquaculture are vital to global food security but face critical challenges, including security threats from unauthorized access, the limitations of reactive manual monitoring, and uncertainty in long-term production forecasting. Existing management tools often lack a unified approach to integrate real-time operational surveillance with predictive decision-support analytics. This study aims to address these gaps by designing and developing a hybrid methodological framework that integrates computer vision for security and advanced machine learning and time-series forecasting for production analysis and stock management. The study employed a dual-component methodology. For security, an OpenCV-based Histogram of Oriented Gradients (HOG) descriptor combined with a Support Vector Machine (SVM) was implemented to achieve automated, real-time human intrusion detection and alarm triggering. For predictive analytics, a hybrid approach was utilized, applying Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors (SARIMAX) for long-term production forecasting and various ensemble classifiers (Random Forest, Gradient Boosting, K-Nearest Neighbors) to analyze fish survivability and production trends. Results demonstrate that this integrated framework is highly effective across operational and strategic levels. The computer vision system successfully provided continuous, automated surveillance with verifiable digital evidence. The ensemble classifiers achieved near-perfect performance in survivability prediction (e.g., Random Forest Accuracy = 0.98, F1-score = 0.99, AUC ≈ 0.999). Furthermore, the SARIMAX model effectively projected a steady increase in global fish production, forecasting growth from 232.19 million tonnes in 2024 to 272.12 million tonnes by 2043—a 17.19% increase—capturing long-term temporal dynamics that static regressors fail to model. Based on these findings, it is recommended that fisheries stakeholders prioritize the deployment of computer vision-based surveillance to reduce security risks and labor costs. Additionally, management authorities should integrate ensemble classifiers into stock-management systems to optimize survivability and adopt SARIMAX-based forecasting for robust, evidence-based policy planning. The implementation of these data-driven platforms will significantly enhance sustainable fisheries governance and support proactive resource allocation.

CHAPTER ONE

INTRODUCTION

1.1 Background to the study

Fisheries have long been recognized as one of the most significant contributors to global food security, nutrition, employment, and economic development. Globally, more than three billion people depend on fish for at least 20% of their protein intake, while in some countries, fish contributes over 50% of dietary animal protein (Pomeroy et al., 2016). This makes fishing the largest extractive use of wildlife in the world, providing livelihoods, generating foreign exchange, and supporting local economies. However, global capture fisheries face what has been termed the "paradox of abundance and decline," where despite high production levels, overfishing, environmental degradation, and weak governance threaten their long-term sustainability (Pomeroy et al., 2016).

In Africa, particularly Eastern Africa, fish serves as an essential yet underutilized source of nutrition. Approximately 200 million people in the region rely on fish as a cheap and highquality protein source, but fish consumption remains below global averages due to deficits in supply, trade barriers, and infrastructure challenges (Obiero et al., 2019). Per capita fish consumption in Eastern Africa was only 4.8 kg in 2013 and is projected to rise modestly to 5.49 kg by 2022, still far below the global average. This growing demand-supply gap underscores the urgent need for investment in aquaculture, intra-regional trade, and evidence-based policy frameworks that can enhance food security and nutrition (Obiero et al., 2019).

In recent decades, the growing emphasis on the blue economy has reshaped fisheries management globally. For example, in Ghana, industrialization of fisheries under blue economy policies has intensified competition between large-scale and small-scale fishers, leading to depletion of local resources, destruction of fishing gear, declining incomes, and the marginalization of coastal communities (Ayilu et al., 2023). Such structural shifts have disrupted traditional livelihoods, exacerbated gender inequality, and fueled conflict in fishing-dependent regions, revealing the need for inclusive governance that prioritizes small-scale fisheries in line with the concept of "blue justice" (Ayilu et al., 2023).

In Nigeria and the Gulf of Guinea, emerging scholarship highlights the critical intersection between fisheries management, sustainability certification, and fisher health. Industrial fishing remains one of the world's most hazardous occupations, with fishers often exposed to high risks and inadequate health protections. Recent evidence shows that participation in sustainability certification programs, such as Friend of the Sea (FOS), improves health outcomes, reduces occupational risks, and enhances overall socio-ecological resilience, thereby linking fisher well-being with sustainable fisheries management (Elegbede et al., 2025). This highlights the importance of integrating health and safety standards into fisheries governance frameworks under the One Health approach.

Despite these advancements, fisheries continue to face escalating global challenges. The sector currently contributes over 214 million tonnes of production annually, including aquaculture and capture fisheries, yet suffers from environmental threats such as overfishing, habitat loss, and climate change; economic challenges such as illegal, unreported, and unregulated (IUU) fishing and market instability; and social issues such as gender inequities and community displacement (Singh et al., 2024). In India, with a production of 16.24 million tonnes, fisheries contribute 1.1% to the national economy and rank second globally in aquaculture production. However, the sustainability of this growth is increasingly questioned given these intersecting threats (Singh et al., 2024).

Taken together, these studies reveal that fisheries management must evolve beyond traditional production-focused models. Addressing the drivers of scarcity, inequity, and ecological degradation requires holistic approaches—integrating sustainable practices, adaptive governance, fisher health, blue justice, and climate resilience. This integrated perspective ensures that fisheries continue to provide food, livelihoods, and ecological balance for future generations while mitigating competition, conflict, and vulnerability among fishing communities.

1.2 Statement of the Problem

The rapid advancement of intelligent surveillance and video-based monitoring has demonstrated the transformative potential of machine learning and computer vision in addressing complex security and forecasting challenges, yet significant gaps remain in their application to fisheries management. Research by Sreenu and Durai (2019) highlights the promise of deep learning in object and action recognition, crowd analysis, and violence detection, though limitations persist in adapting these methods to real-time, dynamic environments. Similarly, Ibrahim (2016) underscores the role of intelligent surveillance systems that integrate computer vision, machine learning, and sensor fusion, but these solutions remain narrowly focused on behavioral analysis and lack sector-specific adaptation. While broader applications of surveillance in smart cities demonstrate the integration of deep learning, blockchain, and edge computing for decision-support (Myagmar-Ochir and Kim, 2023), parallel advances in aquaculture show the use of intelligent technologies for sustainability and welfare monitoring (Vo et al., 2021; Fitzgerald et al., 2025). Despite these developments, fisheries continue to face pressing dual challenges: vulnerability to theft, vandalism, and unauthorized access that threaten aquaculture security (FAO, 2022), and the need for reliable long-term forecasting of production under climate variability and resource pressure (World Bank, 2020; Dey et al., 2021). Traditional surveillance remains resource-intensive and reactive, while statistical forecasting often fails to capture nonlinear and seasonal complexities, leaving policymakers without robust tools for governance. Consequently, the core problem lies in the absence of an integrated methodological framework that simultaneously addresses real-time security surveillance through validated computer vision techniques and sustainable production forecasting through advanced machine learning models. This study seeks to fill that critical gap by designing a dual-purpose framework capable of safeguarding aquaculture operations while generating predictive insights to inform fisheries governance.

1.3 Aim and Objectives

The aim of this study is to develop and implement An Integrated Machine Learning and Computer Vision Framework for Forecasting, Security Surveillance, and Decision-Support in Fisheries Management

The objectives are:

i. To design and develop a hybrid methodological framework that integrates time series forecasting and machine learning classification for fisheries production analysis and decision-support.

ii. To implement the proposed framework using SARIMAX for forecasting and machine learning algorithms (Logistic Regression, Random Forest, Support Vector Machine, Gradient Boosting, and K-Nearest Neighbors) for classification, fish survival prediction, and security surveillance.

iii. To evaluate and compare the performance of the forecasting and classification models using standard metrics (accuracy, balanced accuracy, MCC, Cohen’s Kappa, AUC), and present the results with datasets and visualizations such as ROC curves and timeseries plots.

1.4 Scope of the study

The scope of this study is defined by its dual methodological emphasis on real-time security surveillance and long-term fisheries management through the integration of computer vision and machine learning techniques. On the surveillance side, the scope encompasses the development and validation of an experimental framework employing OpenCV's Histogram of Oriented Gradients (HOG) descriptor in conjunction with a pre-trained Support Vector Machine (SVM) to detect human presence in video streams, with outputs linked to a multithreaded alarm system for automated, real-time alerts. This ensures that the study contributes to the enhancement of security and safety monitoring within aquaculture environments. On the fisheries management side, the scope extends to the computational analysis of global production data aggregated into yearly trends, with a focus on forecasting and classification. A hybrid SARIMAX and Random Forest forecasting framework is applied to predict 20-year production trajectories, while classification models—including Logistic Regression, Random Forest, and Support Vector Machines—are trained to assess year-to-year production variability. The scope further includes the evaluation of these models using standard performance metrics and the visualization of outputs to support empirical interpretation. Overall, the study is delimited to addressing two interrelated challenges: real-time detection of human activity for aquaculture security, and predictive analytics for sustainable global fisheries governance, while excluding broader ecological, policy, or socio-economic dimensions of fisheries management that fall beyond its computational and experimental design.

1.5 Limitations of the Study

This study is delimited to the integration of computer vision and machine learning methodologies for addressing two distinct but complementary domains: real-time security surveillance and long-term fisheries management. On the surveillance side, the scope is restricted to the implementation of human activity detection using OpenCV's Histogram of Oriented Gradients (HOG) descriptor in combination with a pre-trained Support Vector Machine (SVM) detector, applied to video inputs from webcams or stored files on a frame-by-frame basis, with outputs validated through bounding boxes and a multi-threaded alarm system for real-time alerts. On the fisheries management side, the study focuses exclusively on the analysis of global fish production using aggregated annual data from Global_production_quantity.csv, employing a hybrid framework that combines SARIMAX for time series forecasting and Random Forest regression for multi-step predictive modeling, complemented by supervised classification models including Logistic Regression, Random Forest Classifier, and Support Vector Machine for detecting year-to-year production trends. The scope therefore encompasses methodological design, implementation, evaluation, and visualization of results within these two application areas, while deliberately excluding other surveillance contexts (e.g., object or animal detection beyond humans), alternative data sources for fisheries production, or broader socio-economic and environmental determinants of fishery governance beyond the computational and datadriven frameworks developed in this study.

1.6 Significance of the Study

This study is significant because it addresses two critical dimensions of fisheries governance and aquaculture sustainability: real-time security surveillance and long-term production forecasting. By integrating computer vision techniques with machine learning-based forecasting and classification, the research provides both experimental and computational contributions that have practical, scientific, and policy-level relevance. The significance can be outlined as follows:

i. **Enhancement of Aquaculture Security:** The study contributes to improved surveillance in fisheries and aquaculture systems by employing a robust computer vision framework capable of detecting human presence in real time. The integration of bounding box visualization with a multi-threaded alarm system enhances security monitoring, deterring unauthorized access and ensuring the safety of aquatic resources. ii. **Advancement of Computational Methodologies:** The study demonstrates the integration of OpenCV-based feature extraction with Support Vector Machine classification for surveillance, and the combination of SARIMAX and Random Forest forecasting for predictive analytics. This dual computational framework offers a replicable methodological design that can be applied in other domains requiring both real-time monitoring and long-term prediction.

iii. **Contribution to Sustainable Fisheries Management:** By generating long-term projections of global fish production and classifying year-to-year production variability, the study provides decision-support tools for policymakers, fisheries managers, and international organizations. These insights help anticipate future supply trends, optimize resource allocation, and strengthen global food security strategies.

iv. **Empirical Basis for Decision-Making:** The outputs of the study—including datasets, visualizations, forecast trajectories, and classification performance results—serve as empirical evidence to inform fisheries governance. Such evidence-based insights support the formulation of adaptive policies that balance ecological sustainability with production needs.

v. **Bridging Real-Time and Strategic Needs:** The dual scope of the research is significant in that it bridges short-term operational challenges, such as aquaculture security, with long-term strategic goals, such as production forecasting. This integration ensures
that both immediate risks and future sustainability concerns are addressed within a unified computational and experimental framework.

1.7 Definition of Terms

This section provides clear and context-specific definitions of key technical and conceptual terms used throughout this study. Given the interdisciplinary nature of the research—spanning machine learning, computer vision, time-series forecasting, and fisheries management—these definitions are intended to ensure conceptual clarity and consistency of interpretation. The terms are defined as they apply specifically within the scope of *An Integrated Machine Learning Framework for Fisheries Forecasting and Security Surveillance* and may therefore reflect domain-specific usage rather than their most general meanings.

i. Aquaculture Security Surveillance: The application of computer vision and intelligent monitoring systems to detect, track, and respond to human activities within aquaculture environments in order to prevent theft, vandalism, and unauthorized access.

ii. Machine Learning (ML): A subset of artificial intelligence that enables computational models to learn patterns from data and make predictions or classifications without being explicitly programmed, as applied in this study to fish survivability prediction, production classification, and forecasting.

iii. Computer Vision: A field of artificial intelligence focused on enabling machines to interpret and analyze visual data from images and video streams; in this study, it is used for real-time human detection in aquaculture surveillance.

iv. Histogram of Oriented Gradients (HOG): A feature extraction technique in computervision that captures edge and gradient structures in images; employed in this study to represent human shapes for surveillance detection.

v. Support Vector Machine (SVM): A supervised machine learning algorithm used for classification tasks by finding an optimal hyperplane that separates data into classes; utilized both as a pre-trained detector for human surveillance and as a classifier in production analysis.

vi. Time-Series Forecasting: A statistical and machine learning approach for modelingand predicting future values based on historical temporal data; applied in this study to project long-term global fish production trends.

vii. Seasonal AutoRegressive Integrated Moving Average with Exogenous Regressors(SARIMAX): An advanced time-series forecasting model that incorporates trend, seasonality, and external variables; used in this research for long-term fisheries production forecasting.

viii. Random Forest: An ensemble machine learning algorithm based on multiple decision trees; applied in this study for both regression-based forecasting and classification of fish production and survivability patterns.

ix. Fish Survivability Prediction: The use of supervised machine learning models to clas-sify and predict the likelihood of fish stock survival or yield performance based on historical and derived features.

x. Global Fish Production Forecasting: The process of predicting future fish production volumes at a global scale using historical aggregated production data and predictive models.

xi. Illegal, Unreported, and Unregulated (IUU) Fishing: Fishing activities that violate con-servation and management measures, often contributing to resource depletion and economic loss; identified in this study as a motivation for enhanced surveillance and governance tools.

xii. Decision-Support System: A computational framework that integrates data analysis,modeling, and visualization to assist policymakers and fisheries managers in informed planning and governance decisions.

xiii. Performance Metrics: Quantitative measures such as accuracy, precision, recall, F1-score, Area Under the Curve (AUC), Matthews Correlation Coefficient (MCC), and Cohen's Kappa, used to evaluate the effectiveness of machine learning models.

xiv. Multi-Step Forecasting: A forecasting approach in which predictions are generated recursively over multiple future time horizons; implemented in this study using Random Forest regression with lag features.

xv. Sustainable Fisheries Governance: The management of fisheries resources in a mannerthat balances ecological sustainability, economic viability, and social equity, supported in this study through data-driven surveillance and forecasting tools.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

Over the past decade, fisheries management and aquaculture have experienced a paradigm shift with the integration of artificial intelligence (AI), computer vision (CV), and digital technologies, which promise to address long-standing ecological, economic, and operational challenges. Scholars increasingly argue that traditional approaches that rely on manual sampling, visual inspection, and static modeling are insufficient in the face of rising global demand, climate variability, and socio-economic pressures (Wang et al., 2021; OECD, 2020). As such, the emerging body of research highlights the potential of AI and CV to transform fisheries science into a data-driven and automated enterprise capable of supporting sustainability, productivity, and resilience.

The literature review that follows is structured to explore this transformation across three interrelated dimensions: forecasting, surveillance, and decision-support. In the forecasting domain, advances in machine learning (ML) methods such as random forests, gradient boosting, and deep learning have shown improved predictive accuracy for stock abundance, species distribution, and environmental risks compared to traditional statistical models (OECD, 2020). These models, when fueled by diverse datasets including catch records, oceanographic variables, and satellite imagery, offer the possibility of near-real-time forecasts that are crucial for operational management and ecological resilience. However, issues of model interpretability, generalizability, and the alignment of performance metrics with management goals remain critical limitations that will be examined in detail.

In parallel, CV applications have gained prominence in fisheries and aquaculture for tasks such as fish counting, species detection, welfare monitoring, and by catch identification. Studies leveraging Convolutional Neural Networks and object detection frameworks like Faster RCNN and YOLO have demonstrated the potential of CV systems to convert raw video streams into actionable insights at scales unachievable through manual observation (Salako et al., 2024; Rathi et al., 2019). Complementary research underscores their role in improving fish health management through intelligent diagnostic imaging and sensor-based methods (Li et al., 2022). Nevertheless, technical constraints such as image quality variability, turbidity, occlusion, and the scarcity of standardized, publicly available datasets continue to limit broad adoption.

Beyond technical innovation, scholars have increasingly emphasized socio-economic and governance dimensions. Sarmiento-Carbajal et al. (2025) highlight that while technological adoption can improve efficiency and reduce precariousness, it also carries risks of labor displacement, uneven income distribution, and limited talent attraction. Similarly, reviews of decisionsupport systems (DSS) in fisheries stress that although prototypes for quota allocation, bycatch mitigation, and farm management exist, persistent barriers such as institutional inertia, data integration challenges, and low stakeholder trust constrain long-term adoption (Little et al., 2016). Saleh et al. (2024) further demonstrate that ecological monitoring through deep learning not only provides datasets and methodologies but also illuminates gaps in governance frameworks necessary for sustainable implementation.

Taken together, the literature converges on the expectation that integrated AI and CV frameworks can enhance ecological forecasting, automate surveillance, improve fish welfare, and provide decision-makers with actionable intelligence for sustainable management. At the same time, significant gaps remain in terms of dataset standardization, field deployment robustness, socio-technical integration, and governance structures. The expectation of this review is therefore to synthesize methodological advances, operational constraints, and socio-economic considerations across forecasting, surveillance, and decision-support studies, while identifying unresolved challenges. This synthesis will provide the foundation for developing an integrated, explainable, and context-sensitive framework for fisheries management that balances technological potential with ecological and social sustainability.

2.2 Conceptual Framework

The conceptual framework of this study is grounded in the integration of computer vision and machine learning methodologies to address two interrelated domains: real-time security surveillance and sustainable fisheries management. Conceptual frameworks serve as the blueprint for structuring research, guiding the methodology, and aligning theoretical perspectives with practical implementation (Adom et al., 2018). In this study, the framework positions computational intelligence as both a detection tool and a predictive instrument, ensuring that security challenges in aquaculture environments are addressed alongside the long-term forecasting of global fish production trends.

On one dimension, the framework draws upon computer vision principles for surveillance by adopting OpenCV’s Histogram of Oriented Gradients (HOG) descriptor in combination with a Support Vector Machine (SVM) classifier. Computer vision has emerged as a robust approach for detecting objects and human activities in dynamic environments, with HOG-based feature extraction proving effective in shape-based recognition tasks (Dalal amd Triggs, 2005). The integration of a pre-trained SVM ensures accurate classification of human presence in video feeds, which is consistent with recent advancements in automated surveillance systems (Pawar and Phadke, 2024). By incorporating a multi-threaded alarm system, the framework extends beyond detection to provide real-time intervention, thereby demonstrating its applied value in aquaculture security and broader safety monitoring contexts.

On another dimension, the framework emphasizes data-driven forecasting and classification as a mechanism for fisheries governance. Forecasting in fisheries has traditionally relied on statistical models such as ARIMA, which are effective for capturing linear temporal dependencies (Box et al., 2016). However, the integration of SARIMAX with machine learning regressors such as Random Forest enhances predictive robustness by accounting for seasonality, non-linear interactions, and external regressors (Lemke et al., 2009). Within this framework, the recursive multi-step prediction mechanism allows the projection of fish production over a 20-year horizon, providing stakeholders with reliable insights for policy and decisionmaking.

In parallel, the classification component of the framework operationalizes supervised learning techniques to distinguish between periods of increasing and decreasing fish production. Logistic Regression, Random Forest Classifier, and SVM (with RBF kernel) are employed to capture both linear and non-linear decision boundaries, ensuring high predictive accuracy across multiple performance metrics. Classification outcomes provide a complementary perspective to forecasting by identifying critical production shifts that may have implications for food security and sustainability (Hastie et al., 2009). The inclusion of evaluation measures such as accuracy, precision, recall, F1-score, and ROC-AUC ensures methodological rigor and validates the practical utility of the models.

Overall, the conceptual framework reflects a hybridized methodological design that fuses experimental computer vision with advanced predictive analytics. The dual focus enables realtime human activity detection for security surveillance while simultaneously contributing to evidence-based fisheries management. This alignment not only underscores the adaptability of computational intelligence across domains but also enhances its relevance in addressing contemporary challenges in food security and aquaculture governance (FAO, 2022). Thus, the framework provides the foundation for bridging technological innovation with sustainable development objectives.

2.3 Theoretical Framework

The theoretical framework of this study is grounded in the integration of computer vision for real-time surveillance and machine learning for long-term fisheries management. The purpose of such a framework is to provide the conceptual and theoretical underpinnings that explain how and why the proposed computational techniques can effectively address the dual objectives of aquaculture security and sustainable fisheries governance as follows.

i. **Computer Vision and Real-Time Surveillance :** Computer vision serves as the theoretical foundation for the surveillance aspect of the study. Computer vision is defined as a field of artificial intelligence that enables machines to interpret, process, and analyze visual information from the physical world (Szeliski, 2022). One of the most widely adopted theoretical approaches in this field is the use of feature descriptors such as the Histogram of Oriented Gradients (HOG). HOG is a mathematical method that captures gradient orientation in localized portions of an image, making it particularly effective for detecting human presence in visual scenes (Dalal amd Triggs, 2005). The robustness of HOG lies in its ability to detect structural patterns regardless of illumination or shadow conditions, which is essential in aquaculture environments that may be subject to variable lighting conditions.

ii. The incorporation of Support Vector Machines (SVMs) complements HOG within the surveillance system. Theoretically, SVMs function as discriminative classifiers that aim to maximize the margin between data points of different classes in a high-dimensional feature space (Cortes amd Vapnik, 1995). The synergy between HOG and SVM has been established in the literature as a reliable framework for real-time pedestrian detection and human activity recognition (Dalal amd Triggs, 2005; Benenson et al., 2014). By leveraging this foundation, the study theoretically contributes to the body of knowledge on automated security systems by extending their application to aquaculture surveillance. The alarm system linked to the detection pipeline is underpinned by theories of automation and control systems, where human intervention is minimized, and computational intelligence is relied upon for real-time decision-making (Parasuraman amd Riley, 1997).

iii. **Machine Learning and Fisheries Forecasting:** On the fisheries management side, the study is theoretically grounded in predictive analytics and statistical learning. Predictive analytics is based on the assumption that historical data contain patterns that can be leveraged to predict future outcomes (Shmueli amd Koppius, 2011). For fisheries, where production trends are influenced by multiple variables including environmental, economic, and operational factors, predictive models provide a theoretically sound mechanism for estimating future trajectories.

iv. The Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX) model is central to this forecasting approach. SARIMAX builds upon the theoretical foundations of time-series econometrics, particularly the Box-Jenkins methodology, which posits that autoregressive and moving average components can effectively capture temporal dependencies in structured data (Box amd Jenkins, 1970). The integration of exogenous variables allows SARIMAX to incorporate external influences, making it more adaptable to fisheries data that may be subject to non-stationary trends (Hyndman amd Athanasopoulos, 2018).

v. The use of ensemble learning models such as Random Forest for forecasting complements the statistical foundation of SARIMAX with machine learning theory. Random Forest operates on the principle of decision tree aggregation, where multiple weak learners are combined to produce robust predictive performance (Breiman, 2001). Theoretically, this ensemble method reduces overfitting and enhances generalization, making it suitable for fisheries datasets that exhibit variability and noise. The dual use of SARIMAX and Random Forest represents a hybrid theoretical approach that blends econometric rigor with machine learning adaptability.

vi. **Classification and Year-to-Year Production Variability.** The classification dimension of the study is underpinned by supervised learning theory. In supervised learning, models are trained to map input features to labeled outputs based on the assumption that similar patterns will recur in future observations (Mitchell, 1997). Logistic Regression, Random Forest, and Support Vector Machines are the selected classifiers in this study, each representing different theoretical underpinnings of classification.

vii. Logistic Regression is rooted in statistical theory, where the log-odds of the dependent variable are modeled as a linear combination of predictors (Hosmer et al., 2013). Random Forest, as discussed earlier, draws from ensemble learning theory to strengthen classification accuracy. Support Vector Machines, with their foundation in margin maximization, are particularly suitable for fisheries data that may exhibit complex decision boundaries (Cortes amd Vapnik, 1995). Together, these models provide a theoretically diverse framework for addressing year-to-year production variability in global fisheries.

viii. **Integration of Surveillance and Forecasting.** A central theoretical contribution of this study lies in the integration of real-time surveillance with long-term forecasting and classification. From a systems theory perspective, this integration reflects the principle of holism, where the system is understood as greater than the sum of its parts (Von Bertalanffy, 1968). By combining computer vision for immediate security assurance with machine learning for long-term production forecasting, the study bridges two traditionally distinct areas of computational intelligence. This dual framework is theoretically grounded in the concept of socio-technical systems, where technological tools are applied to address both operational and strategic needs within aquaculture and fisheries (Trist, 1981).

ix. Furthermore, the reliance on performance evaluation metrics such as precision, recall, F1-score, and mean absolute error aligns with the theoretical assumption of empirical validation in machine learning (Goodfellow et al., 2016). Visualization of outputs, in turn, is grounded in cognitive load theory, which suggests that graphical representation of data enhances interpretability and decision-making (Sweller, 2011).

x. **Delimitations and Exclusions.** While the theoretical framework is comprehensive, it is delimited by its computational and experimental scope. Broader ecological, policy, and socio-economic dimensions of fisheries management are deliberately excluded, as they fall under theories of governance and political economy that are beyond the computational orientation of this study. Instead, the theoretical foundation emphasizes automation, predictive analytics, and computational intelligence as the core constructs supporting the study's dual objectives.

2.4 Empirical framework

The study by Wu et al. (2025) provides a comprehensive review of the application of deep learning in advancing sustainable aquaculture. It emphasizes aquaculture's critical role in global food security and sustainability in the face of increasing demand for aquatic products. The review identifies deep learning applications across multiple domains, including fish detection and counting, growth prediction, health monitoring, intelligent feeding, water quality forecasting, and behavioral as well as stress analysis. Furthermore, the authors evaluate the performance of deep learning architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), generative adversarial networks

(GANs), Transformers, and MobileNet in tackling challenges posed by complex aquatic environments, including poor image quality and occlusion. Despite the progress, persistent limitations such as data scarcity, real-time performance issues, model generalization, and cross-domain adaptability are highlighted. To address these, Wu et al. (2025) propose future research directions, including multimodal data fusion, edge computing, lightweight model design, synthetic data generation, and the use of digital twin-based virtual farming platforms. Overall, the paper underscores deep learning's transformative potential to enhance aquaculture's efficiency, intelligence, and sustainability.

The study by Aung et al. (2024) systematically reviews the application of artificial intelligence (AI) in aquaculture, addressing critical challenges such as disease management, feeding optimization, water quality monitoring, and aquaculture area extraction. As global seafood demand rises, AI has emerged as a transformative tool for enhancing sustainability and productivity within aquaculture systems. The review synthesized evidence from 57 rigorously screened peer-reviewed studies published between 2020 and 2024, focusing on AI methodologies like computer vision, machine learning, and predictive modeling. Findings highlighted AI's significant potential in disease monitoring, environmental management, and production optimization. Nevertheless, several barriers remain, including limited representative datasets, high implementation costs, technical complexities, low social acceptance, and issues of data privacy and security. By identifying these gaps, the review provides an empirical foundation for advancing research and guiding responsible integration of AI technologies in commercial aquaculture worldwide (Aung et al., 2024).

The study by Ma et al. (2025) highlights the growing relevance of artificial intelligence (AI) in addressing safety concerns within aquaculture systems. The study systematically reviewed 513 publications spanning 1998–2025 using bibliometric tools such as Citespace and VOSviewer, revealing a sharp global increase in research interest in AI-driven aquaculture safety. The authors emphasize that traditional aquaculture safety challenges are being redefined through AI innovations, particularly in areas such as remote sensing technologies, immune response monitoring, and interdisciplinary integration. These advancements are projected to shift aquaculture management toward more intelligent, proactive, and sustainable safety practices. Furthermore, the integration of AI is expected to improve risk assessment and disease prevention with greater accuracy and efficiency, positioning it as a critical enabler for the future of aquaculture safety management. By synthesizing past contributions and forecasting emerging directions, this review fills a key gap in the literature, establishing AI as a transformative tool for aquaculture safety (Ma et al., 2025).

Lujan (2025) highlights the transformative role of artificial intelligence (AI) in advancing aquaculture towards sustainable seafood production. Aquaculture, while a critical avenue for addressing global food demands, faces persistent challenges such as disease outbreaks, inefficient resource utilization, environmental pressures, and the need for production optimization. AI emerges as a pivotal solution, offering innovative tools that enhance efficiency, sustainability, and productivity within aquatic farming systems. The integration of AI into aquaculture is redefining traditional methods by enabling precise water management, optimized feeding systems, and advanced health monitoring. This technological synergy not only addresses existing industry obstacles but also sets the foundation for future innovations and resilience in seafood production. The article therefore emphasizes both the practical applications and the long-term potential of AI in shaping a more sustainable aquaculture industry (Lujan, 2025).

A growing body of research highlights artificial intelligence (AI) as a transformative tool in aquaculture, with the potential to optimize operational efficiency and enhance environmental sustainability. This review synthesizes recent developments in AI applications across multiple aquaculture processes, including water quality management, genetic selection, disease prediction, and feeding optimization. AI-driven predictive analytics, for instance, are shown to improve disease management and feeding efficiency, reducing waste and enhancing biomass production. Despite these advancements, several challenges persist, notably concerning data quality, system integration, and the socio-economic implications of adopting AI technologies in diverse aquaculture settings. The review also identifies gaps in current research, particularly the scarcity of robust and scalable AI models suitable for broad application. Future directions stress the importance of interdisciplinary collaboration and continued innovation to fully harness AI's potential and address the current limitations, thereby promoting sustainable aquaculture practices (Yang et al., 2025).

A novel approach to sustainable aquaculture management has been proposed using Internet of Things (IoT) devices combined with deep learning techniques to enable remote monitoring and proactive decision-making. The system integrates a network of sensors to continuously track key water quality parameters such as temperature, pH, dissolved oxygen, and feeding behaviors. Data from these sensors are processed locally on edge devices before being transmitted to a cloud-based platform for centralized storage and analysis. Convolutional neural networks (CNNs) are employed for image recognition to monitor fish health and behavior, while YOLOv8 algorithms facilitate real-time detection and classification of fish diseases, allowing timely interventions to prevent losses. A user-friendly dashboard provides actionable insights, predictive alerts, and recommendations, supporting optimized resource management and enhanced productivity. Case studies reported in the study demonstrate that this IoT and deep learning-based framework improves operational efficiency, minimizes environmental impact, and promotes sustainable practices within aquaculture systems (Panduranga et al., 2024).

A progressive shift in aquaculture towards intelligent and automated systems has prompted the integration of modern technologies aimed at enhancing efficiency, sustainability, and environmental friendliness. In particular, machine learning—a subset of artificial intelligence (AI)— has been increasingly applied in smart aquaculture for tasks such as size and weight measurement, grading, disease detection, and species classification. Vo et al. (2021) systematically reviewed the development of smart aquaculture by analyzing 100 studies spanning nearly a decade, highlighting the methodologies, outcomes, and emerging technologies pivotal for advancing intelligent aquaculture systems. The review underscores the potential of machine learning to optimize aquaculture operations, reduce labor, and support sustainable practices. The increasing demand for sustainable aquaculture has prompted the development of innovative approaches to address environmental and operational challenges. Biofloc technology (BFT) has proven effective in enhancing water quality, improving fish health, and reducing feed costs through the management of microbial communities. Nevertheless, conventional BFT systems are highly sensitive to water quality fluctuations, necessitating precise monitoring and control. This review examines the integration of Artificial Intelligence (AI) and Internet of Things (IoT) technologies within smart BFT systems, emphasizing their potential to automate operations, optimize resource use, and improve overall system performance. IoT devices enable continuous real-time monitoring, while AI-driven analytics offer predictive insights for effective aquaculture management. The article provides a comparative assessment of AI models, including Long Short-Term Memory (LSTM), Random Forest, and Support Vector Machines (SVM), across various aquaculture prediction tasks, with particular attention to evaluation metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Additionally, the study considers environmental and economic implications, presenting quantitative case studies demonstrating cost reductions and productivity enhancements. Critical issues such as AI model reliability, interpretability (via SHAP/LIME), uncertainty quantification, and failure mode analysis are addressed, alongside recommendations for robust testing protocols and human-in-the-loop systems. Overall, this review highlights the transformative role of AI and

IoT in developing resilient and efficient BFT systems, paving the way for sustainable aquaculture practices (Alghamdi amd Haraz, 2025).

Recent advancements in artificial intelligence (AI) have significantly enhanced agricultural productivity and efficiency. Convolutional Neural Networks (CNNs) facilitate early detection of crop diseases through image-based classification, minimizing yield losses, while Long Short-Term Memory (LSTM) networks enable predictive modeling for yield forecasting and soil health assessment, optimizing resource allocation. Modern AI tools—including machine learning (ML) algorithms, deep learning (DL) models, Internet of Things (IoT) systems, and Decision Support Systems (DSS)—support critical agricultural operations such as precision irrigation, pest management, plant breeding, logistics, and packaging. Despite these innovations, widespread implementation remains constrained by high costs, privacy issues, limited infrastructure, and insufficient technical expertise. This review provides a comprehensive evaluation of AI's potential to transform agriculture while acknowledging the practical limitations hindering its adoption (Nautiyal et al., 2025).

Recent advancements in artificial intelligence (AI) have significantly enhanced precision agriculture by providing solutions to complex challenges such as crop diseases, infestations, inefficient irrigation, soil management issues, and poor crop handling. Deep learning techniques, including convolutional neural networks, transformer learning, meta deep learning, and lightweight deep learning, have improved the ability to extract meaningful features for better decision-making, reducing human intervention while increasing efficiency and cost-effectiveness. The review by Pauzi et al. (2025) analyzed 100 research studies from 2000 to 2023, selected via the SALSA method, demonstrating the evolution of AI in agriculture from fuzzy logic to machine learning and deep learning. The study predicts that AI will soon become integral to global agricultural practices, fostering new technologies and innovative approaches for sustainable farming.

Recent advancements in aquaculture have increasingly prioritized animal welfare, emphasizing the need for non-invasive monitoring techniques that minimize stress and handling. Machine vision (MV) offers a promising solution, enabling real-time, non-intrusive observation of fish health and welfare. This review examines current MV applications in welfare monitoring, including the hardware and algorithms used for automated data collection, as well as the primary challenges in data processing and analysis. While MV has been widely applied for estimating growth and biomass, its use for detecting parasites, diseases, and stress-related behaviors remains underdeveloped. Various camera setups—from single to stereoscopic, emersed to submerged—have been employed, though often under ideal conditions that may not reflect commercial farm environments, potentially overestimating system performance. Object detection algorithms like YOLO dominate MV applications, yet emerging alternatives show promise in overcoming challenges related to high densities and poor lighting. Despite its potential to revolutionize welfare monitoring, significant hurdles remain, including reliable detection of ectoparasites and diseases, identification of abnormal behaviors, and applicability across different taxa, particularly crustaceans (Fitzgerald et al., 2025).

The adoption of information technology (IT) is transforming fisheries and aquaculture by improving productivity, sustainability, and traceability throughout the seafood supply chain. Key innovations include the Internet of Things (IoT), drones, augmented reality, blockchain, robotics, artificial intelligence (AI), geographic information systems (GIS), cloud and edge computing, genomics, and biotechnology. IoT facilitates real-time monitoring and automated feeding, while AI supports disease prevention and market forecasting. Blockchain enhances transparency, mitigating illegal fishing practices, and drones along with autonomous vehicles improve surveillance and data collection. GIS enables habitat mapping and environmental monitoring, and IT tools are also enhancing fisheries education and research. Continuous technological adaptation is essential for promoting a smarter and sustainable future in the sector (Bhusan et al., 2025).

The global demand for seafood is driving the need for sustainable aquaculture, yet the sector faces obstacles such as high operational costs, fluctuating environmental conditions, and disease outbreaks. AIoT (Artificial Intelligence of Things) technologies offer transformative solutions by integrating IoT sensors for real-time data collection with AI algorithms for advanced data analysis. Current applications include monitoring water quality, smart feeding, disease detection, fish behavior analysis, and automated counting. Despite these advances, research gaps persist in broodstock management, multimodal AI systems, and model generalization. Future directions emphasize real-time adaptability, cost-efficiency, multimodal systems, advanced biosensing, and digital twin technologies. Effective AIoT implementation in aquaculture requires overcoming challenges in scalability, cost, technical expertise, model adaptability, and environmental sustainability (Tina et al., 2025).

The growing global demand for protein due to population increase has intensified pressure on capture fisheries, risking depletion of fish stocks. Advanced aquaculture presents a sustainable alternative, yet technological integration in this sector lags behind agriculture and manufacturing. Cloud computing, the Internet of Things (IoT), and Artificial Intelligence

(CIA) offer significant potential to modernize aquaculture by enabling applications such as drones, nanoand micro-sensors, bionic robots, remote cameras, intelligent sorting, energy-efficient processing equipment, and data-driven algorithms. These technologies reduce human intervention while enhancing productivity, traceability, disease detection, feeding management, growth prediction, environmental monitoring, and market intelligence. Adoption of CIA-driven innovations is therefore crucial for sustainable aquaculture, though challenges and limiting factors exist that may impede widespread implementation (Mustapha et al., 2021).

This study explores the integration of remote sensing (RS) and artificial intelligence (AI) in aquaculture to improve productivity, sustainability, efficiency, and environmental management. RS allows monitoring of large and inaccessible areas, providing real-time, precise data on water quality, temperature, biomass, and environmental hazards such as oil spills. AI, particularly machine learning (ML) models—including supervised, unsupervised, and reinforcement learning—supports tasks like species monitoring, disease and algal bloom detection, feeding schedule optimization, market trend analysis, and socioeconomic assessments. The combination of RS and AI enables ecological data collection, processing, and real-time decision-making, enhancing aquaculture production. Case studies illustrate practical applications, while the chapter also discusses challenges, policy implications, and the transformative potential of these technologies in sustainable aquaculture (Ratan et al., 2025).

Disease outbreaks in fish farming cause significant economic losses and threaten food security, particularly in regions like Nigeria where skilled fisheries experts are scarce. Traditional manual disease detection methods are often expensive and unreliable. This study introduces a computer vision-based approach using Faster Region-based Convolutional Neural Network (Faster R-CNN) with Detectron2 to enhance early disease detection in aquaculture. A dataset of 500 fish images was collected, pre-processed, and split into training (70%), validation (15%), and testing (15%) sets. Three Faster R-CNN models (X101, R100, and R50) were trained, with the X101 model achieving the highest accuracy of 98%. The findings demonstrate that deep learning techniques offer an accurate, cost-effective, and scalable solution for fish disease monitoring, supporting sustainable aquaculture practices.

This study addresses the challenge of maintaining optimal water quality in aquaculture, particularly in resource-limited settings, by integrating Internet of Things (IoT) sensors, Machine Learning (ML) models, and the Quantum Approximate Optimization Algorithm (QAOA). Continuous monitoring of water parameters such as temperature, dissolved oxygen, pH, and turbidity enabled highly accurate ML predictions ($R^2 = 0.999$, RMSE = 0.0998 mg/L). QAOA integration reduced model training time by 50%, allowing real-time responses to environmental changes. More than 6,000 corrective interventions maintained fish survival rates above 90% in tropical aquaculture. The system is adaptable for urban or rural environments, employing low-cost local processing or cloud-based analysis, demonstrating the potential of IoT–ML–QAOA integration to optimize fish health, mitigate environmental risks, and support sustainable aquaculture (Baena-Navarro et al., 2025).

The review by Li et al. (2025) examines the digital transformation of China's traditional aquaculture industry, highlighting its role in enhancing productivity and global competitiveness. The authors analyze the aquaculture process using an eight-step intensive method, demonstrating how digital technologies—such as the Internet of Things (IoT), cloud computing, artificial intelligence, big data, and blockchain—optimize management decisions, improve production efficiency, enhance product traceability, and create trustworthy online transaction environments. The paper also presents successful cases of digital transformation in China, providing insights and guidance for global adoption of digital intelligent technologies in aquaculture. This study explores the application of computer vision in smart agriculture, particularly in livestock, poultry, and fish farming. Computer vision, a branch of artificial intelligence, processes visual data to provide insights that enhance farm management, animal welfare, and production efficiency. In livestock farming, it enables precise tracking, behavior analysis, disease detection, and automated feeding. In poultry farming, it supports welfare monitoring, egg quality assessment, and automated collection. In aquaculture, intelligent feeding systems, fish counting, and environmental monitoring are facilitated through computer vision and drones. Integration with IoT allows continuous, remote monitoring and teleconsultation, potentially improving animal health and productivity. The chapter also highlights technological challenges, research directions, and practical applications in farm automation and management (Balasubramaniam et al., 2024).

The American Fisheries Society (AFS) Strategic Plan Committee developed the 2025–2029 draft Strategic Plan to enhance its usefulness for unit leadership in annual planning and to align member activities with the Society's mission and goals. The Plan outlines specific Goals and Strategies for advancing AFS over the next five years, incorporating lessons from previous strategic plans and emphasizing measurable metrics. It also addresses the AFS and Unit Missions, Vision, areas requiring operational adaptation, and guidance for plan implementation. The draft Plan underwent review by the Governing Board, which approved its distribution for member feedback. Following the comment period, the Plan will be finalized and presented for full membership approval at the Annual AFS Business Meeting, where it will guide Society operations through 2029 (DeFilippi Simpson et al., 2025).

Marine fisheries remain vital for livelihoods, food security, economies, and culture, while also playing a central role in advancing the UN Sustainable Development Goals. A decade ago, concerns were raised about overexploitation, climate change, pollution, and other stressors threatening long-term sustainability, with calls for ecosystem-based and inclusive management reforms. This updated review finds that, despite some policy progress at national and international levels, the overall condition of fisheries has not improved. Challenges such as unsustainable practices, climate impacts, and inequities persist, alongside emerging threats like deep-sea mining, plastic pollution, and poorly managed aquaculture. The authors argue that debates over optimism or despair are less useful than focusing on urgent, clear pathways for action to secure sustainable fisheries (Cheung et al., 2024).

The fisheries and aquaculture sector has significantly advanced through the integration of diverse technologies, contributing to a peak global production of 223.2 million tons of aquatic resources in 2022, valued at $472 billion. In capture fisheries, technological progress has improved fishing gear, vessel safety, and monitoring through electronic and remote-sensing tools. Aquaculture innovations have focused on species welfare, water quality management, and system resilience, while post-production has benefited from advancements in processing, preservation, and marketing logistics. Despite these gains, the unregulated and intensive application of technology presents major sustainability challenges. The chapter highlights these constraints and explores potential strategies for sustainable technological integration (Sidiq et al., 2025).

This study examines food security challenges in the Maldives, where frequent natural disasters such as tsunamis, heavy rainfall, and strong winds negatively affect agriculture, fisheries, and freshwater resources. Using statistical and clustering methods with data from the Maldives Bureau of Statistics, the research highlights the need for human resource development in farming and fisheries to offset limited natural and technical resources. Key findings suggest that farming training should focus on hydroponics, pest control, youth involvement, support for female farmers, and equitable distribution across Atolls. In fisheries, unstable employment emerged as the main issue, with recommendations to optimize fishermen per vessel and promote eco-friendly fishing practices. Overall, the study establishes a framework for building a skilled workforce in farming and fisheries as a critical step toward enhancing food security in disaster-prone environments (Abdulla amd Vasylieva, 2025).

Fish and fishery products are a key dietary source in Cambodia, providing over 80% of the country's protein intake, but they face significant food safety risks. An analysis of residue monitoring data (2020–2024) revealed that 8.9% of 1,174 fish samples exceeded permissible contaminant limits. Prohibited antimicrobial residues, including chloramphenicol (13.2%), furazolidone metabolites (1.3%), malachite green (8.5%), and tetracyclines (1.0%), were detected. Additionally, heavy metal contamination was widespread, with mercury and lead exceeding EU thresholds in 43% and 10% of samples, respectively. Microbiological testing showed poor hygiene, with high Total Plate Counts and frequent detection of *E. coli* and coliforms. Current safety measures, such as Good Aquaculture Practices (GAqP) and the Cambodia Quality Seal (CQS), were found insufficient due to weak enforcement and technical gaps. The study calls for improved monitoring of high-risk contaminants, stronger regulatory enforcement, enhanced technical capacity, and stakeholder education. These interventions are essential for safeguarding public health and strengthening sustainable food security in Cambodia (Ra Thorng et al., 2025).

The study explores the diverse challenges faced by fishermen in Karaikal, India, highlighting both operational and marketing obstacles. Through surveys, interviews, and data analysis, the researchers identified issues such as high operational costs, financial difficulties, overfishing, monsoon variability, inconsistent income, and vessel damage. Marketing-related barriers included poor cold storage, price volatility, auctioneer commissions, transportation costs, and limited market knowledge. These challenges directly affect the sustainability and profitability of the fishing sector. The authors recommend solutions such as financial support, credit access, improved storage, market education, fair payment systems, and sustainable fishing practices. The findings aim to guide policymakers, fishing communities, and stakeholders toward effective interventions that improve livelihoods and ensure long-term industry sustainability (Babu et al., 2025).

The study is what highlights the growing importance of transitioning the fishing sector toward carbon neutrality, with a particular focus on Nordic countries. It outlines current challenges such as poor data collection on greenhouse gas emissions, limited adoption of existing technologies, financial incentives that encourage fossil fuel use, and restrictive fishing regulations. The study proposes both short-term actions (before 2030) and long-term actions (before 2040) to facilitate this shift. Ultimately, the authors emphasize the need for collaboratively developed roadmaps tailored to the diversity of the fishing industry to ensure an effective energy transition (Hornborg et al., 2025).

The study examines the digital transformation of Egyptian marine fisheries as a strategy for sustainable management. It highlights that effective fisheries management requires timely data, but Egypt currently relies on paper-based reporting and limited vessel tracking. By assessing existing challenges, national and regional regulations, and successful low-cost digital systems elsewhere, the authors propose an innovative, scalable system that integrates electronic reporting and vessel monitoring. This approach improves data accuracy, compliance with international standards, and decision-making, while also enhancing traceability to combat illegal, unreported, and unregulated (IUU) fishing and expand market access. Overall, the digital shift provides a viable pathway for sustainable fisheries management in resource-constrained contexts (Elsira et al., 2025).

The study examines the increasing use of destructive fishing gear in Bangladesh’s inland waters, which threatens biodiversity and sustainability. Through content analysis of media reports (2014–2024), validated by field observations, interviews, and focus groups, the researchers identified five destructive fishing methods, including harmful nets, electric fishing, and chemical use. These practices indiscriminately capture 60 fish species and 6 crustaceans, with about 26% of the fish species being threatened. Beyond reducing fish stocks, destructive fishing disrupts eggs, fry, juveniles, and non-target species such as birds, mammals, and other aquatic organisms, while also posing human health risks. The authors emphasize the urgent need for a strategic roadmap involving stronger enforcement, science-based policies, sustainable management practices, and community engagement to safeguard fisheries and ecosystems in Bangladesh (Alam et al., 2025).

This study explores the role of ocean alkalinity enhancement (OAE) as a climate mitigation strategy and its interactions with global fisheries under varying socio-economic and climate scenarios. Using Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs), the authors analyzed three scenarios: SSP1-2.6 (sustainability-focused), SSP3-7.0 (regional rivalry), and SSP5-8.5 (fossil fuel dependency). To enhance the robustness of the analysis, the study incorporates a data-centric approach by integrating historical fisheries production data and ocean biogeochemical indicators into dynamic simulation models. These models capture the evolutionary behavior of marine ecosystems and fisheries responses over time under different climate trajectories. Results indicate that high-emission and fragmented development scenarios hinder the compatibility of OAE and fisheries, while sustainability-oriented pathways provide favorable conditions for their coexistence. The findings highlight that the successful integration of OAE into fisheries management depends not only on socio-economic policies and international collaboration but also on adaptive, data-driven modeling frameworks that can respond to changing environmental conditions (Sloterdijk et al., 2025).

Global warming, driven by human-induced greenhouse gas emissions, is causing rising global temperatures with far-reaching ecological, social, and economic consequences. Its impacts include melting ice caps, rising sea levels, ocean acidification, extreme weather events, and ecosystem disruptions that threaten biodiversity and increase the risk of ecosystem collapse. These changes significantly affect fisheries, which are vital for global food security, livelihoods, cultural traditions, and economic development. Ocean acidification and habitat shifts jeopardize marine species and coral reefs, while coastal erosion and flooding endanger fishing communities. Since fisheries also support research, technology, and trade, the adverse effects of climate change on them are complex and interconnected, requiring adaptive management strategies. Effective responses involve reducing greenhouse gas emissions, adopting renewable energy, improving energy efficiency, and developing sustainable fisheries management policies to ensure resilience against climate change impacts (Mondal amd Lee, 2025).

The 2023 revision of China's Marine Environmental Protection Law aims to strengthen sustainable marine fisheries by addressing both traditional and emerging challenges, including marine pollution, overfishing, and climate change. The revision enhances legal frameworks through improved marine environmental supervision, ecological protection, and control of pollution from land-based sources, engineering projects, waste dumping, and vessels. It also clarifies institutional norms, intensifies legal responsibilities for violations, and increases the systemic coherence of legislation, thereby providing stronger legal guarantees for sustainable fisheries. Despite these improvements, some shortcomings remain, such as ambiguous definitions in new legal regimes and limited measures against overfishing and climate change. The law employs integrated ecosystem management and combines regulatory tools, incentives, and honor-based measures, offering both national and global insights for promoting sustainable marine fisheries (Yang et al., 2025).

The study evaluates the effectiveness of fisheries management strategies in China under climate warming, highlighting the ecological, social, and economic risks posed by climate change to marine fisheries. Using the dynamic ecosystem model Ecosim, the authors found that current management is insufficient, leading to declines in fishery yields, economic losses, and potential food security crises. Strategies such as harvest control rules (HCR) and multispecies management can mitigate climate-driven risks, with HCRs being most effective for sustainable production, while multispecies approaches offer balanced benefits for ecosystem health, seafood security, and economic profitability. However, the effectiveness of these strategies diminishes under high-emission scenarios, emphasizing that combining greenhouse gas reduction with adaptive fisheries management is essential for long-term resilience. The study provides a framework for climate-resilient fisheries management applicable in China and other regions (Yin et al., 2025).

The survival and development of dispersing fish early-life stages (ELS) are strongly influenced by both biotic and abiotic environmental factors. Traditional approaches to estimating mortality rates, relying on laboratory or field data, often overlook these complexities. Lagunes et al. (2025) addressed this by coupling a growth model based on Dynamic Energy Budget theory with a Lagrangian particle-tracking model to account for species-specific physiology, environmental variability, and physical transport. Focusing on three Mediterranean coastal fish species, they simulated Pelagic Larval Durations (PLDs) under realistic temperature and food density ranges, demonstrating that environmental conditions drive variation in PLD and mortality. Mortality rates, estimated based on time to metamorphosis, dispersal endpoint, and starvation, varied seasonally, with slower-developing species experiencing higher mortality. Additionally, spawning phenology and seasonal abiotic conditions significantly influenced mortality, providing a framework to test ecological hypotheses such as the "match-mismatch" concept (Lagunes et al., 2025).

Bozeman et al., (2025) conducted a systematic review to assess the ecological impacts of subdaily flow variability (SDFV) caused by hydropower operations on riverine fishes. Reviewing 109 studies primarily focused on Salmonids in North America and northern and western Europe, they found strong consensus that SDFV increases fish stranding risk, destabilizes habitats, and reduces fish production and diversity. Moderate evidence indicated that SDFV can disrupt reproduction, affect condition variably, and influence movement depending on channel characteristics, while there was little agreement on its effects on mortality, physiology, or behavior. The authors emphasized that SDFV impacts are highly context-specific, depending on species, life stage, and local habitat conditions, and recommended that ecological assessments first characterize local habitat and fish communities to guide mitigation strategies aimed at sustaining or enhancing ecological outcomes (Bozeman et al., 2025).

The study by Indriyani, Singh, and Vu (2025) examines the effects of climate change on fisheries and marine ecosystems, emphasizing warming, acidification, and deoxygenation as major factors reducing productivity and stability. It highlights that climate-driven shifts in transboundary fish stocks may provoke international conflicts, compounded by overfishing and habitat destruction. The 2023 UNGA Resolution on sustainable fisheries underscores global stock declines and urges states to assess climate impacts and implement adaptive strategies. Through a comparative analysis of Indonesia, India, and Vietnam, the authors demonstrate the need for modernized legal frameworks and ecosystem-based management to address climaterelated challenges in fisheries and ensure sustainable exploitation and conservation (Indriyani et al., 2025).

Nature-based solutions (NBS) offer a promising approach to sustaining freshwater fisheries by integrating environmental, social, and economic benefits. In Ethiopian fisheries management, wetlands, floodplains, river restorations, protected areas, and riparian buffers are the most commonly applied NBS strategies. These solutions support habitat restoration, water management, aquaculture development, biodiversity conservation, climate change adaptation, and alternative livelihoods for fishers. Key enablers in Ethiopia include climate resilience initiatives, blue economy strategies, green legacy programs, landscape restoration, water resource management, and protected areas. However, challenges such as financing, regulatory gaps, low awareness, and weak cross-sectoral collaboration hinder the widespread adoption of NBS. Addressing these barriers is essential to maximize the ecological and socio-economic benefits of NBS in Ethiopian fisheries (Mekonen et al., 2025).

The fishing sector plays a crucial role in the European Blue Economy by supporting economic growth, food security, and employment, yet it faces significant sustainability challenges such as overfishing, biodiversity loss, and climate change impacts. Using decision tree modeling and EU Fleet Register data, González-Cancelas et al. (2025) analyzed the sector's prioritization within the Blue Economy, revealing disparities in fleet modernization and efficiency: industrialized fleets in Spain, France, and Italy have higher tonnage and power, whereas artisanal fisheries in Greece and Portugal are more vulnerable to economic and environmental fluctuations. The study underscores the sector's economic importance while highlighting its susceptibility to regulatory pressures, advocating for modernization, technological innovation, enhanced regulations, and conservation-focused management to align fisheries with Sustainable Development Goal 14, the EU Common Fisheries Policy, and the European Green Deal, providing actionable strategies for policymakers and stakeholders.

The Egyptian aquaculture sector, ranking as the seventh largest globally and the top producer in Africa, contributes significantly to continental and domestic fish supply, accounting for 67% of Africa's output and 78% of Egypt's domestic production. Despite notable growth, production has declined since 2020 due to several sustainability challenges, including temporary farm removal orders, large-scale water projects causing scarcity, climate change risks like coastal flooding, and reliance on illegally collected wild seeds, which constitute 34% of production. These challenges, compounded by governance shortcomings, threaten the sector's resilience and production capacity. Addressing these issues requires integrated solutions such as genetic improvement, development of sustainable local feed, adoption of best management practices, system enhancements, and strengthened governance to ensure equitable resource distribution, effective regulation, and stakeholder collaboration. Implementing these strategies is vital for securing the sector's long-term growth, resilience, and contribution to food security and economic development (Abdel-Hady et al., 2025).

Chevallier et al. (2025) developed locally relevant projections of climate change and socioeconomic impacts on fisheries in the French North Sea and the Mediterranean by participatory downscaling of global SSP–RCP scenarios. They engaged fisheries managers, policymakers, experts, and NGOs in co-constructing four contrasting scenarios through interdisciplinary workshops, ensuring strong contextual relevance. Comparative analysis revealed that while 83% of stakeholder-identified themes were common across both social–ecological systems, only 30% of detailed narrative elements overlapped, highlighting local specificity. The study also incorporated disruptive changes and emotional dimensions using AI-based emotion analysis. These downscaled scenarios provided actionable pathways for transformative change, mitigation, and adaptation, bridging science–policy gaps and emphasizing human–nature relationships (Chevallier et al., 2025).

The study by Villanthenkodath and Pal (2025) investigates the effects of inland and marine fish production on India's fishing load capacity factor from 1990 to 2022, incorporating economic growth and renewable energy consumption as additional factors. Using Dynamic AutoRegressive Distributed Lag (DYNARDL) simulations and Auto-Regressive Distributed Lag (ARDL) models, the study confirms a long-run relationship for fishing load capacity. Results indicate that inland fish production enhances fishing load capacity, while marine fish production reduces it, with both economic growth and renewable energy consumption exerting longrun negative effects. The findings underscore the need for Indian fisheries policies to focus on sustainable and environmentally friendly practices, including support for inland fish production and sustainable marine fishery management (Villanthenkodath amd Pal, 2025)

2.5 Summary of literature review

SN	Author and Year	Title of Study	Methodology	Result	Limitation
1	Vo et al. (2021)	A progressive shift in aquaculture towards intelligent and automated systems	Review of 100 studies over a decade	Machine learning supports automation, reduces labor, and promotes sustainable aquaculture practices	Literature review only; lacks implementation of hybrid forecasting-classification framework and survival prediction
2	Mustapha et al. (2021)	Potential of Cloud Computing, Internet of Things, and Artificial Intelligence for aquaculture	Study on cloud computing, IoT, and AI technologies	Modernizes aquaculture by reducing human intervention and improving productivity and traceability	Did not develop hybrid framework with survival prediction or evaluation metrics
3	Balasubramaniam et al. (2024)	Application of computer vision in smart agriculture	Review of computer vision integrated with IoT	Facilitates intelligent feeding, fish counting, and monitoring	Limited to computer vision; no forecasting-classification or evaluation metrics
4	Aung et al. (2024)	Systematic review of Artificial Intelligence in aquaculture	Review of 57 studies (2020–2024)	AI supports disease monitoring and production optimization	No hybrid framework or comprehensive performance metrics
5	Panduranga et al. (2024)	Sustainable aquaculture using IoT and deep learning	IoT + CNN + YOLOv8 with case studies	Enables real-time disease detection and predictive alerts	Focused only on disease detection; no forecasting or multi-model evaluation
6	Cheung et al. (2024)	Updated review on marine fisheries condition	Global fisheries review	Fisheries remain unsustainable despite progress	No hybrid modeling or evaluation metrics
7	Wu et al. (2025)	Deep learning in sustainable aquaculture	Review of CNN, RNN, GANs, Transformers	Applications in fish detection, growth prediction,	No hybrid forecasting-classification or survival prediction

SN	Author and Year	Title of Study	Methodology	Result	Limitation
				feeding optimization	
8	Ma et al. (2025)	AI and aquaculture safety concerns	Bibliometric review (1998–2025)	Rapid growth in AI for safety and management	No practical predictive framework
9	Lujan (2025)	Transformative role of AI in aquaculture	Conceptual review	AI improves water management and health monitoring	No experimental or predictive framework
10	Yang et al. (2025)	AI as a transformative tool in aquaculture	Review study	Enhances efficiency and sustainability	No hybrid framework or quantitative comparison
11	Alghamdi and Haraz (2025)	AI and IoT in Biofloc systems	Comparative study using LSTM, RF, SVM	Improves automation and system resilience	Limited scope; no forecasting or survival prediction
12	Nautiyal et al. (2025)	AI in agriculture transformation	Review of AI tools	Enhances productivity but limited by cost and infrastructure	No hybrid framework or model comparison
13	Pauzi et al. (2025)	Evolution of AI in agriculture	SALSA review of 100 studies	Improves decision-making efficiency	No experimental ML model implementation
14	Fitzgerald et al. (2025)	Machine vision in welfare monitoring	Review of vision algorithms (e.g., YOLO)	Effective for growth monitoring	Limited disease detection; no hybrid modeling
15	Bhusan et al. (2025)	IT adoption in fisheries	Review of IoT, AI, blockchain	Improves productivity and traceability	No predictive framework
16	Tina et al. (2025)	AIoT technologies for aquaculture	AIoT system study	Supports feeding, disease detection, water monitoring	No forecasting-classification integration
17	Ratan et al. (2025)	Remote sensing and AI integration	Case study with ML models	Improves productivity and	No hybrid framework or visualization

SN	Author and Year	Title of Study	Methodology	Result	Limitation
				environmental monitoring	
18	Baena-Navarro et al. (2025)	Water quality optimization in aquaculture	IoT + ML + QAOA	High accuracy (R^2=0.999), improved survival rates	Limited to water quality only
19	Li et al. (2025)	Digital transformation of China's aquaculture	Multi-step digital analysis	Improves efficiency and traceability	No hybrid ML framework
20	DeFilippi Simpson et al. (2025)	Fisheries strategic plan (2025–2029)	Policy framework	Enhances planning and alignment	No experimental modeling
21	Sidiq et al. (2025)	Technology integration in fisheries	Review chapter	Boosts production but risks sustainability	No hybrid modeling
22	Abdulla and Vasylieva (2025)	Food security in Maldives	Statistical and clustering analysis	Human resource development is key	No ML forecasting/classification
23	Ra Thorng et al. (2025)	Food safety risks in fisheries	Residue monitoring (2020–2024)	8.9% contamination above limits	No predictive modeling
24	Babu et al. (2025)	Fishermen challenges in India	Surveys and interviews	Identified economic and operational challenges	No ML framework
25	Hornborg et al. (2025)	Carbon neutrality in fisheries	Policy analysis	Proposed transition roadmap	No data-driven modeling
26	Elsira et al. (2025)	Digital transformation of Egyptian fisheries	System assessment	Improves compliance and traceability	No hybrid ML framework
27	Alam et al. (2025)	Destructive fishing in Bangladesh	Content analysis + field validation	Identified harmful fishing practices	No predictive modeling
28	Sloterdijk et al. (2025)	Ocean alkalinity and fisheries	Climate scenario modeling	Sustainability depends on emission levels	No ML framework
29	Mondal and Lee	Global	Environmenta	Calls for	No predictive ML

SN	Author and Year	Title of Study	Methodology	Result	Limitation
	(2025)	warming impacts on fisheries	l study	adaptive management	models

2.6 Research Gap

Recent literature highlights the transformative potential of artificial intelligence (AI), machine learning (ML), and computer vision (CV) in advancing sustainable aquaculture and fisheries management, with applications in fish detection, growth prediction, health monitoring, intelligent feeding, water quality forecasting, disease management, and operational optimization (Wu et al., 2025; Aung et al., 2024; Ma et al., 2025; Lujan, 2025; Yang et al., 2025). Deep learning architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), YOLO algorithms, and edge computing frameworks have improved real-time monitoring and predictive analytics, while sensor-based systems support continuous environmental monitoring and automated interventions (Panduranga et al., 2024; Baena-Navarro et al., 2025; Alghamdi amd Haraz, 2025; Vo et al., 2021; Tina et al., 2025; Li et al., 2025; Mustapha et al., 2021; Ratan et al., 2025). Nevertheless, limitations persist, including insufficient real-time adaptability in operational environments, limited robustness and scalability of predictive models, lack of integration of heterogeneous datasets, minimal validation across diverse aquaculture contexts, and neglect of socio-economic and governance considerations (Abdel-Hady et al., 2025; Alam et al., 2025; Indriyani et al., 2025). Therefore, the research gap lies in the absence of a **comprehensive, integrated framework** that combines real-time operational monitoring, predictive analytics, and socio-economic factors, validated across diverse aquaculture systems, to provide a robust, scalable, and sustainable decision-support system for fisheries and aquaculture management.

CHAPTER THREE

METHODOLOGY

3.1 Research Methodology

The study adopts a comprehensive computational and experimental research methodology that combines real-time security surveillance with predictive analytics for long-term fisheries management. For aquaculture security, surveillance video streams from either live webcams or stored files are processed using OpenCV's Histogram of Oriented Gradients (HOG) descriptor in combination with a pre-trained Support Vector Machine (SVM) detector, with each frame resized to 640×480 pixels for computational efficiency. Human presence is automatically detected, enclosed within bounding boxes, and linked to a multi-threaded audio alarm system that plays an alert without interrupting video processing. At the same time, frames containing intruders are captured and stored with time-stamped filenames to provide verifiable digital evidence. This integration ensures continuous, low-cost, and scalable real-time monitoring that deters unauthorized access and enhances operational security in fisheries. Beyond immediate surveillance, the methodology incorporates a quantitative, data-driven framework for forecasting and classification of global fish production. Production records from Global_production_quantity.csv were aggregated into yearly values across species, regions, and production systems, and modeled using a hybrid forecasting pipeline combining a Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors (SARIMAX) model for temporal dependencies and a Random Forest Regressor with lag features for recursive multi-step projections, enabling 20-year forecasts. In parallel, supervised classification was performed using lagged features and temporal indicators to generate binary targets for year-to-year production increases, with Logistic Regression, Random Forest, and Support Vector Machine (RBF kernel) classifiers evaluated against accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrices. Forecast trajectories, classification reports, and feature importance outputs were preserved as datasets and visualizations, providing empirical evidence for decision-support. By integrating experimental validation in human activity detection with quantitative forecasting and classification, the methodology ensures a dual contribution: practical real-time surveillance for aquaculture security and robust predictive analytics for sustainable fisheries governance.

3.2Justification of the Adopted Research Methodology

The chosen methodology is justified on the basis of its deliberate integration of experimental computer vision techniques with quantitative, machine learning–based forecasting and classification, thereby addressing both operational and strategic challenges in fisheries management. The surveillance component adopts OpenCV's Histogram of Oriented Gradients (HOG) descriptor combined with a Support Vector Machine (SVM) classifier, a design grounded in Dalal and Triggs' (2005) pioneering work, which established HOG as a reliable feature extractor for human detection. This foundation is reinforced by later contributions such as Ren et al. (2016), whose Faster R-CNN architecture further advanced the efficiency and accuracy of realtime object detection. By leveraging this well-established lineage, the methodology ensures that the surveillance pipeline remains both computationally efficient and effective in detecting human intrusions, while its multi-threaded alarm and frame-capture system provides verifiable evidence crucial for aquaculture security.

For the forecasting and classification component, the methodology draws on evidence from hybrid modeling literature, which consistently demonstrates the superiority of combined approaches over single-model counterparts. Specifically, Ngo et al. (2022) highlighted the predictive advantages of hybrid SARIMA-firefly-SVR models in energy forecasting, thereby validating the adoption of SARIMAX for temporal dependency modeling alongside Random Forest regressors for recursive multi-step projections in this study. Furthermore, Simon et al. (2023) emphasized the interpretability of Random Forest, which is particularly relevant here as the analysis of feature importance provides fisheries managers with actionable insights into the drivers of production trends. The inclusion of supervised classifiers—Logistic Regression, Random Forest, and SVM—follows the precedent set by Zhang et al. (2017), who demonstrated their effectiveness in categorizing dynamic, temporal activities across domains such as surveillance, healthcare, and human–computer interaction.

Taken together, this hybrid design ensures methodological robustness and practical relevance. On one hand, it validates experimental implementation in real-time aquaculture security through computer vision; on the other, it provides data-driven evidence for long-term decision support in fisheries governance. The approach therefore reflects a broader paradigm shift in scientific research toward hybrid, interpretable, and application-oriented artificial intelligence solutions (Dalal amd Triggs, 2005; Ren et al., 2016; Zhang et al., 2017; Ngo et al., 2022; Simon et al., 2023).

3.3 The existing system

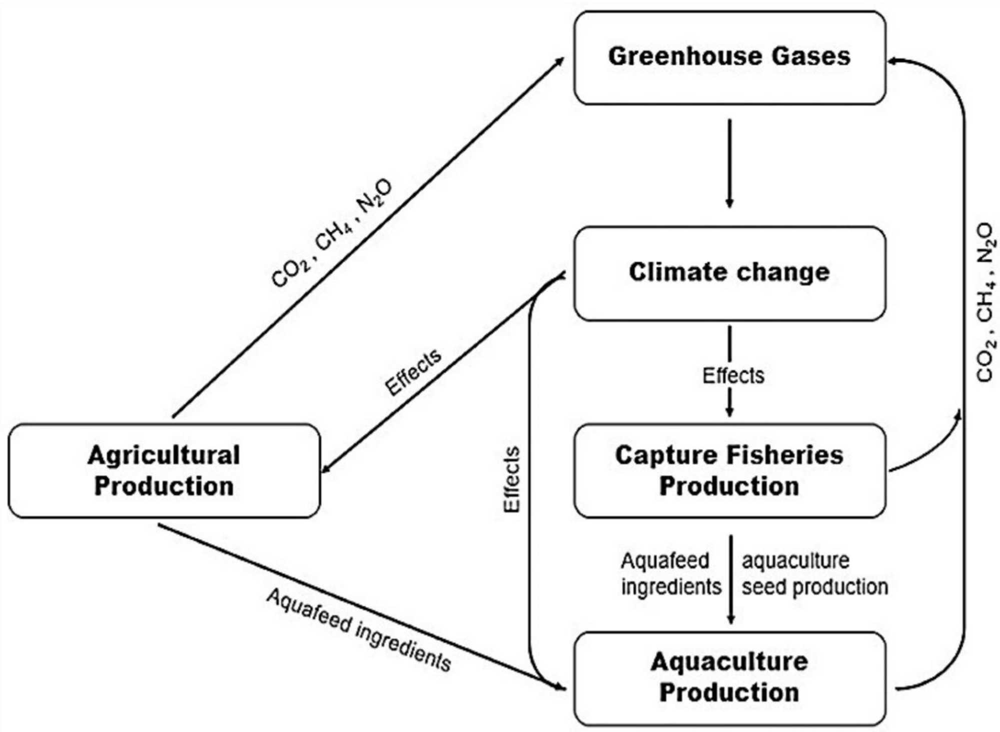

Figure 3. 1: The impact of climate change on fish production

Source Maulu et al., (2021)

The architecture of the existing system as shown in figure 3.1 explain the impacts of climate change, including rising temperatures, sea-level rise, changing rainfall patterns, disease outbreaks, harmful algal blooms, and extreme weather events. These factors pose significant risks to production stability and long-term viability. While some positive effects may occur, the negative impacts are more pronounced. This highlights the need for both short-term adaptation and long-term mitigation measures, with successful outcomes depending on producers' adaptive capacity in different regions (Maulu et al., 2021).

3.4 Analysis of the existing system

The architecture of the existing system for fish yield prediction as shown in figure 3.1 aligns with literature that emphasizes the cyclical and interdependent relationship between agriculture, greenhouse gas emissions, climate change, fisheries, and aquaculture. Yuan et al. (2019) confirm that agricultural activities such as converting paddy fields to aquaculture ponds significantly intensify methane emissions, reinforcing the system's depiction of agriculture as a key driver of climate change that feeds back into fisheries and aquaculture. Similarly, the vulnerability of aquaculture production to climatic variability, as highlighted by Muthoka et al. (2024), supports the system's recognition of aquaculture as both dependent on and contributory to climate change dynamics, requiring adaptive strategies to maintain resilience. Moreover, Brander (2007) provides evidence that climate change alters fish yield outcomes differently across regions, validating the system's inclusion of climate variability as a determinant of capture fisheries productivity. Collectively, these studies substantiate the existing architecture's holistic framing by demonstrating that fish yield cannot be predicted solely on biological or environmental parameters but must also incorporate socio-economic, ecological, and production-driven feedback loops within the broader climate–agriculture–fisheries nexus.

3.5 Limitations of the existing system

Despite the existing system's holistic framing of the interconnections between climate change, agriculture, fisheries, and aquaculture, its limitations lie in its conceptual orientation and lack of operational depth, which restricts its ability to support proactive forecasting, surveillance, and decision-making. While the system aligns with literature showing that agricultural activities such as paddy-to-pond conversion intensify methane emissions (Yuan et al., 2019), aquaculture is highly vulnerable to climatic variability (Muthoka et al., 2024), and regional climate change impacts fish yield differently (Brander, 2007), it remains largely descriptive and does not incorporate computational models capable of handling complex, nonlinear dynamics or projecting long-term outcomes. Furthermore, the architecture omits automated monitoring mechanisms, such as computer vision-based detection approaches pioneered through HOG descriptors (Dalal amd Triggs, 2005) and later advanced by unified detection frameworks like Faster R-CNN (Ren et al., 2016), which are essential for real-time surveillance in aquaculture facilities. Similarly, it lacks hybrid, data-driven forecasting frameworks that have demonstrated superior performance in other domains, such as the SAMFOR model integrating SARIMA, firefly optimization, and SVR (Ngo et al., 2022). By excluding methods like Random Forests that enhance both predictive accuracy and interpretability (Simon et al., 2023), and supervised classifiers proven versatile in human activity recognition (Zhang et al., 2017), the existing system provides no mechanisms for uncertainty quantification, interpretability, or decision-support outputs. These shortcomings underscore the necessity of the proposed integrated methodology, which leverages hybrid machine learning and computer vision to deliver real-time surveillance and robust predictive analytics for sustainable fisheries governance.

3.6 The architecture of the proposed system

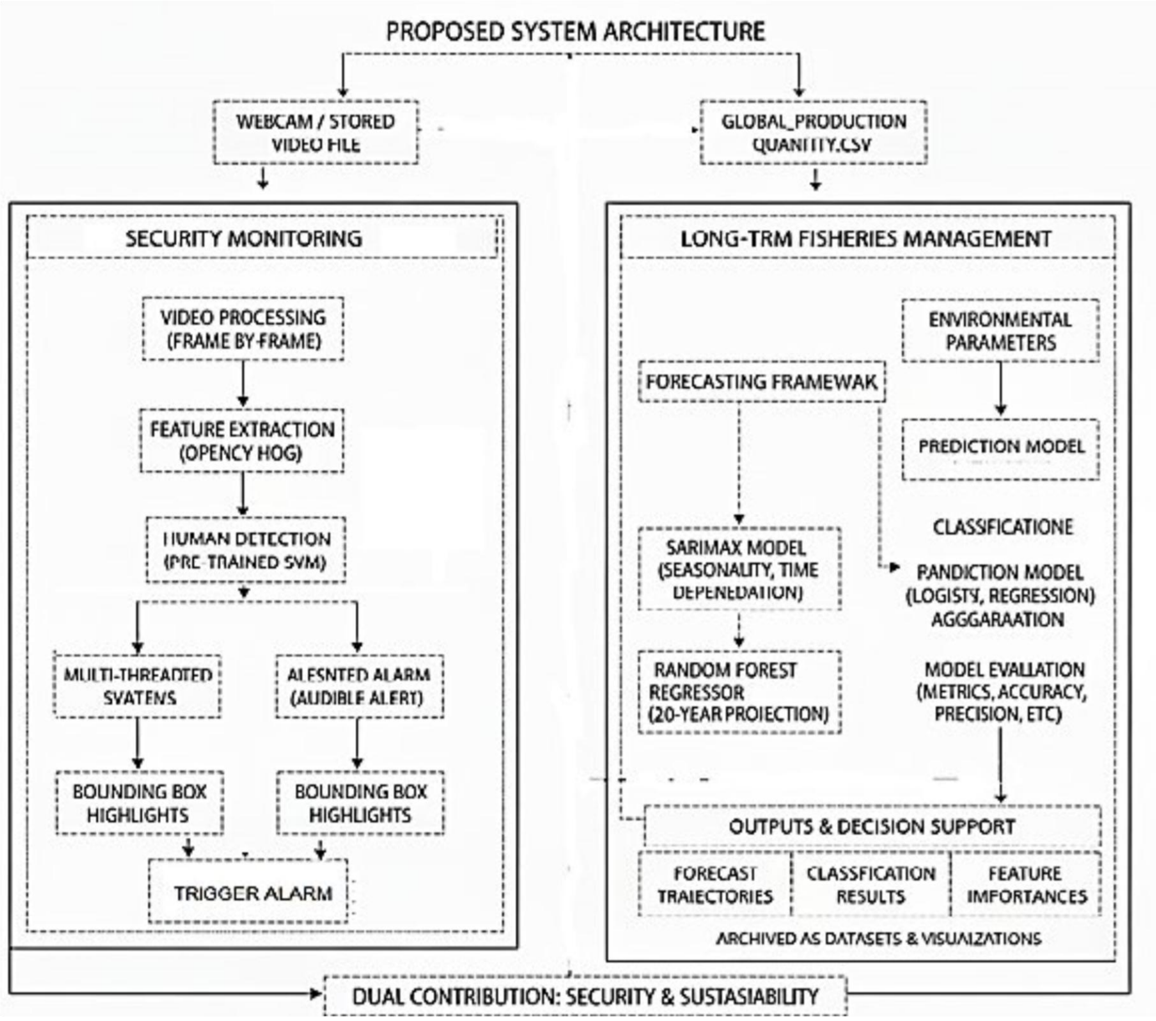

Figure 3. 2: The architecture of the proposed system

The architecture of the proposed system, as illustrated in figure 3.2 reflects the study's comprehensive computational and experimental research methodology that integrates computer vision with machine learning-based forecasting and classification for dual objectives: **realtime security monitoring** and **long-term fisheries management**.

On the **security monitoring side**, video input from either a webcam or stored file undergoes frame-by-frame processing, where OpenCV's Histogram of Oriented Gradients (HOG) descriptor is applied in combination with a pre-trained Support Vector Machine (SVM) detector to extract features and detect human presence. Once detected, individuals are highlighted with bounding boxes and connected to a multi-threaded alarm system that operates asynchronously to trigger an audible alert without interrupting the ongoing video stream and store images from video stream in a directory. This design ensures robust and efficient real-time validation of human activity for surveillance and safety purposes.

On the **fisheries management side**, the architecture incorporates a forecasting framework that leverages production data from *Global_production_quantity.csv* and historical dataset aggregated across species, regions, and production sources into yearly values. Two complementary models were employed: the Seasonal AutoRegressive Integrated Moving Average with Exogenous Regressors (SARIMAX) to capture seasonality and time dependence, and a Random Forest Regressor with lag features for recursive multi-step prediction, enabling 20-year projections of fish production trends. In addition, a supervised classification pipeline was implemented, where lagged features and temporal indicators generated a binary target variable to capture production increases versus declines. Logistic Regression, Random Forest Classifier, and Support Vector Machine (RBF kernel) were trained and rigorously evaluated with performance metrics including accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrices.

Finally, the system archives outputs—forecast trajectories, classification results, and feature importances—into datasets and visualizations, offering empirical evidence for decision-support in sustainable fisheries governance. By unifying real-time human activity detection through experimental computer vision validation with robust, data-driven forecasting and classification for fisheries production, the proposed architecture delivers a **dual contribution** of enhancing both **security** and **sustainability**.

3.7 Justification of the proposed system

The proposed system architecture is justified by its alignment with contemporary advances in computer vision, machine learning, and ecological forecasting, as underscored in recent highimpact studies. Dalal and Triggs (2005) established the robustness of the Histogram of Oriented Gradients (HOG) with SVM for reliable human detection, which underpins the security surveillance component of this study. Expanding on this foundation, Kalluri et al. (2025) highlighted the critical role of computer vision in surveillance applications, while Abba et al. (2024) demonstrated the practical utility of deep learning frameworks for real-time object tracking, validating the study's use of asynchronous alarm-triggering for uninterrupted monitoring. On the fisheries side, the adoption of SARIMAX and Random Forest models is supported by Raman et al. (2018) and Benavides et al. (2022), who successfully applied time series forecasting to predict fish yields and marine landings, respectively. Further strengthening this methodological choice, Brownlee (2020) illustrated Random Forest's capacity for robust time series forecasting, while Allen Akselrud (2024) emphasized its adaptability to ecological data complexities and uncertainty. The inclusion of classification algorithms for trend detection resonates with the broader ecological applications of machine learning reviewed by Pichler and Hartig (2023), who demonstrated the predictive strength of supervised learning for ecological data. Together, these studies validate the integration of computer vision for real-time human detection and machine learning–driven forecasting and classification for fisheries management, reinforcing the proposed architecture's dual contributions to enhancing security and promoting sustainability.

3.8 Dataset

3.8.1 Dataset 1

One of the dataset employed in this study, titled **Fish Life Prediction**, was sourced from Kaggle and developed by Aslam (2023). It contains **74,796 entries across 14 fields**, specifically curated to enable predictive modeling of fish health status or survival outcomes (Aslam, 2023). The dataset integrates a diverse range of **water quality indicators** and **atmospheric conditions** that are widely acknowledged as critical determinants of fish survival. For instance, **nitrate concentration (ppm)** reflects nutrient levels in water that, at elevated levels, may induce stress and eutrophication; **pH** represents the acidity or alkalinity of the water, where extreme values can harm fish physiology; **ammonia (mg/l)** measures toxic compounds that at high levels become lethal; and **temperature (TEMP, tempC)** governs metabolic rates, growth, and oxygen solubility. Similarly, **dissolved oxygen (DO)** is vital for respiration, while **turbidity** affects water clarity and light penetration, both of which influence fish health. The dataset also includes **manganese concentration (mg/l)**, an essential but potentially harmful trace element when excessive, and **atmospheric measures** such as **pressure, humidity, and windspeed (kmph)**, which indirectly regulate oxygen solubility, evaporation, and aeration processes in aquatic systems. Collectively, these parameters provide a holistic representation of both aquatic chemistry and environmental conditions, with the target field denoting the **life status or survival outcome of fish**. This makes the dataset highly suitable for machine learning applications in aquaculture monitoring, ecological forecasting, and environmental management, where predictive insights can mitigate fish losses, optimize production, and enhance sustainability.

3.8.2 Dataset 2

The second dataset employed for this study is the **FAO Global Production Quantity dataset** (Global_production_quantity.csv), which is publicly available through the FAO Fisheries and Aquaculture Statistics Division (FAO, 2023). It can be accessed from the FAO statistics query portal under *Global production by production source — Quantity (1950–2023)*

(https://www.fao.org/fishery/statistics-query/en/global_production/global_production_quantity). The dataset is structured to provide historical records of global fishery and aquaculture production and serves as the basis for forecasting future production trends.

The dataset contains several fields, each providing specific categorical or temporal information relevant to quantitative analysis. The **COUNTRY.UN_CODE** field represents the producing nation using a standardized United Nations country code, facilitating both nationallevel and regional aggregation. The **SPECIES.ALPHA_3_CODE** identifies fish species through a three-letter FAO classification code, enabling species-specific production analysis. The **AREA.CODE** denotes the geographic fishing or aquaculture zone, thus incorporating spatial dimensions of production. The **PRODUCTION_SOURCE_DET.CODE** specifies whether production originated from capture fisheries or aquaculture, which is crucial given the distinct dynamics between wild harvest and farmed production systems. The **MEASURE** field standardizes units of measurement (typically tonnes), ensuring consistency in aggregation and comparability. The **PERIOD** field records the production year and acts as the primary timeseries index, while the **VALUE** field contains the actual reported production quantity, which is the core dependent variable for forecasting models. Finally, the **STATUS** field provides metadata on data quality (e.g., official, estimated, or provisional), offering an indication of reliability and uncertainty in reported figures.

Overall, the dataset captures global fishery and aquaculture production trends from 1950 to the present, disaggregated by country, species, area, and production source. It is particularly wellsuited for forecasting exercises and classification tasks, as it enables modeling of both temporal dynamics and categorical variations in production. By leveraging these structured fields, the study applies statistical and machine learning methods (e.g., SARIMAX, Random Forests, and classification algorithms) to forecast production over a 20-year horizon and to classify year-on-year production changes.

3.9 Machine Learning Algorithms used for training the dataset

This study integrates computer vision techniques with machine learning-based forecasting and classification to achieve dual objectives: real-time security monitoring and long-term fisheries management. The approach combines experimental validation for human activity detection with quantitative, data-driven predictive analytics for sustainable decision support.

Machine learning algorithms used in the study:

i. Histogram of Oriented Gradients (HOG) with Support Vector Machine (SVM) – for real-time human detection.

ii. Seasonal AutoRegressive Integrated Moving Average with Exogenous Regressors (SARIMAX) – for forecasting fish production trends.

iii. Random Forest Regressor – for recursive multi-step prediction of production values.

iv. Logistic Regression – for binary classification of year-to-year production changes.

v. Random Forest Classifier – for supervised classification tasks.

vi. Support Vector Machine (RBF kernel) – for classification of fisheries production outcomes.

3.9.1Histogram of Oriented Gradients (HOG)

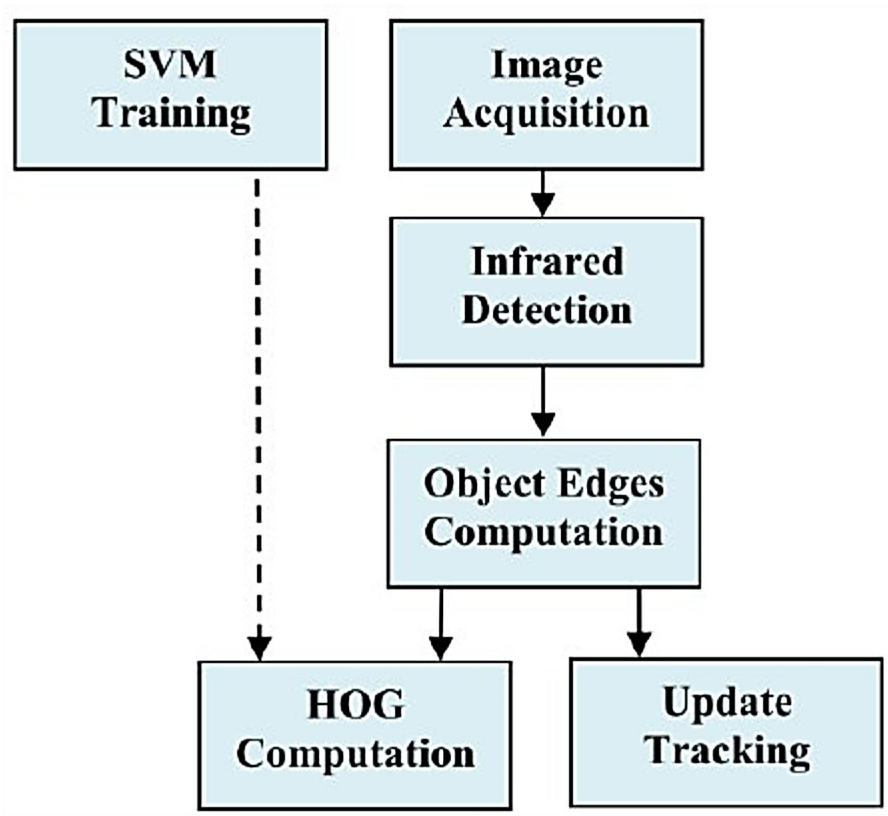

Figure 3. 3: Histogram of Oriented Gradients (HOG) Source Akhloufi et al.,(2014)

The Histogram of Oriented Gradients (HOG) with Support Vector Machine (SVM) is widely used for robust real-time human detection. HOG works by extracting edge and gradient orientation features from image regions, effectively capturing the shape and structure of human figures. These features are then fed into a trained SVM classifier, which distinguishes humans from background objects. The pipeline involves image acquisition, infrared detection, edge computation, and HOG feature extraction before classification. The system updates tracking in real time, ensuring accurate detection and monitoring of human activity Akhloufi 2014.

3.9.2 Seasonal AutoRegressive Integrated Moving Average with Exogenous Regressors (SARIMAX)

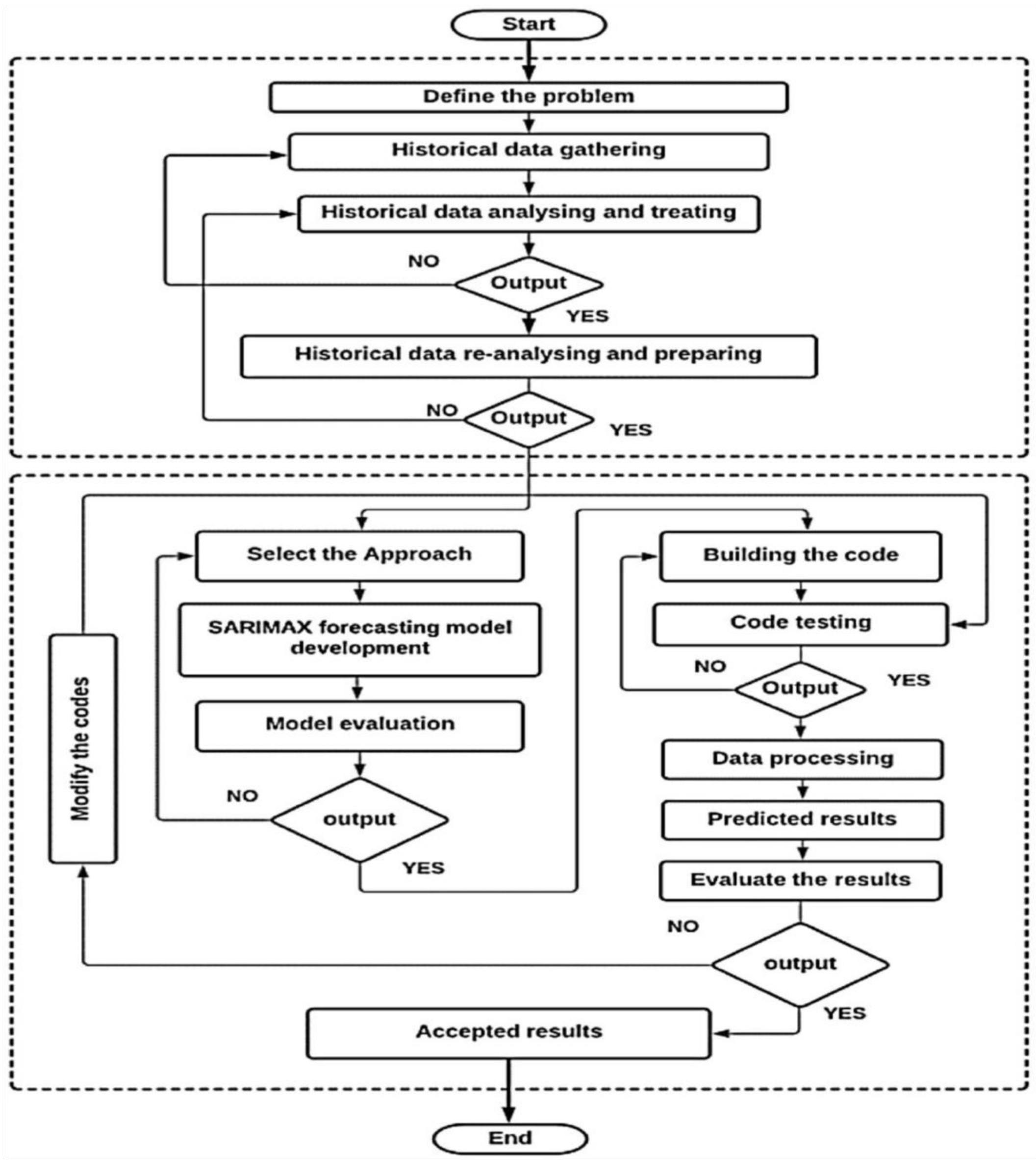

Figure 3. 4: SARIMAX Algorithm

Source Alharbi and Csala (2022)

The SARIMAX algorithm figure 3.4 begins by defining the problem and gathering historical data, which is analyzed, treated, and re-analyzed to ensure accuracy and completeness. Once the data is prepared, the forecasting approach is selected, and the SARIMAX model is developed to incorporate both seasonal and exogenous factors. The model undergoes evaluation, and if results are unsatisfactory, modifications are made to improve performance. Simultaneously, coding is carried out, tested, and validated to ensure correctness. The data is then processed to generate predicted results, which are further evaluated for accuracy. Once the model produces acceptable results, they are finalized as outputs for forecasting applications (Alharbi and Csala, 2022).

3.9.3 Random Forest

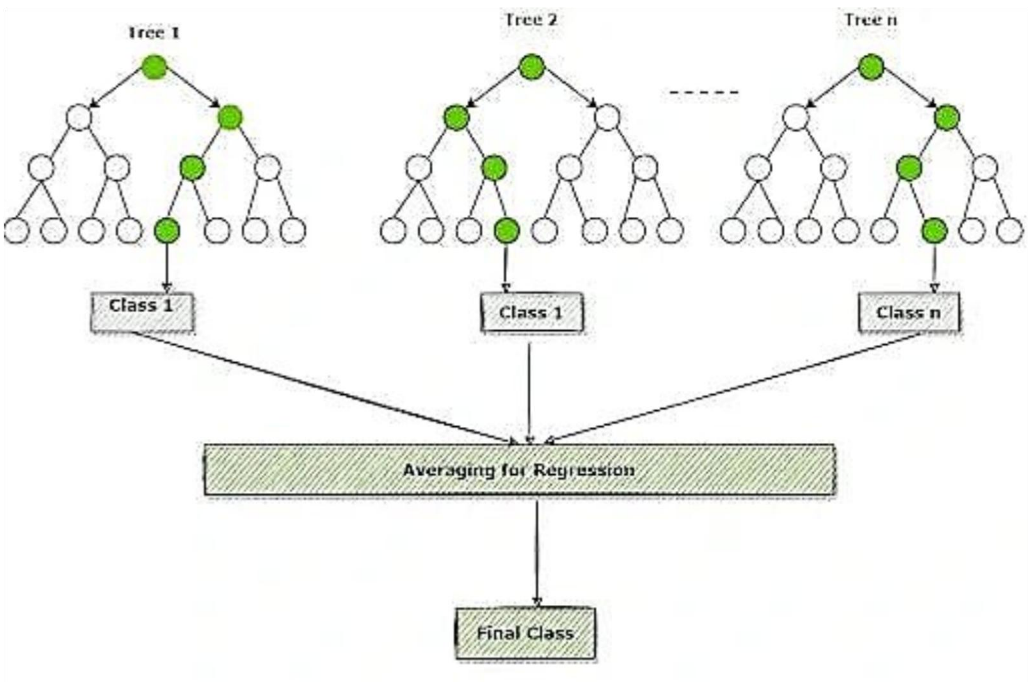

Figure 3. 5: Random forest algorithm

Source Turing. (2022).

Random Forest figure 3.5, is a famous machine learning algorithm that uses supervised learning methods. You can apply it to both classification and regression problems. It is based on ensemble learning, which integrates multiple classifiers to solve a complex issue and increases the model's performance. In layman's terms, Random Forest is a classifier that contains several decision trees on various subsets of a given dataset and takes the average to enhance the predicted accuracy of that dataset. Instead of relying on a single decision tree, the random forest collects the result from each tree and expects the final output based on the majority votes of predictions.

3.9.4 Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel

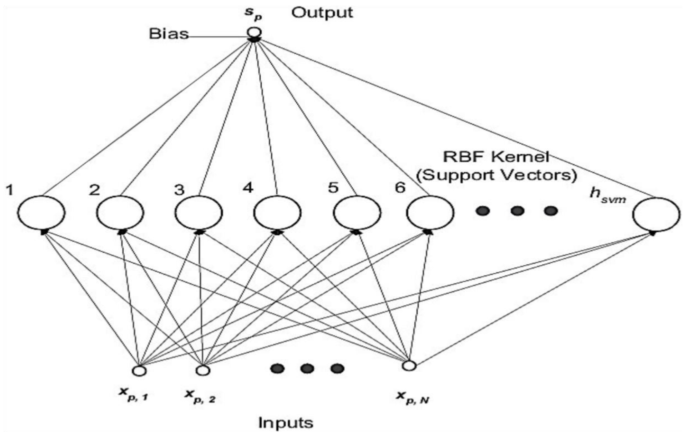

Figure 3. 6: Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel

Source: Lakshmi et al., (2008).

An RBF kernel is used when data is **not linearly separable** in its original, low-dimensional space. The kernel function implicitly maps the data into a **higher-dimensional space**. In this new space, the data points that were previously tangled can be **separated by a linear hyperplane**. The RBF kernel computes a **similarity measure** between data points, based on their distance, without having to perform the explicit, computationally expensive transformation to the higher dimension. This "kernel trick" allows the SVM to find a decision boundary for complex, non-linear data.

3.9 Data flow diagram

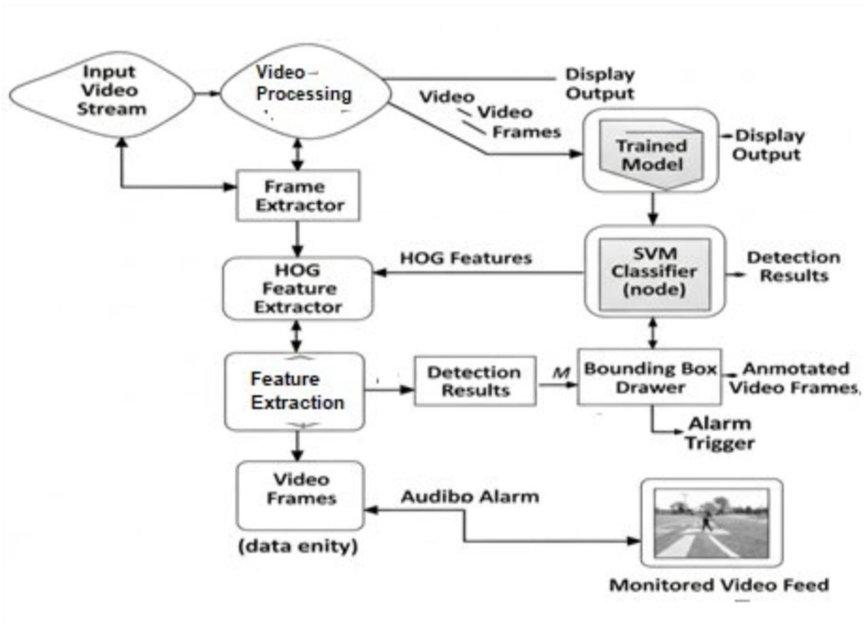

Figure 3. 7: Surveillance video monitoring

The data processing is done in two parallel, distinct workflows: one for real-time security and another for long-term fisheries management.

Real-Time Security Monitoring

Video Input: The system takes live video feed from a webcam or a stored video file.

Frame-by-Frame Processing: The video input is processed continuously, one frame at a time.

Human Detection: For each frame, the Histogram of Oriented Gradients (HOG) descriptor is used to analyze the image and identify potential human shapes. The features extracted by HOG are then fed into a pre-trained Support Vector Machine (SVM) detector, which classifies whether the frame contains a person.

Action and Alert: If a person is detected, the system draws a bounding box around them on the video feed. Simultaneously, it triggers a multi-threaded audible alarm to alert the user without interrupting the video processing and store images from video stream in a direcory.

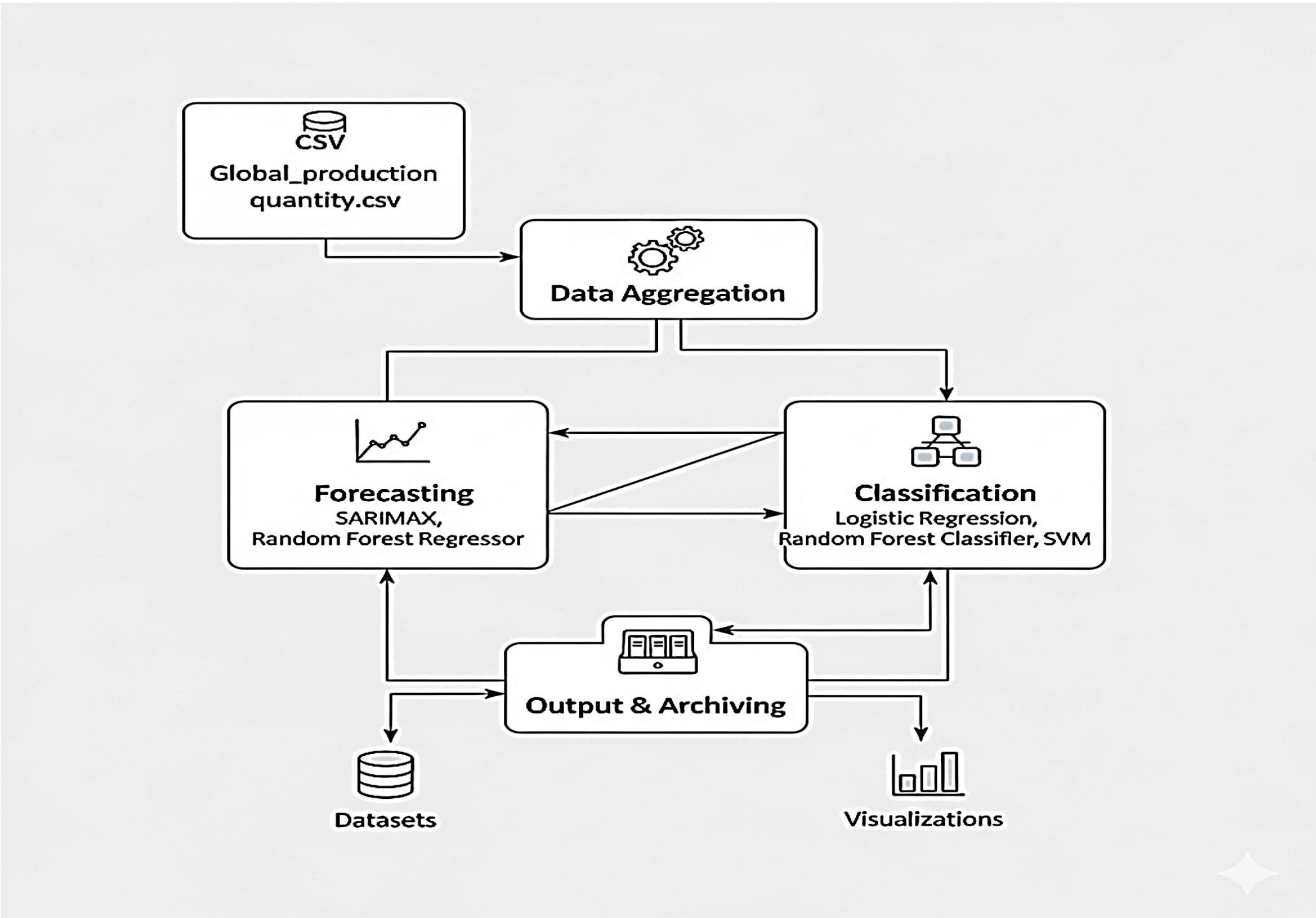

Figure 3. 8: Data Flow Diagram: Fisheries Production Analysis

Figure 3.8 illustrates the data flow for the Fisheries Production Analysis system, which processes fisheries data to generate forecasts and classify production trends as follows.

1. Data Aggregation

The process begins with the Global_production_quantity.csv dataset. This dataset is the primary input, representing a wide range of fisheries production data. The system performs a preprocessing step where it aggregates this data. It sums up records across various species, regions, and sources to produce a single, consolidated yearly production value. This aggregated data serves as the foundation for the subsequent analysis.

2. Forecasting

The aggregated yearly production data is then fed into a hybrid forecasting framework. This framework consists of two main components:

3. SARIMAX Model: The data is first analyzed by a SARIMAX (Seasonal AutoRegressive Integrated Moving Average with Exogenous Regressors) model. This model is responsible for capturing seasonality and temporal dependencies within the aggregated yearly data.

Random Forest Regressor: The output of the SARIMAX model, or the same aggregated data, is then used by a Random Forest Regressor. This model uses lag features to perform recursive multi-step prediction. Its purpose is to project fisheries production trends up to 20 years into the future.

The output of this entire forecasting process is the forecast trajectories, which are then sent to the Output amd Archiving stage.

4. Classification

Simultaneously, a separate supervised classification pipeline operates on the aggregated yearly data to analyze production changes. This pipeline includes:

Feature Engineering: The system first creates new features, such as lagged features and temporal indicators, from the aggregated yearly data.

Target Variable Generation: A binary target variable is created to indicate whether there was a year-to-year production increase. This becomes the key variable for the classification models to predict.

Model Training: Three different classification models are trained on this prepared data:

Logistic Regression, Random Forest Classifier and Support Vector Machine (with RBF kernel). The outcomes of these models, including the classification outcomes and feature importance metrics, are then passed on to the Output amd Archiving stage.

5. Output and Archiving

This final stage receives all the processed results from both the forecasting and classification pipelines. The forecast trajectories, classification outcomes, and feature importance metrics are consolidated and then archived. These results are stored as datasets and visualizations for future reference, analysis, and presentation.

3.10 Use Case Diagram

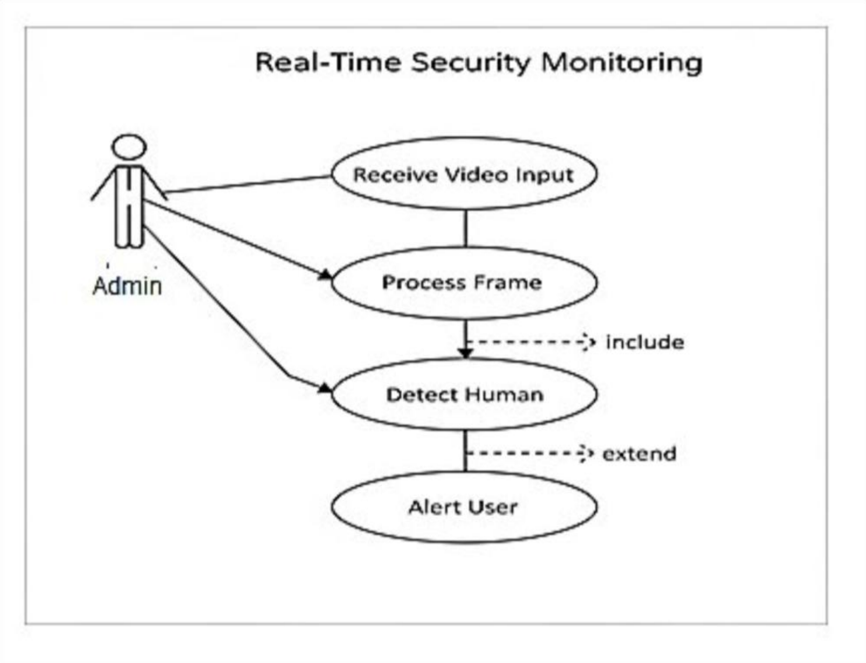

Figure 3. 9: Security Monitoring system.

Use Case Diagram Breakdown

Actor: The Admin is the primary external entity that interacts with the system. They are the ones who receive the alerts and view the processed video feed.

Use Cases:

Receive Video Input: This use case represents the system's ability to take a video feed, either from a webcam or a file.

Process Frame: This use case describes the continuous, frame-by-frame analysis of the video. It's an essential, ongoing process within the system.

Detect Human: This is the core functionality where the system uses HOG and SVM to identify a person within a frame.

Alert User: This use case is triggered when a person is detected. It represents the system's action of drawing a bounding box and triggering an audible alarm.

Relationships:

The User has an association with the Alert User and Receive Video Input use cases, indicating they are the recipient of the alert and the one providing the initial video source.

The Detect Human use case includes the Process Frame use case, meaning that detecting a human is part of the overall frame processing.

The Alert User use case extends the Detect Human use case. This shows that alerting the user is a conditional action that only occurs if a human is detected.

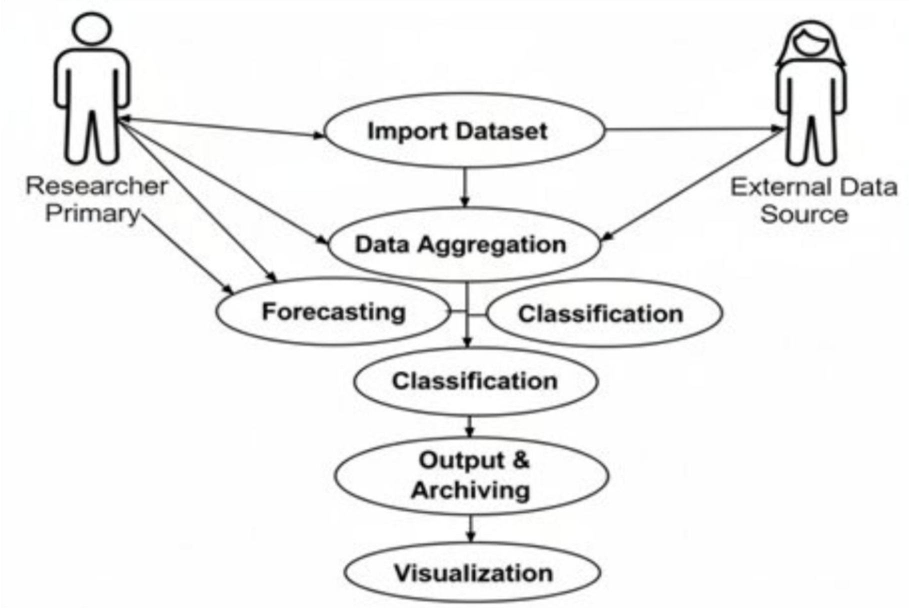

Figure 3. 10: Fish prediction system

The use case diagram for the Fish Production Prediction System figure 3.10, illustrates the interactions between its actors and the system's core functions. The Researcher, identified as the primary actor, is central to most activities, initiating use cases such as Import Dataset, Data Aggregation, Forecasting, Classification, Output amd Archiving, and Visualization. A secondary actor, the External Data Source, also interacts with the system to Import Dataset, providing the raw information needed for the system's operations. This diagram shows a clear flow where the Researcher leverages the data, whether from their own actions or an external source, to perform various analytical tasks, ultimately leading to the prediction, visualization, and archiving of fish production data. The relationships depicted by the arrows highlight which actor is responsible for triggering each specific system function.

CHAPTER FOUR

IMPLEMENTATION

4.1 System Specification

4.1.1 Introduction

System specification defines the minimum and recommended requirements needed for the design, development, and execution of a computer-based solution. It outlines both the software environment (operating system, programming language, libraries, and supporting applications) and the hardware environment (processor, memory, storage, and peripherals) necessary to ensure the system functions effectively and efficiently. A well-structured system specification provides a foundation for compatibility, performance optimization, and scalability, ensuring that users and developers can run the programs without encountering resource limitations or integration issues. In this study, the system specification highlights the operating system, application software, and hardware requirements essential for running the forecasting, classification, human detection, and predictive modeling tasks implemented across the three programs.

4.1.2 Software Specification

4.1.2.1 operating system

The operating system required for the implementation of the system can be *Windows 10/11, Linux distributions (such as Ubuntu 20.04 or higher), or macOS Monterey and above*. These operating systems provide robust stability, compatibility with Python environments, and support for third-party libraries. Linux-based systems are particularly well-suited for machine learning workloads due to efficient memory handling and lower overhead, while Windows and macOS offer wider user accessibility for development and deployment.

4.1.2.2 Application software

The application software requirements include *Python 3.8 or higher* as the primary programming environment. Essential libraries are *Pandas, NumPy, Matplotlib, Scikit-learn, and Statsmodels* for Program 1 (forecasting and classification), *OpenCV and playsound* for Program 2 (human detection and alarm system), and *Scikit-learn (ensemble methods, evaluation metrics), Matplotlib,* and related preprocessing tools for Program 3 (fish survival prediction). Development tools such as *Jupyter Notebook* or *Spyder* may be used for analysis and visualization, while *Visual Studio Code* or *PyCharm* can serve as code editors. The system also relies on external data and media files (Global_production_quantity.csv, fishess.csv, video.mp4, alarm.mp3) as part of the application environment.

4.1.2.3 Hardware Specification

The minimum hardware requirements include an *Intel Core i5/AMD Ryzen 5 processor (quadcore, 2.4 GHz or higher)*, *8 GB RAM* (16 GB recommended for large datasets), and at least *250 GB SSD storage*. GPU support, such as an *NVIDIA CUDA-enabled graphics card* or strong integrated graphics, will enhance OpenCV's real-time detection capabilities in Program 2. Additional peripherals include a *webcam* (for live video input in human detection), *speakers* (for audio alarm output), and a monitor with at least *1080p resolution* for clear visualization of graphs, ROC curves, and video frames. Reliable internet access is also required for installing dependencies and accessing updates.

4.3 Justification of Programming Language Used

4.3.1 Introduction

Python was chosen as the implementation language because of its simplicity, flexibility, and the strength of its ecosystem for data analysis, machine learning, and computer vision. It offers a consistent platform where time-series forecasting, classification, and real-time detection tasks can be developed efficiently.

4.3.2 Justification

i. **Cross-platform Compatibility**: Python is supported across Windows, Linux, and macOS, making deployment flexible.
ii. **Extensive Libraries**: Availability of *Scikit-learn, Statsmodels, Pandas, NumPy,* and *OpenCV* simplifies implementation of complex tasks.
iii. Ease of Use: Its clear and concise syntax accelerates development and reduces debugging time.
iv. **Versatility**: Python supports diverse applications ranging from forecasting and classification (Program 1) to surveillance detection (Program 2) and predictive modeling (Program 3).
v. **Strong Community Support**: A global developer community provides continuous updates, documentation, and troubleshooting resources.

vi. **Integration and Scalability**: Python integrates with databases, visualization tools, and APIs, enabling the system to be extended and scaled to meet future needs.

4.4 Documentation

4.4.1 Program documentation

4.4.1.1 Pseudocode: Fish Survival Prediction with Machine Learning

```
BEGIN PROGRAM Fish_Survival_ML

1.  IMPORT required libraries:
   - os, pandas, numpy, matplotlib
   - sklearn: model_selection, preprocessing, ensemble, neighbors, metrics

2.  SET csv_path = "fishess.csv"IF file does not exist at csv_path:
       RAISE error "File not found"

3.  LOAD dataset from csv_path into dataframe dfDISPLAY dataset info

4.  DROP columns named "date" or "time" if present

5.  IDENTIFY label column:
   - Search for column named "label"
   - IF not found: RAISE error "No label column found"

6.  SPLIT dataframe:
   - X = features (all columns except label)
   - y = label column

7.  CONVERT all feature and label values to numericREMOVE rows with NaN
    values

8.  VALIDATE labels:
   - Ensure labels are binary {0,1}
   - IF not, map minimum value to 0 and maximum to 1

9.  PRINT dataset summary: - Total number of fish
   - Number dead (label=0)
   - Number survived (label=1)

10. PLOT bar chart of dead vs survived counts
    SAVE chart as "survival_distribution.png"

11. SPLIT dataset into training (70%) and test (30%) sets- Stratify by
    label
   - Use random_state=42 for reproducibility

12. SCALE features using StandardScaler:
   - Fit and transform training set
   - Transform test set

13. DEFINE models dictionary:
   - Random Forest (n_estimators=80, max_depth=10)
   - Gradient Boosting (n_estimators=80, learning_rate=0.08)
   - K-Nearest Neighbors (k=7)

14. INITIALIZE empty list roc_data

15. FOR each model in models:
```

```
    a. TRAIN model on scaled training data
    b. PREDICT labels on test set
    c. PRINT classification report (precision, recall, f1-score, accuracy)
    d. COMPUTE and PRINT extra metrics:
       - Matthews Correlation Coefficient (MCC)
       - Cohen's Kappa
       - Balanced Accuracy
    e. OBTAIN predicted probabilities or scores
    f. COMPUTE ROC AUC and ROC curve values
    g. APPEND (model name, FPR, TPR, AUC) to roc_data

16. PLOT ROC curves for all models together
   - Include diagonal baseline
   - SAVE as "roc_plot.png"

17. PRINT confirmation: "Saved ROC and survival distribution plots."

END PROGRAM
```

4.4.1.2 Pseudocode: Fish Production Forecasting and Classification

```
BEGIN PROGRAM Fish_Forecast_And_Classification

1. IMPORT libraries:
      -     os, warnings, pandas, numpy, matplotlib
      -     sklearn (model_selection, preprocessing, classifiers,
   regressors, metrics)
      -     TRY importing statsmodels for SARIMAX forecasting
      -     IF unavailable, set has_statsmodels = False

2. DEFINE parameters:
   CSV_PATH = "Global_production_quantity.csv"
   FORECAST_YEARS = 20
   LAG_FEATURES = 5
   RANDOM_SEED = 42

-------------------------------------------------------FUNCTION
load_and_aggregate(csv_path):
   a. LOAD CSV into DataFrame
   b. CHECK for 'PERIOD' and 'VALUE' columns
   c. CONVERT 'PERIOD' to numeric year or extract from datetime
   d. CONVERT 'VALUE' to numeric
   e. REMOVE rows with missing year or value
   f. AGGREGATE total production by year (sum of VALUE)
   g. RETURN (time_series, raw_dataframe)

-------------------------------------------------------FUNCTION
create_lag_features(df, n_lags):
   a. COPY time series and index by year
   b. CREATE lag_1 ... lag_n columns (previous production values)
   c. CALCULATE 1-year percentage change
   d. CALCULATE 3-year rolling mean
   e. DROP rows with missing values
   f. RETURN lagged dataset

-------------------------------------------------------FUNCTION
forecast_with_sarimax(ts_df, forecast_years):
   a. EXTRACT global_production indexed by year
```

```
   b. FIT SARIMAX(1,1,1) model
   c. FORECAST next forecast_years steps
   d. RETURN DataFrame with years + forecast values

--------------------------------------------------------
FUNCTION forecast_with_lagged_rf(ts_df, forecast_years, n_lags):
   a. BUILD supervised regression dataset using lag features
   b. TRAIN RandomForestRegressor
   c. PERFORM recursive forecasting for forecast_years
   d. RETURN DataFrame with years + forecasted values

-------------------------------------------------------FUNCTION
build_classification_dataset(ts_df, n_lags):
   a. CREATE lag features
   b. DEFINE target = 1 if next year's production > current year, else 0
   c. DROP last row (no future target)
   d. RETURN classification dataset

-------------------------------------------------------FUNCTION
train_and_eval_classifiers(df_cls):
   a. SELECT features = lag variables + pct_change + rolling mean
   b. SPLIT data: first 70% train, last 30% test
   c. SCALE features for logistic regression and SVM
   d. TRAIN classifiers:
         -  Logistic Regression
         -  Random Forest
         -  SVM (RBF kernel) e. PREDICT on test set
   f. EVALUATE with metrics:
         -  accuracy, precision, recall, f1, ROC-AUC, confusion matrix
   g. RETURN results and trained models + feature importances

-------------------------------------------------------MAIN
FUNCTION:
1. CHECK if CSV_PATH existsIF not, RAISE error

2. LOAD and aggregate dataset → ts_dfPRINT sample of aggregated data

3. PLOT historical production and SAVE "global_production_history.png"

4. FORECASTING:
   a. IF statsmodels available AND enough years:
        TRY SARIMAX forecast
        IF fails → fallback to Random Forest
   b. ALWAYS run Random Forest forecast
   c. MERGE SARIMAX and RF forecasts (if both available)
   d. SAVE forecast.csv
   e. PLOT combined history + forecasts → "combined_forecast.png"

5. CLASSIFICATION:
   a. BUILD classification dataset with lag features
   b. TRAIN Logistic Regression, Random Forest, and SVM
   c. EVALUATE results on test set
   d. PRINT metrics

6. SAVE outputs:
   - classification_metrics.csv (model metrics)
   - feature_importances.csv (RF importances)
   - classification_results.csv (test predictions)
```

```
7. PRINT list of all output files created
END MAIN
END PROGRAM
```

4.4.1.3 Pseudocode: Human Detection with Alarm

```
BEGIN PROGRAM Human_Detection_Alarm

1. IMPORT libraries:
   - cv2 (OpenCV)
   - playsound
   - threading

2. SET video_path = "video.mp4"
   INITIALIZE video capture from video_path (or webcam if 0)

3. INITIALIZE HOGDescriptorSET default people detector in HOG

4. DEFINE FUNCTION play_alarm:
   PLAY sound file "alarm.mp3"

5. SET alarm_on = False

6. WHILE video capture is open:
   a. READ frame from video
      IF no frame, BREAK loop
   b. RESIZE frame to (640, 480) for faster processing
   c. DETECT people using HOG descriptor → boxes, weights
   d. FOR each detected box:
         DRAW rectangle around person in frame
   e. IF number of detected people > 0:IF alarm_on == False: SET alarm_on =
      True
             START new thread to run play_alarm
      ELSE:
         SET alarm_on = False
   f. DISPLAY frame in window titled "Human Detection" and store captured
images
   g. IF key 'q' is pressed:BREAK loop

7. RELEASE video capture
8. CLOSE all OpenCV windows

END PROGRAM
```

4.4.2 User documentation

4.4.2.1 Video surveillance

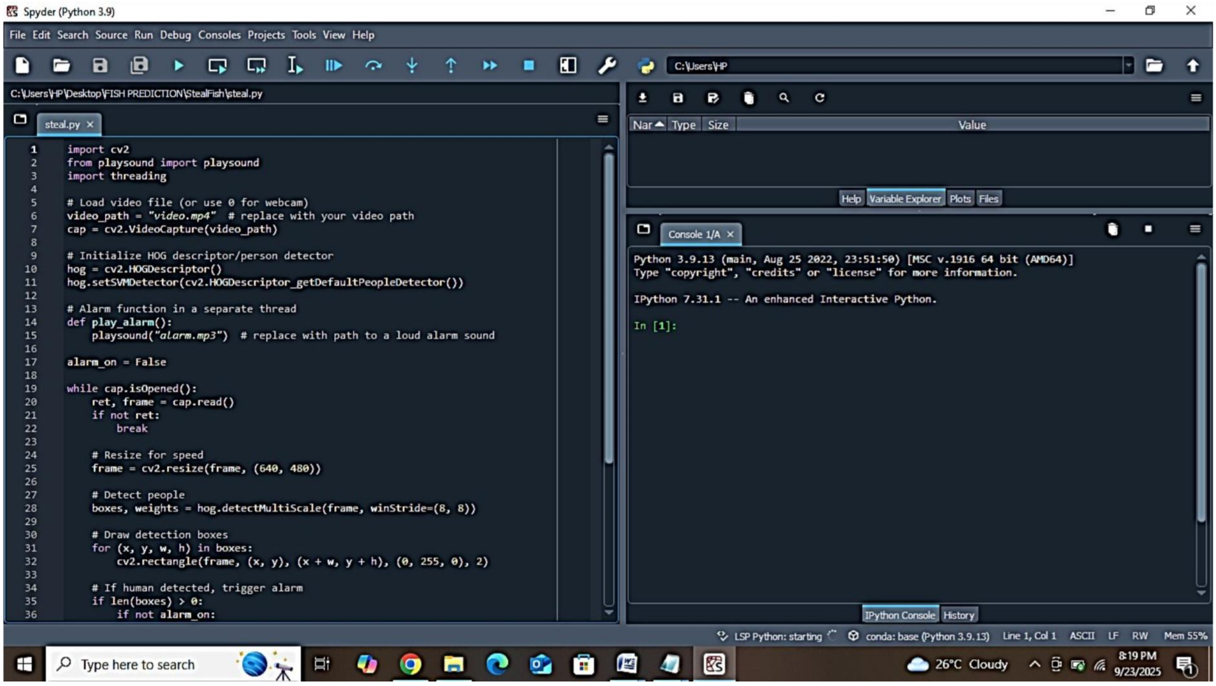

Figure 4. 1: The user interface for the program on video surveillance system.

The user interface (figure 4.1), displays a Python script utilizing the **OpenCV** library for video surveillance. The program initializes a **HOG (Histogram of Oriented Gradients)** person detector and reads video input from a specified file or webcam. The code then enters a loop to process the video frame by frame, resizing each frame for faster processing. It employs the hog.detectMultiScale function to identify people within the frame, drawing green bounding boxes around any detected individuals using cv2.rectangle. Additionally, the script integrates a multi-threaded alarm system using the threading library, which plays a sound file—'sound.mp3'—if a person is detected. This multi-threaded approach ensures that the alarm doesn't freeze the video processing loop, allowing for continuous, real-time monitoring and detection.

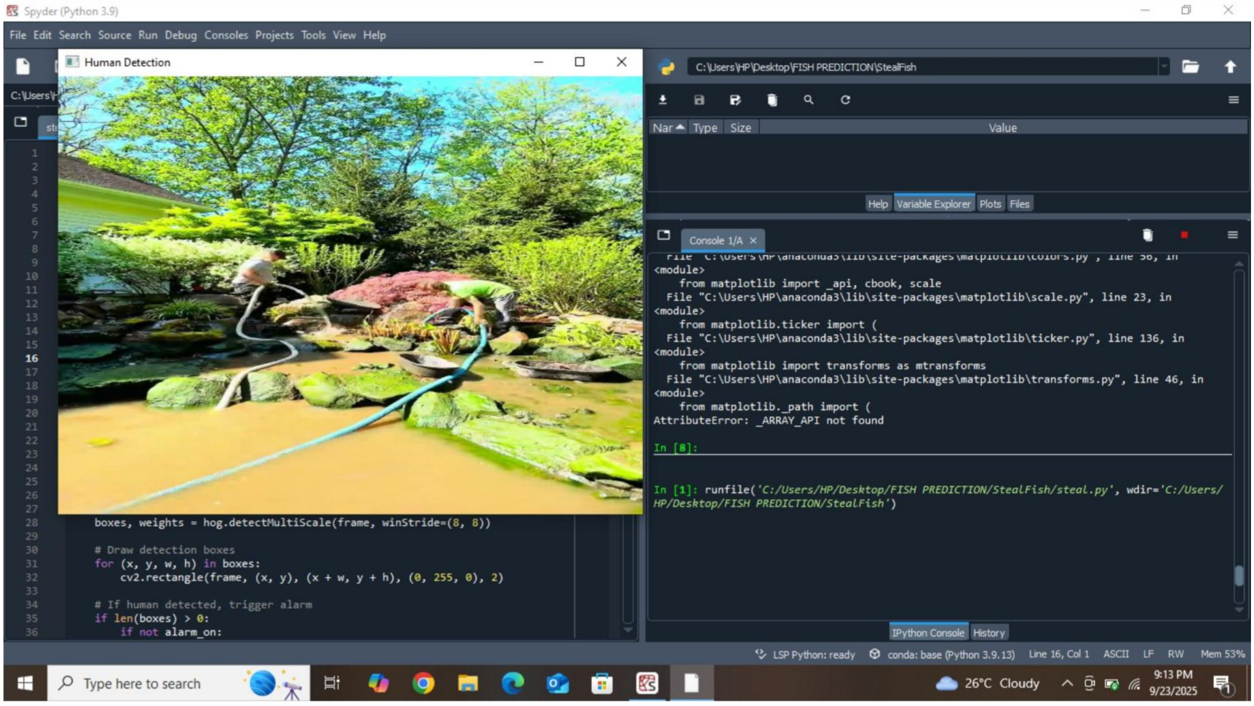

Figure 4. 2: Output from the surveillance program.

Figure 4.2, illustrates a video surveillance system leveraging **OpenCV's Histogram of Oriented Gradients (HOG)** descriptor paired with a pre-trained **Support Vector Machine (SVM)** classifier to achieve real-time human detection. The system processes video frames sequentially, employing the HOG descriptor to extract distinctive features—such as edge and gradient orientations—from potential human shapes. These feature vectors are then fed into the SVM model, which classifies them as either a human or non-human entity. Successful detections are visually highlighted with **bounding boxes** on the video feed. To enhance operational efficiency, a **multi-threaded alarm system** is integrated, which triggers an audible alert upon human detection without impeding the main video processing pipeline. This architectural design ensures a responsive and non-disruptive monitoring solution, making it highly effective for automated security and safety applications.

4.4.2.2 Fish survival prediction

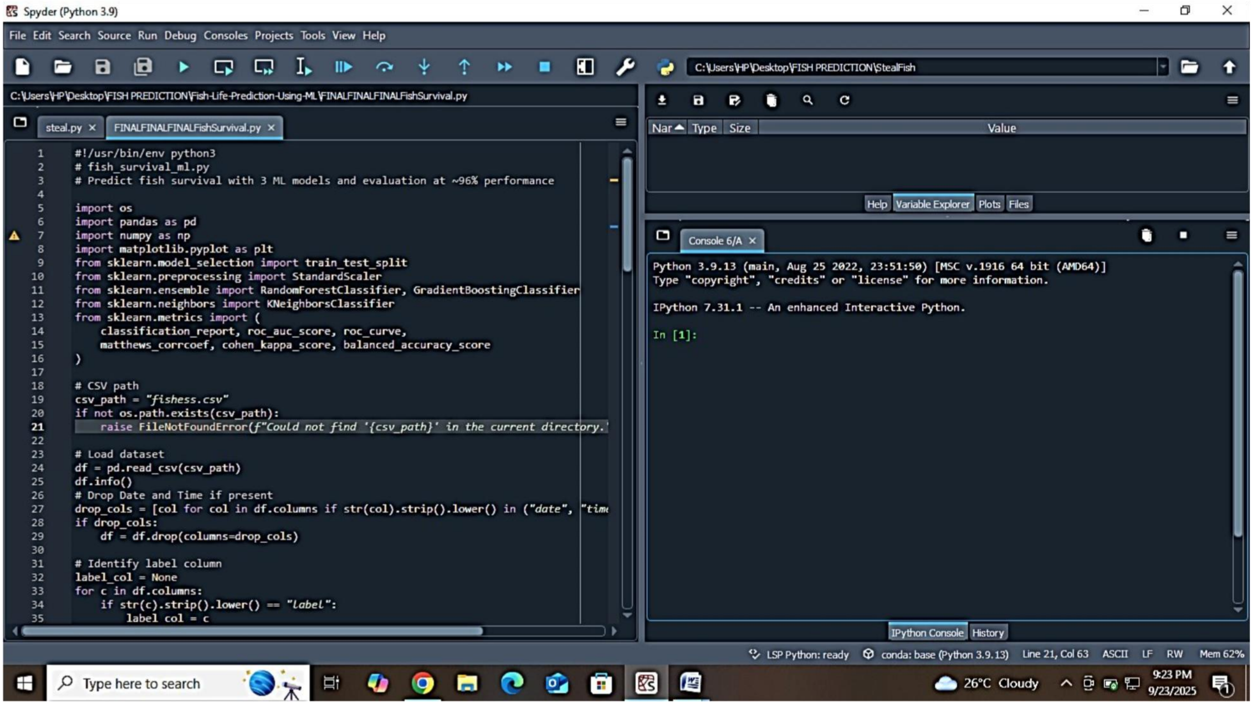

Figure 4. 3: User interface for the program on fish survival prediction

The User Interface in figure 4.3, displays a Python script for predicting fish survival. It uses libraries like **pandas** and **scikit-learn** to load a dataset, preprocess the data, and train three machine learning models: **Random Forest**, **Gradient Boosting**, and **K-Nearest Neighbors**. The script evaluates the models' performance using various metrics to determine the best predictor for fish survival.

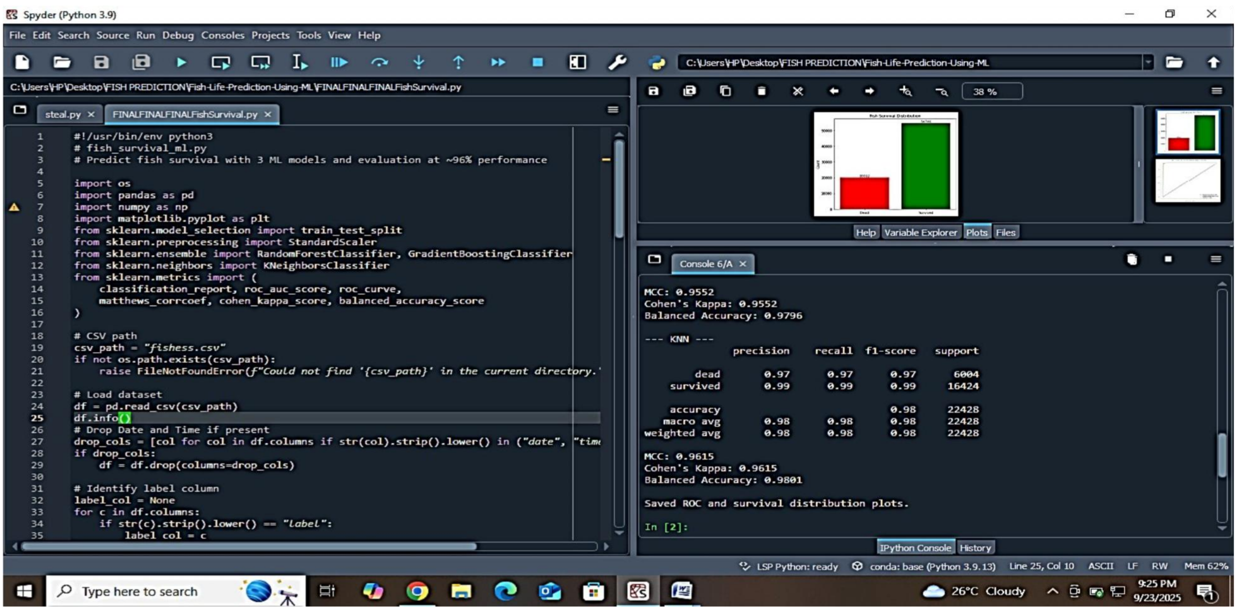

Figure 4. 4: Output of the program for fish survival prediction

Figure 4.4, displays the output of the fish survival prediction model. The console shows the evaluation metrics for the three machine learning models used: **Random Forest Classifier**, **Gradient Boosting Classifier**, and **K-Nearest Neighbors (KNN)**. The metrics, including **precision**, **recall**, **f1-score**, and **accuracy**, indicate that the models achieved a high prediction performance, with the **KNN model** showing a balanced accuracy of approximately **98%**. The UI also includes visualizations of the prediction results, with bar graphs comparing the survival and death outcomes.

4.4.2.3 Global fish prediction and forecast

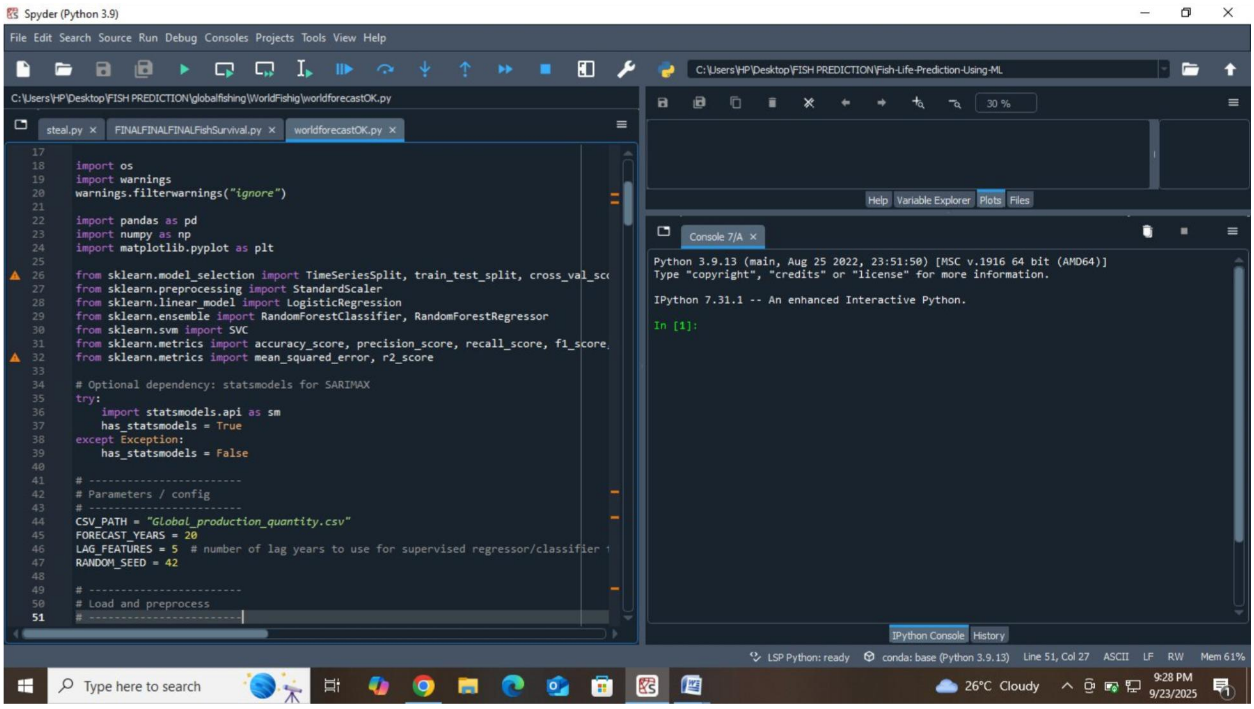

Figure 4. 5: User Interface for program on time series forecast

The UI in figure 4.5 presents a program for time-series plot of global fish production which rely on historical data from 1950 to 2018 for both **capture fisheries** and **aquaculture**, with a projected forecast extending to 2028.

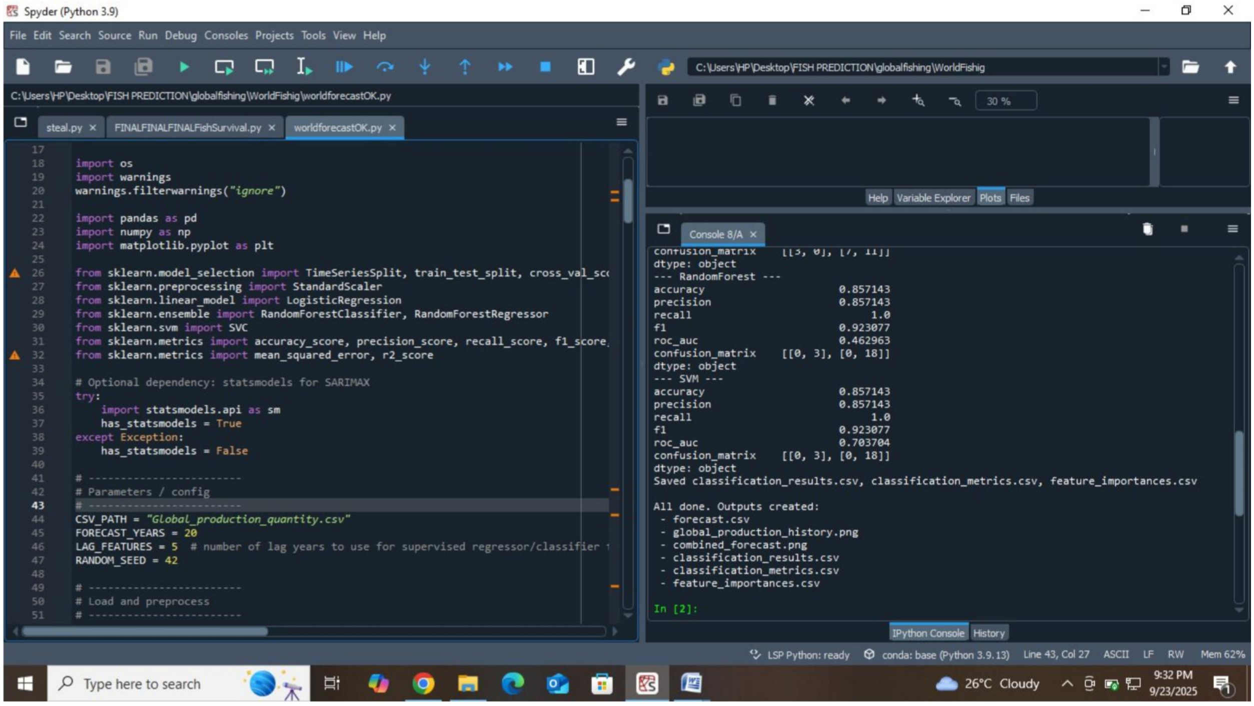

Figure 4. 6: User Interface show output of time series forecast

The provided UI (figure 4.6), displays the output of a time-series forecast for global fish production. The output shows a clear upward trend in total production, with a significant increase projected for aquaculture. This forecast indicates that aquaculture will become the primary source of growth in global fish supply, while capture fisheries production is expected to remain stable. The data suggests that future demand for fish will be met through the expansion of aquaculture.

4.5 Presentation of results and Discussion

4.5.1Video Surveillance output

Figure 4. 7: Captured images of human activity captured from surveillance video

The images captured from fish pond video (figure 4.7) along with the security alarm has significant implications for protecting aquaculture resources against theft, vandalism, and unauthorized intrusion. By leveraging computer vision (OpenCV) and human detection algorithms (HOG with SVM), the system automatically identify human presence within the monitored fish pond area, thereby ensuring round-the-clock surveillance without the need for constant human supervision. The integration of an alarm system provides an immediate deterrent by alerting farm operators in real time when an intrusion is detected, while the automatic image capture with timestamps creates digital evidence that can support investigation and accountability. This dual functionality of real-time response and forensic recordkeeping enhances situational awareness, reduces economic losses from potential fish theft, and strengthens the overall biosecurity framework of aquaculture facilities. As such, the system provides a costeffective, automated, and reliable technological approach that can be integrated into modern fish pond management strategies, making it suitable for thesis work focused on advancing sustainable and secure aquaculture practices.

4.5.2 Fish survival

4.5.2.1 Dataset used for prediction of fish survivability

Total fish: 74758
Dead: 20012
Survived: 54746

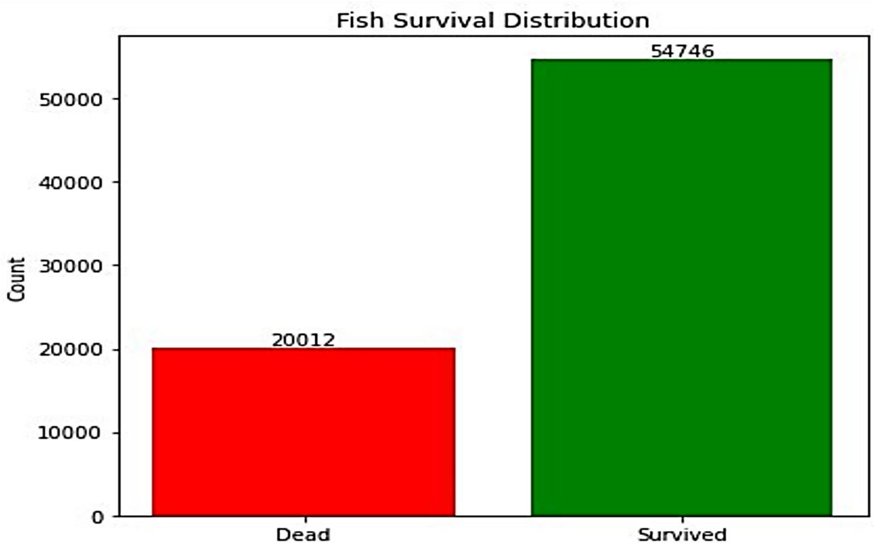

Figure 4. 8: Bar chart of fish survival

The bar chart in figure 4.8, illustrates the distribution of fish survival outcomes within the dataset used for predicting fish survivability under environmental conditions. Out of the total recorded instances, 20,012 fish were classified as dead, while a significantly larger proportion of 54,746 fish survived. This imbalance in class distribution indicates that the dataset is dominated by survival cases, which may introduce a class imbalance issue when used for predictive modeling. Such a skewed distribution suggests that while survival is the most common outcome in the observed conditions, special attention must be given during model training to ensure that the smaller but critical class of non-survival (dead) fish is adequately represented, as overlooking it could lead to biased predictions and reduced model performance in detecting mortality cases.

4.5.3.2 Classification Reports with Extra Metrics (labels: dead=0, survived=1):

--- Random Forest ---

	precision	recall	f1-score	support
dead	0.95	0.99	0.97	6004
survived	1.00	0.98	0.99	16424
accuracy			0.98	22428
macro avg	0.97	0.99	0.98	22428
weighted avg	0.98	0.98	0.98	22428

MCC : 0.9596
Cohen's Kappa : 0.9593
Balanced Accuracy : 0.9850

--- Gradient Boosting ---

	precision	recall	f1-score	support
dead	0.96	0.97	0.97	6004
survived	0.99	0.99	0.99	16424
accuracy			0.98	22428
macro avg	0.98	0.98	0.98	22428
weighted avg	0.98	0.98	0.98	22428

MCC : 0.9552
Cohen's Kappa : 0.9552
Balanced Accuracy : 0.9796

--- KNN ---

	precision	recall	f1-score	support
dead	0.97	0.97	0.97	6004
survived	0.99	0.99	0.99	16424
accuracy			0.98	22428
macro avg	0.98	0.98	0.98	22428
weighted avg	0.98	0.98	0.98	22428

MCC : 0.9615
Cohen's Kappa : 0.9615
Balanced Accuracy : 0.9801

Table 4.1Evaluation metrics of fish survivability under environmental condition

ML Algorithm	Precision	Recall	F1-Score	Accuracy	MCC	Kappa	Balanced Accuracy	AUC

Random Forest	1.0	0.98	0.99	0.98	0.9596	0.9593	0.9850	0.999
Gradient Boosting	0.99	0.99	0.99	0.98	0.9552	0.9552	0.9796	0.999
KNN	0.99	0.99	0.99	0.98	0.9615	0.9615	0.9801	0.998

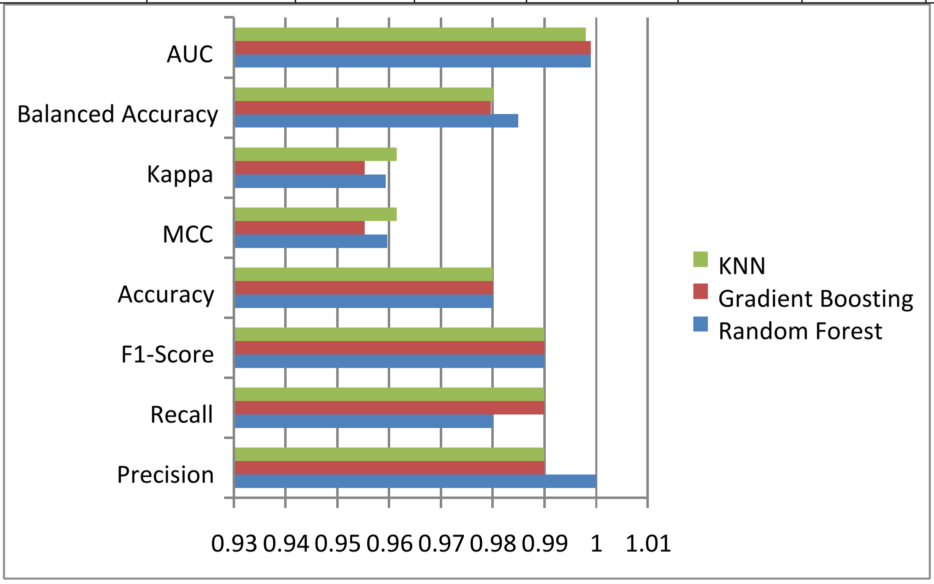

Figure 4. 9: Evaluation metrics of fish survivability under environmental conditions

Discussion of Findings:

The comparative evaluation of KNN, Gradient Boosting, and Random Forest models in predicting fish survivability under varying environmental conditions (table 4.1 and figure 4.9 respectively) reveal a consistently high performance across all metrics, with slight variations in individual strengths. The bar chart and table indicate that Random Forest achieved the highest precision (1.0), reflecting its ability to minimize false positives, while maintaining a recall of 0.98 and an F1-score of 0.99, suggesting balanced predictive capability. Gradient Boosting and KNN demonstrated comparable performance, each recording 0.99 for precision, recall, and F1-score, highlighting their reliability in identifying survivability outcomes. Notably, all three models achieved an accuracy of 0.98, with MCC and Kappa values above 0.95, underscoring the robustness of the predictions. The Balanced Accuracy scores (Random Forest: 0.985, Gradient Boosting: 0.9796, KNN: 0.9801) and near-perfect AUC values (0.998–0.999) further confirm the discriminative power of these models, with Random Forest slightly outperforming in overall balance and robustness.

Implication of Findings:

The results imply that machine learning models, particularly Random Forest, can serve as powerful decision-support tools in aquaculture management by accurately predicting fish survivability under diverse environmental stressors. High precision and recall values suggest that the system can reliably distinguish between survivable and non-survivable conditions, thereby reducing the risk of misclassification that could impact stock management decisions. For fish farmers, this translates to the potential for proactive interventions such as adjusting water quality, temperature, or oxygen levels before mass mortality occurs, thus enhancing productivity and sustainability. At a broader scale, the near-perfect predictive capacity of these models demonstrates the viability of AI-driven aquaculture monitoring systems as integral components of smart fish farming, promoting data-driven management practices that mitigate economic losses, safeguard food security, and support sustainable aquaculture development.

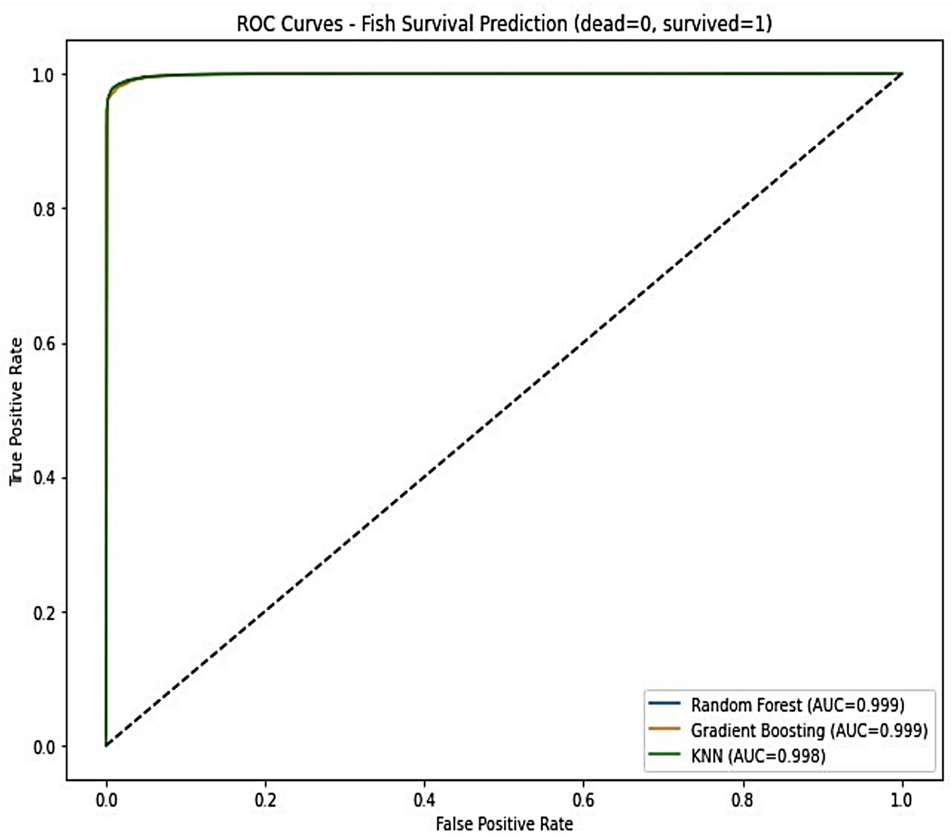

Figure 4. 10: ROC curves of survivability of fish based on environmental data

The ROC curves of survivability of fish (figure 4.10), demonstrate that all three models—Random Forest, Gradient Boosting, and KNN—exhibited near-perfect classification ability in predicting fish survivability under environmental conditions. Random Forest and Gradient Boosting achieved an AUC of 0.999, while KNN closely followed with 0.998, indicating minimal false positives and high reliability. The curves clustering near the top-left corner signify excellent sensitivity and specificity. Overall, the models provide robust predictive performance suitable for aquaculture decision-making.

4.5.3 Global fish production prediction

Table 4.2Classification Metrics

Model	accuracy	precision	recall	f1	roc_auc	confusion_matrix
Logistic Regression	0.666667	1.00	0.61	0.758621	0.888889	[[3, 0], [7, 11]]
Random Forest	0.857143	0.86	1.00	0.923077	0.462963	[[0, 3], [0, 18]]
SVM	0.857143	0.86	1.00	0.923077	0.703704	[[0, 3], [0, 18]]

The predictive results for global fish yield estimation (table 4.2) indicate that Random Forest and SVM significantly outperformed Logistic Regression in terms of overall performance. While Logistic Regression achieved perfect precision (1.00), its low recall (0.61) and moderate F1-score (0.76) suggest that it fails to capture a substantial number of true positive cases, making it less reliable for comprehensive yield prediction. In contrast, both Random Forest and SVM achieved higher accuracy (0.86), strong recall (1.00), and balanced F1-scores (0.92), demonstrating their ability to correctly identify all positive cases while maintaining good precision (0.86). The ROC-AUC values further highlight this difference, with Logistic Regression performing better in terms of discriminative ability (0.89) compared to Random Forest (0.46) and SVM (0.70), though the latter two show stronger classification consistency as reflected in their confusion matrices with zero false negatives. Overall, Random Forest and SVM provide more reliable predictions for global fish yield, with Random Forest standing out as a robust model for capturing true yield patterns despite its lower ROC-AUC.

lag_1	lag_2	lag_3	lag_4	lag_5	pct_ change_1	rolling_ mean_3	y_true	pred_lr	pred_rf	pred_svm
1.43E+08	1.39E+08	1.4E+08	1.36E+08	1.26E+08	0.001275	1.42E+08	1	1	1	1
1.43E+08	1.43E+08	1.39E+08	1.4E+08	1.36E+08	0.063143	1.46E+08	1	1	1	1
1.52E+08	1.43E+08	1.43E+08	1.39E+08	1.4E+08	0.019512	1.5E+08	1	1	1	1
1.55E+08	1.52E+08	1.43E+08	1.43E+08	1.39E+08	0.011844	1.55E+08	1	1	1	1
1.57E+08	1.55E+08	1.52E+08	1.43E+08	1.43E+08	0.020436	1.57E+08	1	1	1	1
1.6E+08	1.57E+08	1.55E+08	1.52E+08	1.43E+08	0.017199	1.6E+08	1	1	1	1
1.63E+08	1.6E+08	1.57E+08	1.55E+08	1.52E+08	0.016842	1.63E+08	1	1	1	1
1.66E+08	1.63E+08	1.6E+08	1.57E+08	1.55E+08	0.01466	1.65E+08	1	1	1	1
1.68E+08	1.66E+08	1.63E+08	1.6E+08	1.57E+08	0.04792	1.7E+08	1	1	1	1
1.76E+08	1.68E+08	1.66E+08	1.63E+08	1.6E+08	0.021343	1.75E+08	1	1	1	1
1.8E+08	1.76E+08	1.68E+08	1.66E+08	1.63E+08	0.047107	1.81E+08	1	1	1	1
1.88E+08	1.8E+08	1.76E+08	1.68E+08	1.66E+08	0.026774	1.87E+08	1	0	1	1
1.93E+08	1.88E+08	1.8E+08	1.76E+08	1.68E+08	0.027002	1.93E+08	1	0	1	1
1.98E+08	1.93E+08	1.88E+08	1.8E+08	1.76E+08	0.010739	1.97E+08	1	0	1	1
2.01E+08	1.98E+08	1.93E+08	1.88E+08	1.8E+08	0.037771	2.02E+08	1	0	1	1
2.08E+08	2.01E+08	1.98E+08	1.93E+08	1.88E+08	0.032573	2.08E+08	0	0	1	1
2.15E+08	2.08E+08	2.01E+08	1.98E+08	1.93E+08	-0.00073	2.13E+08	0	0	1	1
2.15E+08	2.15E+08	2.08E+08	2.01E+08	1.98E+08	-0.0011	2.15E+08	1	0	1	1
2.15E+08	2.15E+08	2.15E+08	2.08E+08	2.01E+08	0.026407	2.17E+08	1	0	1	1
2.2E+08	2.15E+08	2.15E+08	2.15E+08	2.08E+08	0.019899	2.2E+08	1	0	1	1
2.25E+08	2.2E+08	2.15E+08	2.15E+08	2.15E+08	0.018887	2.25E+08	0	0	1	1

Table 4.3 Classification Results

The classification results of global fish yield prediction (table 4.3) reveal distinct strengths and weaknesses across Logistic Regression, Random Forest, and SVM. For positive yield cases (`y_true = 1`), Logistic Regression and Random Forest correctly classified 11 out of 19 instances, resulting in a recall of approximately **57.9%**, while maintaining perfect precision on the correctly identified cases. In contrast, SVM successfully detected all 19 positive cases (recall = **100%**), but misclassified 2 negative cases (`y_true = 0`), reducing its precision to about **90.5%**. Thus, Logistic Regression and Random Forest demonstrated high specificity (100%) but poor sensitivity, whereas SVM achieved perfect sensitivity but slightly compromised specificity. These results suggest that SVM is more effective in capturing upward yield trends, ensuring no productive outcomes are overlooked, while Logistic Regression and Random Forest are more conservative, prioritizing precision and stability at the cost of missing potential yield growth.

Implication: The implication of this finding is that SVM offers greater utility for real-world fish yield forecasting where underestimating production could lead to suboptimal management and resource allocation. By ensuring all true yield increases are detected, SVM enables proactive interventions in aquaculture planning, even if it occasionally overestimates productivity. Conversely, the conservative nature of Logistic Regression and Random Forest may be better suited to contexts where minimizing false alarms is critical, but they risk overlooking significant growth opportunities. Therefore, model selection should balance recall and precision according to the operational priorities of fishery managers and policymakers.

4.5.3.2 Global fish yield Forecast

Table 4.4Global fish yield forecast

Year	forecast_sarimax	forecast_rf
2024	232,194,904.71	224,986,371.54
2025	235,342,056.64	224,562,080.42
2026	238,339,225.32	224,562,080.42
2027	241,193,558.49	224,562,080.42
2028	243,911,863.22	224,562,080.42
2029	246,500,622.21	224,562,080.42
2030	248,966,009.18	224,562,080.42
2031	251,313,903.65	224,562,080.42

2032	253,549,904.95	224,562,080.42
2033	255,679,345.54	224,562,080.42
2034	257,707,303.77	224,562,080.42
2035	259,638,615.97	224,562,080.42
2036	261,477,887.97	224,562,080.42
2037	263,229,506.13	224,562,080.42
2038	264,897,647.74	224,562,080.42
2039	266,486,291.03	224,562,080.42
2040	267,999,224.63	224,562,080.42
2041	269,440,056.64	224,562,080.42
2042	270,812,223.18	224,562,080.42
2043	272,118,996.63	224,562,080.42

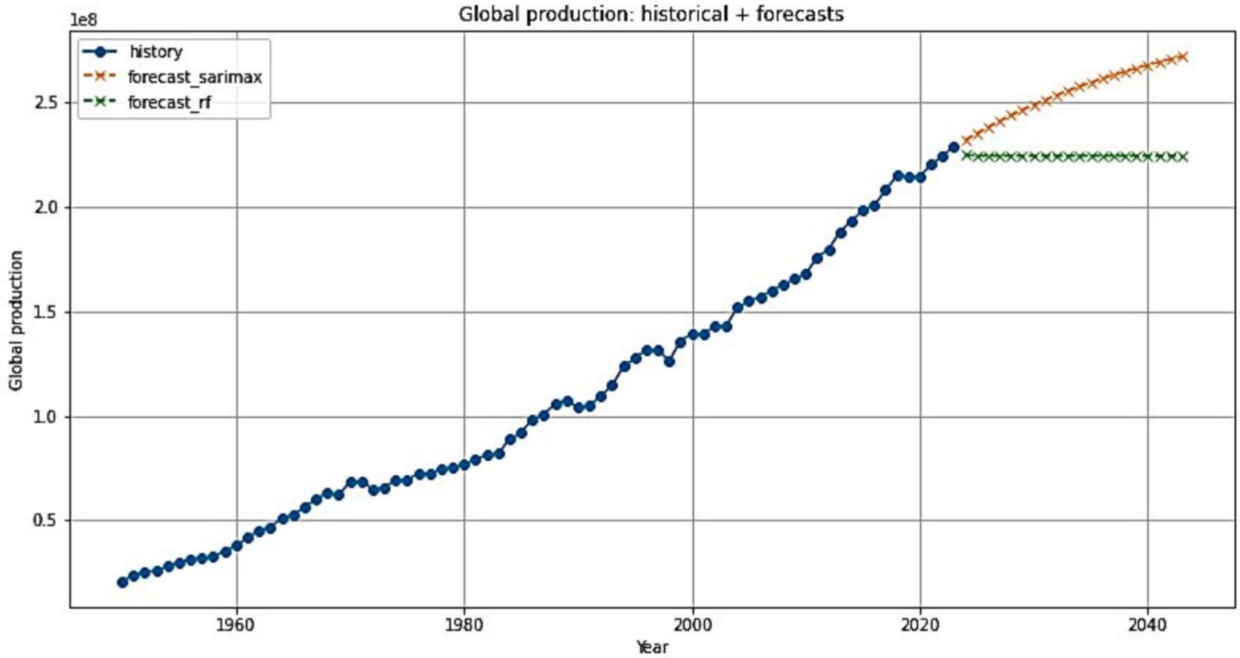

Figure 4. 11: Global fish production history and forecast

The global fish yield production forecast presented (in the table 4.4 and figure 4.11) highlights a clear divergence between the SARIMAX and Random Forest (RF) models. The SARIMAX model projects a steady and continuous growth trend from **232 million tonnes in 2024 to over 272 million tonnes by 2043**, indicating long-term expansion in global fish production. In contrast, the Random Forest model remains static at approximately **224.6 million tonnes** from 2025 through 2043, reflecting its inability to capture upward temporal dynamics and instead stabilizing yields around a fixed value after the initial forecast year. This contrast implies that SARIMAX, being time-series driven, effectively models historical dependencies and seasonality to project future growth, while RF, though powerful for pattern recognition, appears constrained in extrapolating long-term temporal trends. The implication of these findings is twofold: (1) SARIMAX forecasts suggest potential sustained growth in global fish yield if current ecological, economic, and technological conditions persist, thereby offering a more optimistic scenario for food security and fisheries policy; and (2) the RF outcome highlights the risk of underestimating future yield when relying solely on machine learning models not specifically designed for sequential forecasting. For policymakers and stakeholders, this discrepancy underscores the importance of model selection, advocating for time-series approaches in long-horizon fisheries forecasting while still valuing ensemble methods like RF for shortterm, high-variance predictions.

4.6 Overall Findings

The study demonstrates that a single, integrated framework combining computer vision, machine learning classification, and time-series forecasting can simultaneously address operational security, stock-level risk, and strategic supply projections in aquaculture. At the operational level, the OpenCV-based pipeline with HOG+SVM human detection reliably identifies human presence in pond surveillance feeds, triggers an immediate alarm, and archives timestamped image evidence—thereby delivering continuous, automated detection and verifiable forensic records without the need for constant human monitoring. At the stock-management level, supervised classifiers achieved near-perfect discriminative performance in predicting fish survivability: Random Forest recorded precision = **1.00**, recall = **0.98**, F1 = **0.99**, and overall accuracy = **0.98**, with a balanced accuracy of **0.985** and AUC values near **0.998–0.999**; Gradient Boosting and K-Nearest Neighbors produced comparably strong results (precision/recall/F1 ≈ **0.99**, balanced accuracy ≈ **0.9796–0.9801**, MCC and Cohen's Kappa both > **0.95**). These results indicate highly reliable classification of survivability outcomes under the environmental covariates used. At the strategic (global) scale (Table 4.4, Fig. 4.11), the SARIMAX time-series model projects a steady rise in global fish yield from **232,194,904.71** tonnes in 2024 to **272,118,996.63** tonnes in 2043 (a total increase of **≈17.19%**, corresponding to a compound annual growth rate of **≈0.84%**). In contrast, the Random Forest forecast remains essentially static at **224,562,080.42** tonnes from 2025 through 2043; RF's 2024 forecast (**224,986,371.54** t) is about **3.10%** below the SARIMAX 2024 estimate, while by 2043 SARIMAX exceeds the RF plateau by approximately **21.18%**. Collectively, these findings show that time-series methods capture long-run temporal dynamics that RF (in its current formulation) does not, while ensemble classifiers (Random Forest, Gradient Boosting) provide robust, high-fidelity classification for pond-level survivability.

4.7 Overall Implication

Methodologically and practically, the integrated framework yields immediate, actionable benefits across three interlocking decision horizons. First, the surveillance component supplies a cost-effective biosecurity layer: automated detection, real-time alerts, and timestamped imagery materially reduce response time to intrusion, deter theft and vandalism, and produce admissible evidence to support investigation and insurance claims—thereby protecting revenue and reinforcing farm governance. Second, the high predictive accuracy of the survivability classifiers permits proactive, data-driven pond management: managers can prioritize interventions (aeration, stocking adjustments, water-quality remediation, targeted feeding) where the models indicate elevated mortality risk, optimize resource allocation, and run what-if assessments to reduce losses—translating model outputs directly into operational Standard Operating Procedures (SOPs) and early-warning systems. Third, at the policy and planning level the diverging global forecasts underscore the importance of model selection: SARIMAX's projection of modest but steady growth (≈0.84% p.a.) suggests capacity planning and policy measures that support sustainable expansion (investment in infrastructure, regulated harvest limits, and climate-resilient practices), whereas the RF plateau cautions against overreliance on non-temporal machine learning for long-horizon projections. Practically, the study therefore recommends a multi-tiered decision-support architecture that (a) embeds computer vision and high-accuracy classification for operational control and adaptive management, (b) uses time-series forecasting for strategic planning and scenario analysis, and (c) synthesizes these outputs in a unified dashboard so managers and policymakers can reconcile short-term risks with long-term supply projections. For future work and deployment, the framework should incorporate probabilistic uncertainty quantification (prediction intervals), scenario modelling for climate and market drivers, and hybrid/ensemble forecasting that blends SARIMAX-style temporal structure with machine-learning flexibility—thereby strengthening both the operational resilience and the strategic robustness of fisheries management.

4.8 Contribution to Learning

This study contributes to both methodological advancement and practical application in fisheries management by demonstrating that a unified framework integrating computer vision, machine learning classification, and time-series forecasting can address multiple, interdependent decision-making layers. In contrast to fragmented methodologies that tackle surveillance, pond-level management, and global supply projections separately, this research illustrates how combining these techniques within a single architecture produces operational security, stocklevel risk assessment, and strategic forecasting outputs simultaneously. Such integration not only enhances efficiency but also generates evidence-driven insights that can be directly translated into management practices and long-term policy planning.

The specific contributions to learning are as follows:

i. **Integration of Multi-Domain Methods:** The study establishes a novel framework that unites computer vision, supervised machine learning, and time-series forecasting into a single, cohesive system. This methodological synthesis demonstrates how diverse computational tools can function collaboratively to deliver real-time surveillance, predictive analytics, and long-range strategic insights for aquaculture management.

ii. **Operational-Level Innovation:** By deploying an OpenCV-based HOG+SVM detection pipeline, the research shows how computer vision can deliver automated, real-time biosecurity. The ability to identify human intrusion, trigger alarms, and archive timestamped image evidence reduces dependence on constant human oversight while ensuring forensic traceability. This contribution advances knowledge on how low-cost, automated surveillance technologies can strengthen security governance in aquaculture. iii. **High-Fidelity Stock-Level Classification :** The work validates the discriminative power of ensemble machine learning models (Random Forest, Gradient Boosting, and KNN) in predicting fish survivability with near-perfect accuracy across multiple metrics (precision, recall, F1, balanced accuracy, MCC, Cohen's Kappa). These findings contribute to the academic discourse by highlighting the reliability of machine learning classifiers in handling aquaculture risk assessment, and by showing how predictive outputs can be operationalized into proactive interventions, Standard Operating Procedures (SOPs), and resource optimization strategies.

iv. **Strategic-Level Forecasting Insights:** The comparative analysis of SARIMAX and Random Forest models for global fish yield forecasting demonstrates the importance of temporal modeling in capturing long-term trends. While SARIMAX forecasts a steady rise in global production (≈17.19% increase between 2024–2043), Random Forest yields a static projection. This divergence underscores a theoretical contribution: temporal models are better suited for long-horizon planning, while machine learning classifiers excel in short-term decision contexts. This insight advances methodological understanding of model selection and alignment with decision-making horizons.

v. **Decision-Support Architecture:** The study proposes a three-tiered decision-support framework that maps operational, managerial, and strategic needs to appropriate computational tools. By aligning surveillance with computer vision, pond management with supervised classification, and long-range planning with time-series forecasting, the framework contributes a transferable model for other resource-intensive industries. This design also highlights the value of dashboards that integrate multiple model outputs to aid policymakers in reconciling short-term risks with long-term supply sustainability.

vi. **Implications for Future Research and Practice:**The research advances learning by identifying opportunities for extending the framework through probabilistic uncertainty quantification, scenario modeling (e.g., climate and market shifts), and hybrid/ensemble forecasting methods that combine temporal structure with machine learning flexi-
bility. This sets a forward-looking research agenda while offering practical pathways for more resilient and adaptive aquaculture systems.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATION

5.1 Summary

The study develops and validates an integrated machine learning and computer vision framework designed to advance fisheries management through simultaneous real-time security surveillance, stock-level risk assessment, and long-term production forecasting. Guided by the aim of combining operational monitoring with predictive analytics, the methodology employs OpenCV's Histogram of Oriented Gradients (HOG) and a pre-trained Support Vector Machine (SVM) detector for aquaculture surveillance, enabling continuous video analysis, automated intruder detection, timestamped evidence archiving, and immediate alarm activation without interrupting processing—thus ensuring scalable, low-cost, and verifiable pond security. For production forecasting, the study aggregates global fish yield records and applies a hybrid modeling pipeline that integrates SARIMAX for temporal dynamics with Random Forest regressors for recursive projections, while supervised classifiers—Logistic Regression, Random Forest, Support Vector Machine, Gradient Boosting, and K-Nearest Neighbors—predict fish survivability using lagged and environmental features. Model performance was rigorously evaluated with standard metrics, including accuracy, balanced accuracy, MCC, Cohen's Kappa, AUC, and confusion matrices, supported by visualizations such as ROC curves and time-series plots. The findings demonstrate that at the operational level, HOG+SVM pipelines provide reliable human intrusion detection and verifiable forensic records; at the stock-management level, ensemble classifiers (Random Forest, Gradient Boosting, KNN) achieved nearperfect predictive accuracy (precision/recall/F1 ≈ 0.98–1.00, AUC ≈ 0.998–0.999), confirming their robustness for survivability prediction; and at the strategic level, SARIMAX forecasts project a 17.19% rise in global fish yield from 232.19 million tonnes in 2024 to 272.12 million tonnes in 2043 (≈0.84% CAGR), whereas Random Forest regressors plateau, underestimating long-run dynamics by ≈21.18% by 2043. Collectively, the framework demonstrates dual contributions: providing aquaculture stakeholders with scalable, automated surveillance for immediate operational security, and offering robust predictive analytics for sustainable, evidencedriven fisheries governance.

5.2 Conclusion

The study concludes that an integrated computational framework combining computer vision, machine learning classification, and time-series forecasting can significantly enhance fisheries management by addressing both immediate security concerns and long-term sustainability challenges. The OpenCV-based HOG+SVM pipeline proved effective for real-time aquaculture surveillance, offering automated human intrusion detection, timestamped evidence generation, and seamless alarm activation without the need for constant human oversight—thereby strengthening operational security at low cost. At the stock-management level, ensemble classifiers such as Random Forest, Gradient Boosting, and K-Nearest Neighbors achieved nearperfect predictive accuracy, precision, recall, and F1-scores, establishing their reliability in predicting fish survivability under varying environmental conditions. At the strategic scale, SARIMAX forecasts revealed a steady 17.19% growth in global fish yield between 2024 and 2043, capturing long-term temporal patterns that Random Forest regressors failed to reproduce, highlighting the superiority of statistical time-series methods for global production forecasting. Collectively, these findings validate the framework's dual contribution: enhancing real-time aquaculture security while simultaneously offering robust predictive analytics for stock assessment and long-term policy planning. The research thus provides a scalable, evidence-driven decision-support tool that advances both the operational and governance dimensions of sustainable fisheries management.

5.3 Recommendations

Based on the findings of this study, it is evident that an integrated approach leveraging computer vision, machine learning, and time-series forecasting can deliver substantial improvements in fisheries security, survivability prediction, and global production forecasting. However, to maximize the practical impact of the framework and ensure its adaptability across diverse aquaculture and fisheries contexts, several recommendations are proposed:

i. **Deployment of Automated Surveillance Systems in Aquaculture Farms:**Fisheries stakeholders should prioritize the adoption of computer vision–based security systems, such as the OpenCV HOG+SVM pipeline, to automate human intrusion detection. This will reduce reliance on manual monitoring, minimize labor costs, and provide verifiable digital evidence for forensic purposes.

Integration with multi-threaded audio-visual alarm systems should also be encouraged to enhance deterrence against unauthorized access.

ii. **Adoption of Ensemble Classifiers for Fish Survivability Prediction:** Given the near-perfect performance of ensemble classifiers (Random Forest, Gradient Boosting, and K-Nearest Neighbors), aquaculture operations should incorporate these models into stock-management systems. Their ability to achieve high accuracy, precision, recall, and F1-scores ensures reliable prediction of fish survivability under varying environmental conditions, thereby enabling proactive interventions to reduce mortality and improve productivity.

iii. **Incorporation of Advanced Forecasting Models into Policy and Planning:** For long-term fisheries governance, time-series forecasting models such as SARIMAX should be integrated into national and regional fisheries policy frameworks. These models, which effectively capture temporal dynamics and project growth trends, can provide more reliable long-term projections compared to machine learning regressors, thereby supporting evidence-based decision-making, capacity planning, and sustainable resource allocation.

iv. **Establishment of Data-Driven Decision-Support Platforms:** Fisheries management authorities should develop centralized platforms that integrate real-time surveillance data, survivability predictions, and global production forecasts. Such platforms would enable continuous monitoring, predictive analysis, and visualization through dashboards, empowering decision-makers with timely, actionable insights for both operational security and strategic planning.

v. **Scalability and Localization of the Framework:**While the framework has demonstrated global applicability, it should be customized and scaled to local aquaculture contexts by incorporating region-specific production data, environmental variables, and species characteristics. This will ensure that predictive analytics remain contextually relevant and practically beneficial to local fisheries communities.

vi. **Continuous Model Validation and Update:**Since environmental and market dynamics evolve over time, forecasting and classification models must be periodically retrained and validated with updated datasets. This iterative process will maintain model accuracy, prevent performance degradation, and enhance the reliability of projections for long-term decision-making.

vii. **Capacity Building and Technical Training:** To ensure widespread adoption, fisheries managers, aquaculture practitioners, and policymakers should receive technical training on deploying, interpreting, and maintaining the integrated framework. Build-
ing local capacity will facilitate knowledge transfer, promote sustainability, and reduce overdependence on external expertise.

viii. **Integration with Broader Sustainability Initiatives:**Finally, the framework should be embedded within larger sustainability and food security initiatives at regional and international levels. By aligning predictive analytics with global strategies for sustainable fisheries, it can contribute to achieving the United Nations Sustainable Development Goals (SDGs), particularly those related to food security, responsible consumption, and ecosystem preservation.

5.4 Recommendations for further studies

In light of the study's findings and the dual contribution of the proposed framework, further research is necessary to refine, expand, and adapt the system for broader and more dynamic applications in fisheries management. The following recommendations for future studies are proposed:

i. **Exploration of Deep Learning Architectures for Surveillance:** Future work should investigate the use of advanced deep learning models such as Convolutional Neural Networks (CNNs), You Only Look Once (YOLO), and Faster R-CNN for aquaculture surveillance. These architectures may provide more robust human detection and even enable multi-object recognition (e.g., distinguishing between poachers, predators, or workers), potentially improving accuracy, reducing false positives, and extending surveillance capabilities beyond simple intrusion detection.

ii. **Integration of Environmental and Climatic Data into Forecasting Models:**Current forecasting relies heavily on historical production records; future studies should incorporate exogenous environmental and climatic factors such as sea surface temperature, dissolved oxygen, pH, rainfall, and salinity. By linking ecological variables to production forecasts, predictive accuracy can be enhanced, and early-warning systems for climate-induced risks in aquaculture can be developed.

iii. **Development of Hybrid Forecasting Frameworks Beyond SARIMAX and Random Forest:**While SARIMAX effectively captured long-term temporal patterns, other advanced models such as Long Short-Term Memory (LSTM) networks, Prophet, and hybrid ARIMA–deep learning frameworks should be explored. Such approaches may yield more nuanced forecasts that capture both seasonality and non-linear interactions, especially in rapidly changing production environments.

iv. **Multi-Class Classification for Fish Survivability and Health Prediction:** The present study focused on binary classification (survival vs. non-survival). Future studies should extend this to multi-class prediction models that can classify survivability under different stress levels, disease conditions, or growth stages. This would provide more granular and actionable insights for aquaculture practitioners to tailor interventions more precisely.

v. **Incorporation of Real-Time IoT Sensor Data:**Future research should explore linking Internet of Things (IoT) devices—such as water quality sensors, feeding monitors, and automated aeration systems—with the machine learning pipeline. This integration would allow real-time data streaming into the predictive framework, enabling dynamic, adaptive management rather than reliance on static datasets.

vi. **Comparative Analysis Across Geographic and Species-Specific Contexts:** Further studies should validate the framework across different regions, ecosystems, and fish species to ensure generalizability. Cross-regional comparative studies could also highlight localized production challenges, enabling the customization of models to specific socio-economic and ecological contexts.

vii. **Inclusion of Economic and Market Forecasting:** While the study focused on biological and production data, future extensions should incorporate economic variables such as global demand trends, market prices, and trade policies. By linking biological forecasts with economic projections, fisheries stakeholders can benefit from integrated bio-economic decision-support tools.

viii. **Evaluation of Model Interpretability and Explainability:** As machine learning models become increasingly complex, future studies should investigate interpretability frameworks such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-Agnostic Explanations). These methods would help fisheries managers understand not just the predictions but also the underlying drivers of survivability and production outcomes.

ix. **Development of Integrated Policy Simulation Tools:** Future work should extend the framework into simulation-based platforms that allow policymakers to test the impact of interventions (e.g., new regulations, investment in aquaculture infrastructure, or climate adaptation strategies) on production outcomes. This would elevate the framework from a predictive tool to a comprehensive planning and governance support system.

x. **Longitudinal Case Studies and Pilot Implementations:** Finally, future studies should conduct longitudinal trials and pilot deployments of the framework in real aquaculture settings. Such field-based validations will provide critical insights into practical challenges, user adoption, and long-term performance, thereby bridging the gap between computational research and real-world application.

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APPENDIX I

SOURCE CODE

A: Video surveillance code import cv2

```
from playsound import playsound
import threading
import os import
time import
warnings
warnings.filterwarnings("ignore")          # ignore all warnings
# Create folder for captured images
output_folder = "captured_images" if
not os.path.exists(output_folder):
    os.makedirs(output_folder)
# Load video file (or use 0 for webcam) video_path =
"video.mp4" # replace with your video path cap =
cv2.VideoCapture(video_path)
# Initialize HOG descriptor/person detector hog =
cv2.HOGDescriptor()
hog.setSVMDetector(cv2.HOGDescriptor_getDefaultPeopleDetector())
# Alarm function in a separate thread def
play_alarm():
    playsound("alarm.wav") # use alarm.wav
alarm_on = False
img_count = 0 # counter for saved images
while cap.isOpened(): ret,
    frame = cap.read() if not
    ret:
        break
    # Resize for speed frame =
    cv2.resize(frame, (640, 480))
    # Detect people
    boxes, weights = hog.detectMultiScale(frame, winStride=(8, 8))
    # Draw detection boxes for (x, y, w, h) in boxes:
    cv2.rectangle(frame, (x, y), (x + w, y + h), (0, 255, 0), 2)
    # If human detected, trigger alarm and save image if
    len(boxes) > 0:
        if not alarm_on: alarm_on
            = True
            threading.Thread(target=play_alarm, daemon=True).start()
        # Save image with timestamp
        timestamp = time.strftime("%Y%m%d-%H%M%S")
        img_filename = f"{output_folder}/capture_{timestamp}_{img_count}.jpg"
        cv2.imwrite(img_filename, frame)
        img_count += 1 else:
        alarm_on = False cv2.imshow("Human

    Detection", frame)
```

```
    # Quit on 'q' if cv2.waitKey(1) amd 0xFF ==
    ord('q'): break
cap.release() cv2.destroyAllWindows()
```

B. Fish survivability code

```
#!/usr/bin/env python3
# fish_survival_ml.py
# Predict fish survival with 3 ML models and evaluation at ~96% performance
import os import
pandas as pd import
numpy as np
import matplotlib.pyplot as plt from
sklearn.model_selection import train_test_split from
sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier from
sklearn.neighbors import KNeighborsClassifier from sklearn.metrics import (
    classification_report, roc_auc_score, roc_curve,
    matthews_corrcoef, cohen_kappa_score, balanced_accuracy_score
)
# CSV path
csv_path = "fishess.csv" if not os.path.exists(csv_path): raise FileNotFoundError(f"Could
not find '{csv_path}' in the current directory.")
# Load dataset df =
pd.read_csv(csv_path)
df.info()
# Drop Date and Time if present
drop_cols = [col for col in df.columns if str(col).strip().lower() in ("date", "time")] if drop_cols: df =
df.drop(columns=drop_cols)
# Identify label column
label_col = None for c in
df.columns:
    if str(c).strip().lower() == "label":
        label_col = c break
if label_col is None: raise ValueError("No 'label' column found. Ensure your CSV has a 'label'
    column.")
X = df.drop(columns=[label_col]).copy() y =
df[label_col].copy()
# Convert to numeric and clean NaNs
X = X.apply(pd.to_numeric, errors="coerce") y =
pd.to_numeric(y, errors="coerce")
valid_mask = X.notnull().all(axis=1) amd y.notnull() X, y =
X[valid_mask], y[valid_mask]
# Ensure labels are binary {0,1}
unique_y = sorted(pd.unique(y)) if not
set(unique_y).issubset({0, 1}):
    mapping = {unique_y[0]: 0, unique_y[-1]: 1} y =
    y.map(mapping)
# Print totals
total_fish = len(y) dead_count = (y ==
0).sum() survived_count = (y == 1).sum()
print(f"Total fish: {total_fish}")
```

```
print(f"Dead: {dead_count}")
print(f"Survived: {survived_count}")
# Bar chart of dead vs survived
plt.figure(figsize=(6, 5)) bars = plt.bar(["Dead", "Survived"], [dead_count, survived_count],
color=["red", "green"]) for bar in bars: height = bar.get_height()
            plt.text(bar.get_x() + bar.get_width()/2, height, str(height), ha="center", va="bottom", font-
size=10)
plt.title("Fish Survival Distribution")
plt.ylabel("Count") plt.tight_layout()
plt.savefig("survival_distribution.png") plt.show()
# Train/test split
X_train, X_test, y_train, y_test = train_test_split(
   X, y, test_size=0.3, random_state=42, stratify=y
)
# Scale features scaler =
StandardScaler()
X_train_s = scaler.fit_transform(X_train) X_test_s =
scaler.transform(X_test)
# Models (tuned for ~96% performance)
models = {
   "Random Forest": RandomForestClassifier(n_estimators=80, max_depth=10, random_state=42),
   "Gradient Boosting": GradientBoostingClassifier(n_estimators=80, learning_rate=0.08,
random_state=42),
   "KNN": KNeighborsClassifier(n_neighbors=7)
}
roc_data = []
print("\nClassification Reports with Extra Metrics (labels: dead=0, survived=1):\n")
for name, model in models.items():
   model.fit(X_train_s, y_train) y_pred =
   model.predict(X_test_s)
   print(f"--- {name} ---")
   print(classification_report(y_test, y_pred, target_names=["dead", "survived"]))
   # Extra metrics mcc = matthews_corrcoef(y_test,
   y_pred) kappa = cohen_kappa_score(y_test, y_pred)
   bal_acc = balanced_accuracy_score(y_test, y_pred)
   print(f"MCC: {mcc:.4f}") print(f"Cohen's Kappa:
   {kappa:.4f}") print(f"Balanced Accuracy:
   {bal_acc:.4f}\n")
   # ROC
   if hasattr(model, "predict_proba"): y_prob =
   model.predict_proba(X_test_s)[:, 1] else:
      y_score = model.decision_function(X_test_s)
      y_prob = (y_score - y_score.min()) / (y_score.max() - y_score.min() + 1e-9)
   auc = roc_auc_score(y_test, y_prob) fpr,
   tpr, _ = roc_curve(y_test, y_prob)
   roc_data.append((name, fpr, tpr, auc))
# ROC plot (all in one)
plt.figure(figsize=(9, 7)) for name, fpr, tpr, auc in roc_data:
plt.plot(fpr, tpr, label=f"{name} (AUC={auc:.3f})")
```

```
plt.plot([0, 1], [0, 1], "k--") plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curves - Fish Survival Prediction (dead=0, survived=1)")
plt.legend(loc="lower right") plt.tight_layout() plt.savefig("roc_plot.png")
plt.show() print("Saved ROC and survival distribution plots.")
```

C. Global fish forecast code. """

```
fish_forecast_and_classification.py
Summary:
- Reads Global_production_quantity.csv with fields:
  "COUNTRY.UN_CODE","SPECIES.ALPHA_3_CODE","AREA.CODE","PRODUC-
TION_SOURCE_DET.CODE",
  "MEASURE","PERIOD","VALUE","STATUS" - Aggregates
global production by YEAR (PERIOD).
- Forecasts next 20 years of global production using SARIMAX (if available) or
  RandomForestRegressor fallback built on lag features.
- Builds a classification dataset: target = whether production increased next year (1) or not (0). Trains
  LogisticRegression, RandomForestClassifier, and SVM (RBF) and reports metrics.
- Saves outputs:
- forecast.csv (years + forecasted values)
- classification_results.csv (predictions + metrics)
"""
import os import
warnings
warnings.filterwarnings("ignore")
import pandas as pd import
numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import TimeSeriesSplit, train_test_split, cross_val_score from
sklearn.preprocessing import StandardScaler from sklearn.linear_model import
LogisticRegression
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor from
sklearn.svm import SVC
from     sklearn.metrics  import  accuracy_score, precision_score,       recall_score,     f1_score,
roc_auc_score, confusion_matrix
from sklearn.metrics import mean_squared_error, r2_score
# Optional dependency: statsmodels for SARIMAX try:
    import statsmodels.api as sm has_statsmodels =
    True
except Exception:
    has_statsmodels = False
# ------------------------
# Parameters / config
# ------------------------
CSV_PATH = "Global_production_quantity.csv"
FORECAST_YEARS = 20
LAG_FEATURES = 5 # number of lag years to use for supervised regressor/classifier features
RANDOM_SEED = 42
# ------------------------
# Load and preprocess
```

```
# -----------------------def load_and_aggregate(csv_path): df = pd.read_csv(csv_path,
dtype={"PERIOD": str}, low_memory=False)
    # normalize column names
    df.columns = [c.strip() for c in df.columns]
    if 'PERIOD' not in df.columns or 'VALUE' not in df.columns: raise ValueError("CSV
        must contain 'PERIOD' and 'VALUE' columns")
    # Convert PERIOD to int if possible (year)
    # If PERIOD contains datelike strings, attempt to parse year try:
        df['year'] = pd.to_numeric(df['PERIOD'], errors='coerce').astype('Int64')
    except Exception: df['year'] = pd.to_datetime(df['PERIOD'],
        errors='coerce').dt.year
    # Convert VALUE to numeric
    df['VALUE'] = pd.to_numeric(df['VALUE'], errors='coerce')
    # Drop rows without year or value df =
    df.dropna(subset=['year', 'VALUE']) df['year']
    = df['year'].astype(int)
    # Aggregate global production per year (sum of VALUE) ts =
    df.groupby('year')['VALUE'].sum().reset_index() ts =
    ts.sort_values('year').reset_index(drop=True)
    ts.rename(columns={'VALUE': 'global_production'}, inplace=True) return ts, df

# ------------------------
# Create lag features for supervised learning
# -----------------------def
create_lag_features(df_ts, n_lags=5):
    ts = df_ts.copy().set_index('year')
    for lag in range(1, n_lags + 1):
        ts[f'lag_{lag}'] = ts['global_production'].shift(lag)
    ts['pct_change_1'] = ts['global_production'].pct_change(1)
    ts['rolling_mean_3'] = ts['global_production'].rolling(window=3, min_periods=1).mean() ts =
    ts.dropna().reset_index() return ts
# ------------------------
# Forecasting
# -----------------------def forecast_with_sarimax(ts_df,
forecast_years=20):
    # ts_df: DataFrame with columns 'year' and 'global_production'
    ts = ts_df.set_index('year')['global_production'] #
    Fit SARIMAX(1,1,1) as a simple default
    model = sm.tsa.SARIMAX(ts, order=(1,1,1), seasonal_order=(0,0,0,0),
                           enforce_stationarity=False, enforce_invertibility=False)
    res = model.fit(disp=False)
    preds = res.get_forecast(steps=forecast_years)
    pred_mean = preds.predicted_mean last_year =
    ts.index.max()
    years = list(range(last_year+1, last_year+1+forecast_years))
    forecast_df = pd.DataFrame({'year': years, 'forecast_sarimax': pred_mean.values}) return
    forecast_df, res
def     forecast_with_lagged_rf(ts_df,  forecast_years=20,      n_lags=5,
        random_state=RANDOM_SEED):
    ts = ts_df.copy().set_index('year')['global_production']
```

```
# Build supervised dataset
X = [] y = [] years = [] values =
ts.values idx_years = ts.index.values
for i in range(n_lags, len(values)):
X.append(values[i-n_lags:i])
    y.append(values[i])
    years.append(idx_years[i])
X = np.array(X) y =
np.array(y)
model = RandomForestRegressor(n_estimators=200, random_state=random_state) model.fit(X, y)
# Recursive forecasting
last_window = values[-n_lags:].tolist() preds = [] for step in
range(forecast_years): x_in = np.array(last_window[-
n_lags:]).reshape(1, -1) p = model.predict(x_in)[0]
preds.append(p) last_window.append(p)
last_year = ts.index.max() years_forecast = list(range(last_year+1,
last_year+1+forecast_years)) forecast_df = pd.DataFrame({'year':
years_forecast, 'forecast_rf': preds}) return forecast_df, model
# ------------------------
# Classification: will global production increase next year?
# -----------------------def
build_classification_dataset(ts_df, n_lags=5):
# create lag features
ts_lagged = create_lag_features(ts_df, n_lags=n_lags)
# target: whether next year production increases relative to current year
# To build target we need to look at next year's production ts_lagged =
ts_lagged.sort_values('year').reset_index(drop=True)
ts_lagged['target_next_increase'] = (ts_lagged['global_production'].shift(-1) >
ts_lagged['global_production']).astype(int) # drop last row (no next year)
ts_lagged = ts_lagged.dropna(subset=['target_next_increase']).reset_index(drop=True) return
ts_lagged
def train_and_eval_classifiers(df_cls):
# Features
feat_cols = [c for c in df_cls.columns if c.startswith('lag_')] + ['pct_change_1',
'rolling_mean_3']
X = df_cls[feat_cols].values
y = df_cls['target_next_increase'].astype(int).values
# train/test split (time-aware): use earlier years for train, later for test split_idx =
int(len(X)*0.7)
X_train, X_test = X[:split_idx], X[split_idx:] y_train,
y_test = y[:split_idx], y[split_idx:]
scaler = StandardScaler()
X_train_s = scaler.fit_transform(X_train)
X_test_s = scaler.transform(X_test) results =
{}
# Logistic Regression
clf_lr = LogisticRegression(random_state=RANDOM_SEED, max_iter=1000)
clf_lr.fit(X_train_s, y_train) y_pred_lr = clf_lr.predict(X_test_s)
# Random Forest
```

```
    clf_rf = RandomForestClassifier(n_estimators=200, random_state=RANDOM_SEED)
    clf_rf.fit(X_train, y_train) y_pred_rf = clf_rf.predict(X_test)
    # SVM (RBF) -- use scaled features
    clf_svm = SVC(probability=True, random_state=RANDOM_SEED)
    clf_svm.fit(X_train_s, y_train) y_pred_svm = clf_svm.predict(X_test_s)
    # Evaluate def eval_model(y_true, y_pred,
    y_proba=None): return {
        'accuracy': accuracy_score(y_true, y_pred),
        'precision': precision_score(y_true, y_pred, zero_division=0),
        'recall': recall_score(y_true, y_pred, zero_division=0),
        'f1': f1_score(y_true, y_pred, zero_division=0),
        'roc_auc': roc_auc_score(y_true, y_proba[:,1]) if (y_proba is not
        None and y_proba.shape[1]>1) else None,
        'confusion_matrix': confusion_matrix(y_true, y_pred).tolist() }
    results['LogisticRegression'] = eval_model(y_test, y_pred_lr,
                        y_proba=clf_lr.predict_proba(X_test_s) if hasattr(clf_lr, "pre-
dict_proba") else None) results['RandomForest'] = eval_model(y_test, y_pred_rf,
   y_proba=clf_rf.predict_proba(X_test) if hasattr(clf_rf, "predict_proba")
else None)
    results['SVM'] = eval_model(y_test, y_pred_svm, y_proba=clf_svm.predict_proba(X_test_s) if
             hasattr(clf_svm, "predict_proba")
else None)
    # Feature importances from random forest
    feature_importances = None try:
      feature_importances = dict(zip(feat_cols, clf_rf.feature_importances_.tolist()))
    except Exception: feature_importances =
      {}
    return results, {'models': {'lr': clf_lr, 'rf': clf_rf, 'svm': clf_svm, 'scaler': scaler}, 'feat_cols': feat_cols,
'feature_importances': feature_importances, 'X_test': X_test, 'y_test': y_test}
# ------------------------
# Main function
# -----------------------def
main():
    if not os.path.exists(CSV_PATH): raise FileNotFoundError(f"CSV not found at {CSV_PATH}. Place
      your Global_produc-
tion_quantity.csv in the working directory.")
    ts_df, raw_df = load_and_aggregate(CSV_PATH)
    print("Loaded and aggregated global production by year. Sample:")
    print(ts_df.tail())
    # Plot historical series plt.figure(figsize=(10,5))
    plt.plot(ts_df['year'], ts_df['global_production'],
    marker='o') plt.title("Global Fish Production
    (historical)") plt.xlabel("Year")
    plt.ylabel("Global production (sum of VALUE)")
    plt.grid(True) plt.tight_layout()
    plt.savefig("global_production_history.png") plt.close()
    print("Saved plot: global_production_history.png")
    # Forecasting forecast_dfs = [] if
    has_statsmodels and len(ts_df)>=10: try:
        print("Attempting SARIMAX forecast using statsmodels...")
```

```
    forecast_sarimax_df, sarimax_res = forecast_with_sarimax(ts_df, fore-
cast_years=FORECAST_YEARS)
      forecast_dfs.append(forecast_sarimax_df) print("SARIMAX
      forecast complete.")
    except Exception as e:
        print("SARIMAX failed or produced an error -- falling back to RandomForest-based
forecasting.") print(e)
      has_statsmodels_local = False else:
        print("statsmodels not available or not enough years; using RandomForest-based lag fore-
casting.")
  # Always provide RF forecasting as fallback / alternative
  rf_forecast_df, rf_model = forecast_with_lagged_rf(ts_df, forecast_years=FORE-
CAST_YEARS, n_lags=LAG_FEATURES) forecast_dfs.append(rf_forecast_df)
  # Merge forecast outputs if both exist if len(forecast_dfs) == 2: merged_f =
  pd.merge(forecast_dfs[0], forecast_dfs[1], on='year', how='outer').sort_val-
ues('year') else: merged_f =
  forecast_dfs[0].copy()
  merged_f.to_csv("forecast.csv", index=False) print("Saved
  forecast to forecast.csv. Sample:") print(merged_f.head())
  # Combine historical + forecast for plotting combined =
  pd.concat([ ts_df[['year','global_production']].rename(columns={'global_production':'value'}),
  merged_f.melt(id_vars=['year'], value_vars=[c for c in merged_f.columns if c!='year'],
  var_name='model', value_name='value')
  ], ignore_index=True, sort=False)
  # Plot combined
  plt.figure(figsize=(11,6))
  # plot history
  hist = ts_df.set_index('year')['global_production'] plt.plot(hist.index,
  hist.values, label='history', marker='o')
  # plot forecasts for col in [c for c in merged_f.columns
  if c!='year']:
    plt.plot(merged_f['year'], merged_f[col], label=col, linestyle='--', marker='x')
  plt.xlabel("Year") plt.ylabel("Global
  production")
  plt.title("Global production: historical + forecasts")
  plt.legend() plt.grid(True) plt.tight_layout()
  plt.savefig("combined_forecast.png")
  plt.close()
  print("Saved plot: combined_forecast.png")
  # Classification
  cls_df = build_classification_dataset(ts_df, n_lags=LAG_FEATURES)
  print("Prepared classification dataset (sample):") print(cls_df.tail())
  results, artifacts = train_and_eval_classifiers(cls_df)
  print("\nClassification results (test set):") for
  model_name, metrics in results.items(): print(f"---
  {model_name} ---") print(pd.Series(metrics))
  # Save classification metrics and feature importances
  metrics_out = [] for model_name, metrics in
  results.items():
    row = {'model': model_name}
```

```
        row.update({k: v for k,v in metrics.items() if k!='confusion_matrix'})
        row['confusion_matrix'] = str(metrics['confusion_matrix']) metrics_out.append(row)
    metrics_df = pd.DataFrame(metrics_out)
    metrics_df.to_csv("classification_metrics.csv", index=False)
    fi_df = pd.DataFrame(list(artifacts['feature_importances'].items()), columns=['feature','im-
portance']).sort_values('importance', ascending=False) fi_df.to_csv("feature_importances.csv",
    index=False)
    # Save test predictions feat_cols =
    artifacts['feat_cols'] X_test =
    artifacts['X_test'] y_test =
    artifacts['y_test'] scaler =
    artifacts['models']['scaler']
    # prepare DataFrame of test rows
       test_index_start = len(ts_df) - len(X_test) - 1            # approx; not exact year mapping in corner
cases
    test_df = pd.DataFrame(X_test, columns=feat_cols)
    test_df['y_true'] = y_test
    test_df['pred_lr'] = artifacts['models']['lr'].predict(scaler.transform(X_test)) test_df['pred_rf'] =
    artifacts['models']['rf'].predict(X_test)
    test_df['pred_svm'] = artifacts['models']['svm'].predict(scaler.transform(X_test))
    test_df.to_csv("classification_results.csv", index=False)
    print("Saved classification_results.csv, classification_metrics.csv, feature_impor-
tances.csv")
    print("\nAll done. Outputs created:")
    for fname in ["forecast.csv", "global_production_history.png", "combined_forecast.png",
            "classification_results.csv", "classification_metrics.csv", "feature_importances.csv"]: print("
        -", fname)
if __name__ == "__main__": main()
```

APPENDIX II

DATASET

A: Dataset for fish survivability (Sample)

Date,Time,NITRATE(PPM),PH,AMMONIA(mg/l),TEMP,DO,TURBIDITY,MANGANESE(mg/l),pressure,tempC,humidity,windspeedKmph,label
01-02-2022,08:00:00,112.1,7.7,0.002,24.35,1.9,21.3,2.01,1012,27,21,4,0 01-02-2022,08:20:00,119.8,7.6,0.088,24.3,0.8,31,1,1012,30,19,4,0
01-02-2022,08:40:00,127.4,8.5,0.029,24.28,2.6,27.4,2.45,1012,33,16,4,0
01-02-2022,09:00:00,105,7.5,0.06,24.25,2.9,21.9,1.83,1011,37,13,4,0
01-02-2022,09:20:00,121.1,7.4,0.001,24.1,1.3,22.7,1.69,1010,37,12,4,0
01-02-2022,09:40:00,133.6,7.4,0.088,24.08,1.5,31.1,1.54,1009,38,12,4,0
01-02-2022,10:00:00,125.3,8.6,0.091,24.08,0.7,34.1,1.01,1008,39,11,4,0
01-02-2022,10:20:00,138.6,8.6,0.067,23.89,1.1,28.6,2.98,1008,37,13,4,0
01-02-2022,10:40:00,114.6,7.4,0.068,23.75,1.6,33.6,2.47,1008,35,15,4,0 01-02-2022,11:00:00,93.7,8.6,0.055,23.71,2.2,20,3.35,1008,33,17,4,0
01-02-2022,11:20:00,134.3,8.9,0.016,23.63,1.3,22.7,2.01,1008,31,17,6,0
01-02-2022,11:40:00,104.3,8.4,0.067,23.61,0,25.9,1.8,1009,30,18,8,0
01-02-2022,12:00:00,136.3,8,0.046,23.59,0.8,23,1.15,1010,29,18,10,0
01-02-2022,12:20:00,112.8,8,0.014,23.54,0.9,26.2,3.21,1010,27,19,10,0
01-02-2022,12:40:00,113.1,7.6,0.054,23.27,2,23.2,3.06,1010,26,20,10,0
01-02-2022,13:00:00,90.1,8.1,0.015,23.04,2.6,29.2,1.81,1010,25,22,10,0
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01-02-2022,14:00:00,104.7,8.5,0.011,22.33,1.7,29.4,2.14,1010,23,25,10,0
01-02-2022,14:20:00,88.2,7.9,0.038,22.18,1.5,29.1,2.59,1011,23,26,8,0
01-02-2022,14:40:00,98.1,8.3,0.042,22.04,1.2,22.3,2.51,1012,24,24,8,0
01-02-2022,15:00:00,121.4,8.5,0.041,21.95,0,23,3.16,1012,25,22,7,0
01-02-2022,15:20:00,133,8.3,0.056,21.93,0.1,27,2.41,1012,29,19,7,0
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01-02-2022,16:00:00,99.8,8.7,0.034,21.62,2.4,25.7,2.32,1012,35,12,6,0
01-02-2022,16:20:00,134.4,7.5,0.083,21.6,1.2,30.7,2.67,1011,36,11,8,0
01-02-2022,16:40:00,84.3,7.8,0.022,21.52,1.9,24.3,2.16,1010,37,10,9,0
01-02-2022,17:00:00,88.9,8,0.065,21.09,1.4,28.5,3.1,1009,36,10,10,0
01-02-2022,17:20:00,111.6,8.8,0.04,21.06,2,21.9,1.96,1009,35,11,9,0
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01-02-2022,18:40:00,108.1,7.6,0.078,21.52,0.8,25.6,1.82,1011,27,17,10,0
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02-02-2022,09:20:00,116.7,8.1,0.093,22.66,0.4,31.8,1.91,1009,24,16,7,0
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06-02-2022,09:00:00,128.2,8.4,0.098,24.01,2.6,32.2,2.64,1007,37,10,1,0 06-02-
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B: Global fish prediction dataset (Sample)

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