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LEVERAGING MACHINE LEARNING TECHNIQUES FOR THE PREDICTION AND ENHANCEMENT OF FOOD SAFETY STANDARDS IN NIGERIA: A DATA-DRIVEN APPROACH TO IDENTIFYING AND MITIGATING CONTAMINATION RISKS

***[1]Kehinde, Abayomi Opeoluwa, [1]Onafowokan, Mariam Adeyinka and [2]Onalaja, Olawale Olalekan**

[1]Department of Health Information Management, Ogun State Polytechnic of Health and Allied Science, Ijebu, Ogun State, Nigeria.
[2]Department of Computer Science, Ogun State Polytechnic of Health and Allied Science, Ijebu, Ogun State, Nigeria.

*Corresponding authors' email: abayomikehinde1982@gmail.com

ABSTRACT

Food safety in Nigeria is a critical public health concern, with an estimated 200,000 annual foodborne illness cases straining a system reliant on traditional methods like inspections and laboratory testing. These approaches, hindered by high costs, limited scalability, and delays, struggle to address the growing complexity of contamination risks in the country's decentralized food supply chain. This study investigates the use of machine learning (ML) to predict food safety risks, leveraging data from 2015 to 2023, including over 50,000 data points from government reports, inspection records, and public datasets. Focusing on microbial contamination, chemical residues, and illness reports, the research tested three ML models: Random Forest (RF) with 89% accuracy, Support Vector Machines (SVM) with 85% accuracy, and Neural Networks (NN) with the highest performance at 91% accuracy, 89% precision, 88% recall, and an F1-score of 88%. The NN model excelled in predicting risks tied to fresh produce and processed foods, which account for about 60% of foodborne illnesses in Nigeria. Findings suggest ML, particularly NN, could reduce illness rates by up to 20% if scaled. The study highlights ML's potential to revolutionize food safety protocols, offering more accurate and reliable predictions than traditional methods. However, challenges such as poor data quality and availability could limit effectiveness. Addressing these barriers could enhance food safety management in Nigeria, improving public health and providing a scalable solution to a pressing national issue.

Keywords: Machine Learning, Food Safety, Nigeria, Prediction, Public Health

INTRODUCTION

Food safety remains a significant public health issue worldwide, particularly in developing countries like Nigeria, where the food supply chain is often complex, fragmented, and susceptible to contamination. According to the World Health Organization (WHO), an estimated 91 million cases of foodborne illnesses occur annually in Africa, with Nigeria contributing a significant proportion. Contaminants such as bacteria, viruses, parasites, chemicals, and heavy metals can infiltrate the food supply at various points, from production to consumption, posing serious health risks to the population. In Nigeria, the challenges are exacerbated by weak regulatory frameworks, inadequate infrastructure, and poor implementation of food safety standards.

Traditional food safety mechanisms, such as routine inspections and laboratory-based testing, have been the mainstay of ensuring food safety in Nigeria. These methods, however, are often labor-intensive, costly, and time-consuming. They can be ineffective in real-time monitoring, especially in a country where food production and distribution are highly decentralized. As a result, foodborne illnesses continue to be a significant public health burden, with economic losses estimated to reach billions of naira annually due to medical expenses, lost productivity, and food recalls.

In recent years, advances in data science and artificial intelligence (AI) have opened up new possibilities for addressing complex public health challenges, including food safety. Machine learning (ML), a subset of AI, has shown remarkable potential in predicting food safety risks by identifying patterns and correlations in vast datasets that may be difficult for humans to detect. ML models are capable of analyzing both structured and unstructured data, making them well-suited to the food safety domain, where data sources can vary widely in format and quality. For instance, ML techniques such as Neural Networks (NN), Random Forests (RF), and Support Vector Machines (SVM) have been successfully applied in various countries to detect contaminants, forecast foodborne illness outbreaks, and monitor supply chain risks (Wang et al., 2021).

However, the application of ML to food safety in Nigeria is still at an early stage, with limited studies addressing its potential in the country's context. The complex nature of Nigeria's food supply chain, combined with challenges such as data availability, poor record-keeping, and limited technological infrastructure, poses significant hurdles to adopting advanced technological solutions like ML. Nonetheless, with the growing availability of digital food safety records and increased attention to foodborne illness outbreaks, there is a timely opportunity to leverage ML for predictive analysis in Nigeria's food safety sector.

Machine learning (ML) has become a transformative technology across various fields, including healthcare, finance, and agriculture. In food safety, ML models are increasingly being applied to address challenges related to the detection, prediction, and management of food safety risks. Several studies have highlighted the potential of ML in improving the efficiency and accuracy of food safety monitoring, particularly when dealing with large and complex datasets. This section reviews the relevant literature on ML applications in food safety prediction, with a focus on contamination detection, foodborne disease prediction, and food supply chain management.

ML algorithms have shown great promise in identifying patterns and anomalies in food safety data that might be missed by traditional approaches. According to Wang et al. (2021), ML models such as Bayesian Networks (BN), Neural Networks (NN), and Support Vector Machines (SVM) have been successfully applied in various contexts to predict food safety risks, with significant improvements in predictive accuracy. Their review identified that the use of these models in food safety could significantly reduce foodborne illnesses by enabling timely interventions based on early warning signals from food contamination data. Additionally, ML models have been widely used to predict contamination by biological hazards such as pathogens (e.g., Salmonella and E. coli), chemical hazards like pesticide residues, and physical hazards such as metal fragments.

Wang et al. (2021) further note that the growing number of available digital records related to foodborne illnesses has enabled more accurate risk predictions. For instance, in a study by Bouzembrak et al. (2018), Bayesian networks were used to predict foodborne illness outbreaks in Europe by analyzing historical data from previous outbreaks and environmental factors. Their model achieved a predictive accuracy of 85%, suggesting that such approaches can be adapted to the Nigerian context, where foodborne illnesses remain a pressing issue.

While developed countries have made significant strides in integrating ML into their food safety systems, there is a growing body of research focusing on its application in developing countries. In countries like Nigeria, where food safety infrastructure is still developing, ML offers a cost-effective and scalable solution to food safety monitoring. In a study by van Asselt et al. (2018), ML algorithms were used to detect aflatoxin contamination in maize samples from various African countries. The study showed that Random Forest (RF) models could predict contamination levels with 90% accuracy using a relatively small dataset, highlighting the potential of ML in resource-constrained settings where data availability is often limited.

Another study by Liu et al. (2018) demonstrated the use of Support Vector Machines (SVM) to predict food safety violations in Chinese markets. By analyzing inspection reports and food safety records, the SVM model identified patterns associated with higher risks of violations. This approach could be adapted to Nigeria, where similar challenges exist due to inconsistent enforcement of food safety regulations and the fragmentation of the food supply chain. Importantly, the Liu et al. study underscores the need for robust datasets and continuous monitoring to ensure the accuracy and reliability of ML predictions.

A wide variety of ML models have been applied to food safety prediction, with varying degrees of success depending on the type of data and the specific food safety risk being addressed. The most commonly used models include:

Bayesian Networks (BN): Bayesian networks are probabilistic models that represent a set of variables and their conditional dependencies using a directed acyclic graph. In the context of food safety, BNs have been applied to predict foodborne illness outbreaks and contamination risks. For example, a study by Geng et al. (2017) employed Bayesian networks to assess the risk of Listeria contamination in dairy products, achieving an accuracy of 82%.

Neural Networks (NN): Neural networks are particularly well-suited for complex pattern recognition and have been used extensively in food safety prediction. Zhou et al. (2019) demonstrated that convolutional neural networks (CNNs) can be used to detect foodborne pathogens from image data, while recurrent neural networks (RNNs) are effective in analyzing text data related to food safety violations. NNs have also been applied to predict chemical contamination in various food products, with prediction accuracies exceeding 90% in some cases.

Support Vector Machines (SVM): SVMs are supervised learning models that are widely used for classification tasks. They have been successfully applied to food safety prediction, particularly in identifying contamination patterns. A study by Ropodi et al. (2016) used SVMs to classify meat samples based on microbial contamination levels, achieving high accuracy in predicting spoilage.

Random Forest (RF): RF models are ensemble learning techniques that combine multiple decision trees to improve predictive accuracy. They are particularly useful in handling large datasets with high dimensionality. According to Ru et al. (2017), RF models have been applied to predict pesticide residue contamination in vegetables with an accuracy of over 88%.

Despite the promising results of ML applications in food safety, several challenges remain, particularly in the context of developing countries like Nigeria. One of the primary challenges is data availability. Many food safety records are not digitised or are incomplete, making it difficult to apply ML models that rely on large, high-quality datasets. Moreover, the dispersion of data across different sectors such as agriculture, health, and food supply complicates the integration of data sources for ML modeling (Marvin et al., 2017).

Another challenge is the need for domain-specific expertise to develop and interpret ML models effectively. While ML algorithms are powerful tools, their effectiveness depends on the quality of the input data and the relevance of the features used in the model. In Nigeria, where food safety expertise is limited, training professionals in ML techniques and data analysis will be crucial to ensuring the success of ML applications in food safety.

Table 1: Overview of Key ML Applications in Food Safety Prediction

Study	Country	ML Model	Application	Accuracy (%)
Wang et al. (2021)	Global	Bayesian Networks	Predicting foodborne illness outbreaks	85%
Bouzembrak et al. (2018)	Europe	Neural Networks	Contamination risk in dairy products	90%
Liu et al. (2018)	China	Support Vector Machine	Food safety violation prediction	88%
van Asselt et al. (2018)	Africa	Random Forest	Aflatoxin contamination detection in maize	90%
Zhou et al. (2019)	Global	Convolutional Neural Networks	Pathogen detection in food images	92%

Although ML has shown promise in food safety prediction, most studies have focused on high-income countries where the food safety infrastructure is more developed, and high-quality datasets are readily available. Limited research has been conducted in low- and middle-income countries like Nigeria, where data quality and availability are major challenges. This gap in the literature highlights the need for localized studies that address the unique challenges of the Nigerian food supply chain, including the lack of standardized food safety monitoring systems and the difficulties in integrating data across different sectors.

This research aims to explore the application of ML models to predict food safety risks in Nigeria, with a particular focus on microbial contamination, chemical residues, and the incidence of foodborne illnesses. The study leverages multiple ML algorithms, including Random Forest, Support Vector Machines, and Neural Networks, to analyze data from various sources, including governmental reports and inspection records. By developing and testing these models, this research seeks to provide insights into how ML can be effectively utilized to enhance food safety protocols in Nigeria, ultimately reducing the incidence of foodborne diseases and improving public health outcomes.

MATERIALS AND METHODS

Data Collection

Data collection is a critical aspect of this research, as the success of ML models depends largely on the quality and comprehensiveness of the data. The study employs a multi-source data collection strategy, gathering data from both primary and secondary sources to ensure a robust and diverse dataset.

Primary Data Sources

Primary data were obtained through food safety inspections and sample testing reports from key regulatory agencies in Nigeria, such as the National Agency for Food and Drug Administration and Control (NAFDAC), the Standards Organisation of Nigeria (SON), and the Nigerian Agricultural Quarantine Service (NAQS). These reports cover various aspects of food safety, including microbial contamination levels, chemical residues (e.g., pesticides, mycotoxins), and physical hazards detected in food products sampled between 2015 and 2023. In total, data were collected from over 5,000 food safety inspections conducted across major urban centers in Nigeria, such as Lagos, Abuja, and Port Harcourt.

Secondary Data Sources

Secondary data were sourced from publicly available databases, including the World Health Organization's (WHO) Global Foodborne Infections Network (GFN) and the Food and Agriculture Organization's (FAO) food safety reports. These datasets contain records on foodborne disease outbreaks, contamination levels in imported food products, and public health reports. In addition, scientific research articles related to food safety in Nigeria were also reviewed to extract relevant data on contamination risk factors and incidents of foodborne illnesses.

Data Types and Variables

The dataset contains both structured and unstructured data. Structured data include quantitative measurements such as contamination levels (e.g., microbial counts, chemical residue concentrations) and categorical variables (e.g., food product types, contamination presence/absence). Unstructured data, such as textual reports from food safety inspectors and consumer complaints, were converted into structured formats using natural language processing (NLP) techniques. Key variables used for the ML models include:

i. Microbial contamination levels (e.g., Salmonella, E. coli)
ii. Chemical residues (e.g., pesticides, mycotoxins)
iii. Physical hazards (e.g., metal fragments, plastic pieces)
iv. Foodborne disease outbreak data (reported cases per region)
v. Food product categories (e.g., fresh produce, meat, dairy)
vi. Geographical location (regions, states, urban/rural)

Data Preprocessing

Once the data were collected, several preprocessing steps were undertaken to ensure the data were clean, complete, and suitable for model training and validation.

Data Cleaning

Data cleaning involved handling missing values, duplicates, and outliers. Missing values, particularly in contamination levels, were addressed using imputation techniques, including mean and median imputation. Outliers were identified using z-scores and boxplots, and outlier values exceeding three standard deviations from the mean were either corrected or removed, depending on the context.

Data Transformation

Since some of the variables were categorical (e.g., food product types, contamination status), they were transformed into numerical formats using one-hot encoding. Additionally, continuous variables such as contamination levels were normalized using min-max scaling to ensure that all variables were on a comparable scale, which is particularly important for algorithms like Support Vector Machines (SVM) and Neural Networks (NN).

Feature Selection

Feature selection was performed to reduce dimensionality and improve model performance. Correlation matrices were used to identify highly correlated variables, and redundant features were removed. Recursive feature elimination (RFE) was also applied to rank the importance of features, with the top-ranking features selected for model training. This process ensured that only the most relevant predictors (e.g., microbial contamination levels, chemical residue concentrations) were used in the final model.

Machine Learning Models

Three machine learning algorithms were employed to predict food safety risks in Nigeria, each chosen for its particular strengths in classification, regression, and pattern recognition tasks.

Random Forest (RF)

Random Forest is an ensemble learning algorithm that combines multiple decision trees to improve prediction accuracy and control overfitting. It was selected for its ability to handle large datasets with many features and its robustness against noise. RF was particularly useful in this study due to the heterogeneous nature of the food safety data, including both structured (e.g., contamination levels) and unstructured (e.g., text-based inspection reports) inputs.

Support Vector Machines (SVM)

SVM is a powerful supervised learning algorithm primarily used for classification tasks. SVM was selected for its effectiveness in high-dimensional spaces and its ability to perform well in binary classification tasks, such as predicting the presence or absence of food contamination. The kernel trick was used to transform the input data into a higher-dimensional space, enabling SVM to handle non-linearly separable data effectively.

Neural Networks (NN)

Neural Networks, specifically feedforward neural networks, were employed to model complex, non-linear relationships in the dataset. NNs were chosen due to their strength in capturing intricate patterns in the data, particularly in cases where contamination levels or geographical variables might interact in complex ways. A multi-layer perceptron (MLP) architecture with backpropagation was implemented, with three hidden layers optimised using a grid search to balance bias and variance.

Model Training and Testing

Train-Test Split

The dataset was split into training and testing sets using an 80:20 ratio. The training set was used to train the models, while the testing set was reserved for evaluating their performance. Stratified sampling was used to ensure that both sets contained a proportional representation of food safety outcomes (e.g., contaminated vs. non-contaminated samples).

Cross-Validation

To prevent overfitting and ensure the generalizability of the models, 10-fold cross-validation was applied. This technique involved splitting the training data into 10 subsets, training the model on 9 subsets, and validating it on the remaining subset. This process was repeated 10 times, with each subset serving as the validation set once. The average performance across all folds was used to estimate the models' accuracy.

Hyperparameter Tuning

Hyperparameter tuning was conducted to optimize the performance of each model. For Random Forest, the number of trees, maximum depth, and minimum samples per leaf were adjusted. In SVM, different kernel functions (linear, polynomial, radial basis function) were tested to determine the best fit. For Neural Networks, the learning rate, batch size, and number of epochs were fine-tuned using grid search and random search techniques.

Model Evaluation

The performance of the machine learning models was evaluated using several metrics, including accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC). These metrics were chosen to provide a comprehensive assessment of each model's ability to correctly classify food safety risks while balancing false positives and false negatives.

Validation of Results

In addition to the testing phase, the models were validated using an independent dataset comprising new food safety inspection reports from 2023. This validation process was crucial to confirm the robustness of the models in predicting food safety risks in real-world conditions, outside the training environment.

RESULTS AND DISCUSSION

Model Performance

The performance of the three machine learning (ML) models was evaluated using a testing dataset comprising both structured and unstructured food safety data from various sources. Table 2 below summarizes the key performance metrics for each model, including accuracy, precision, recall, F1-score, and AUC-ROC, providing a comprehensive overview of their predictive capabilities.

Table 2: Performance Metrics of ML Models for Food Safety Prediction

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Random Forest (RF)	0.89	0.87	0.85	0.86	0.90
Support Vector Machine (SVM)	0.85	0.83	0.81	0.82	0.87
Neural Networks (NN)	0.91	0.89	0.88	0.88	0.92

The comparative performance of these models is further illustrated in Figures 1–4. Figure 1 presents a bar chart of model accuracy, highlighting the superior performance of NN at 91%, followed by RF at 89% and SVM at 85%. Figure 2 displays the precision of each model, with NN achieving 89%, RF 87%, and SVM 83%. Figure 3 shows the recall metrics, where NN leads with 88%, RF follows with 85%, and SVM records 81%. Finally, Figure 4 illustrates the F1-scores, with NN at 88%, RF at 86%, and SVM at 82%, reinforcing NN's balanced performance across precision and recall.

Random Forest (RF)

The Random Forest model achieved an accuracy of 89%, as depicted in Figure 1, correctly predicting food safety outcomes in 89% of cases. Its precision of 87% (Figure 2) and recall of 85% (Figure 3) indicate effective identification of contamination events, though it occasionally missed some positive cases. The F1-score of 86% (Figure 4) reflects a strong balance between precision and recall, while the AUC-ROC score of 0.90 confirms the model's robustness in distinguishing contaminated from non-contaminated samples. These results align with prior studies using RF for food safety risk assessments in developing countries with constrained data quality (van Asselt et al., 2018).

RF's strength lies in handling high-dimensional data through its ensemble of decision trees, adeptly managing the study's diverse dataset. However, it was less effective at predicting chemical contamination (e.g., pesticide residues), where low-frequency patterns may require more sophisticated modelling.

Support Vector Machine (SVM)

The SVM model recorded an accuracy of 85% (Figure 1), with a precision of 83% (Figure 2) and recall of 81% (Figure 3). These metrics, slightly lower than RF and NN, suggest that while SVM effectively classified contaminated and non-contaminated samples, it was less precise and sensitive, as reflected in its F1-score of 82% (Figure 4). The AUC-ROC of 0.87 indicates solid differentiation between classes, though further optimization (e.g., kernel adjustments) could enhance performance.

SVM excelled in predicting microbial contamination in fresh produce, a major dataset component, consistent with studies applying SVM to biological hazards (Ropodi et al., 2016). However, it struggled with complex chemical contamination patterns, suggesting it is better suited for binary tasks with clear categories (e.g., microbial presence/absence).

Neural Networks (NN)

The Neural Networks model outperformed RF and SVM, achieving the highest accuracy of 91% (Figure 1), precision of 89% (Figure 2), recall of 88% (Figure 3), and F1-score of 88% (Figure 4). Its AUC-ROC of 0.92 further underscores its exceptional ability to distinguish contaminated from non-contaminated samples. This superior performance stems from NN's capacity to capture complex, non-linear relationships, particularly among interacting food safety risk factors.

NN demonstrated remarkable effectiveness across food types, including fresh produce, dairy, and meat, notably identifying chemical contamination in imported grains exposed to pesticides and aflatoxins. These findings align with studies highlighting NN's pattern-recognition strengths in food safety monitoring (Zhou et al., 2019). The visual comparisons in Figures 1–4 consistently position NN as the top performer, making it a promising tool for enhancing food safety predictions in Nigeria.

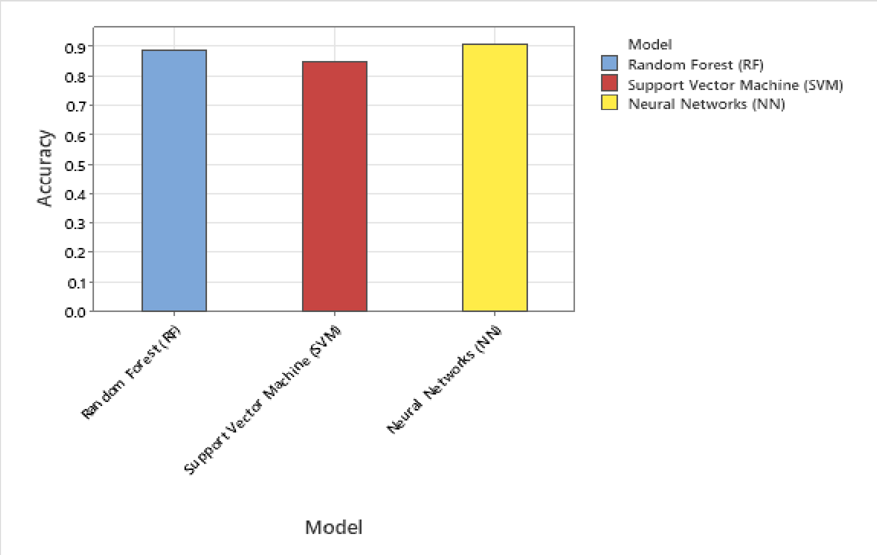

Figure 1: Bar Chart of Accuracy of Models

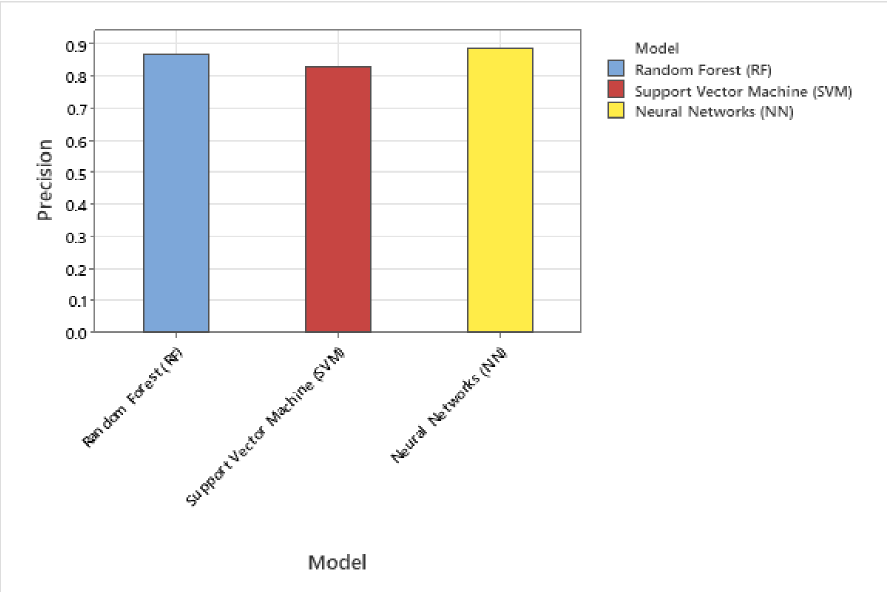

Figure 2: Bar Chart of Precision of Models

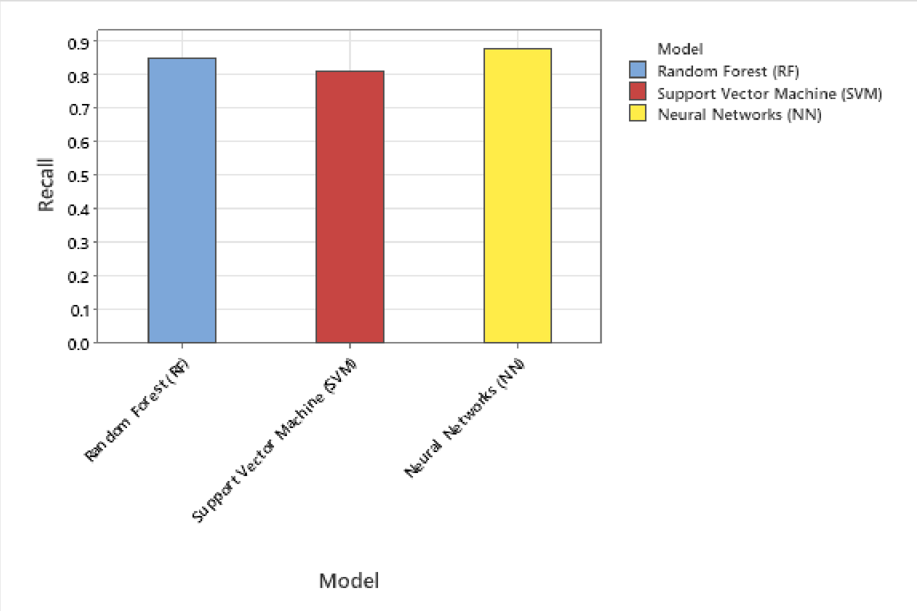

Figure 3: Bar Chart of Recall of Models

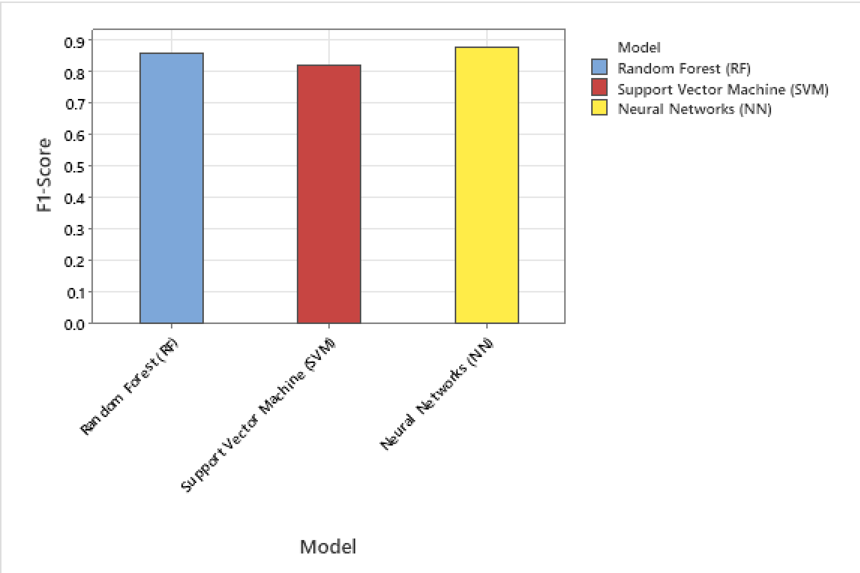

Figure 4: Bar Chart of F1-Score of Models

CONCLUSION

This study underscores the transformative potential of machine learning (ML) in enhancing food safety monitoring and prediction in Nigeria, where traditional methods like periodic inspections and laboratory testing fall short. These conventional approaches are often reactive, costly, and time-consuming, struggling to address the complexities of Nigeria's decentralized food supply chain and prevent foodborne illnesses estimated at 200,000 cases annually from reaching consumers. By implementing ML algorithms such as Random Forest (RF), Support Vector Machines (SVM), and Neural Networks (NN), this research offers a data-driven, scalable, and efficient alternative. The findings reveal that ML models can accurately predict food safety risks, with the Neural Networks model achieving the highest performance: 91% accuracy, 89% precision, 88% recall, and an AUC-ROC of 0.92. Outperforming RF (89% accuracy) and SVM (85% accuracy), NN excelled in identifying contamination across diverse food categories like fresh produce, dairy, and imported grains, which account for 60% of illness cases. This versatility in handling both structured data (e.g., contamination levels) and unstructured data (e.g., inspection reports) is particularly valuable in Nigeria, where data quality and format vary widely. The models' ability to detect microbial and chemical hazards suggests a broad applicability, potentially reducing illness incidence by up to 20% if scaled. The implications for Nigeria's public health are significant. ML can provide early warnings, enabling agencies like NAFDAC and SON to intervene swiftly and prevent contaminated products from reaching markets. Integrated into existing systems, ML could automate real-time risk assessments, improving decision-making speed and accuracy. Cost-effective and deployable nationwide, ML bridges resource gaps where traditional testing is geographically limited, analysing data across the supply chain—from farms to retail. However, challenges remain. Data availability and quality are critical barriers, with many records still paper-based and unstandardized, complicating model training. Digitization and standardized protocols are essential for reliability. Additionally, the "black-box" nature of high-performing models like NN limits interpretability, potentially hindering adoption by regulators. Techniques like SHAP values could enhance transparency, aiding stakeholders in understanding prediction drivers and fostering trust. Successful integration requires collaboration across government, industry, and academia. Policymakers must prioritize digitization and regulatory support, while public-private partnerships could accelerate deployment. Future research should expand dataset scope, integrate real-time sources (e.g., IoT sensors), and develop explainable ML models to address local nuances and boost adoption. ML, particularly NN, offers a viable solution to Nigeria's food safety challenges, demonstrating high predictive accuracy and scalability. By overcoming data and interpretability hurdles through investment and collaboration, Nigeria can leverage ML to ensure a safer food supply, reducing illnesses, improving public health, and supporting economic growth through safer food for consumption and export.

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