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Enhancing Loan Default Prediction Accuracy in Nigerian Banks: A Hybrid ANN-LSTM Approach

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ABSTRACT

Loan defaults pose a significant challenge to Nigerian banks, threatening financial stability and profitability. Existing predictive models often lack the accuracy needed for effective risk management. This study proposes a hybrid Artificial Neural Network-Long Short-Term Memory (ANN-LSTM) model to enhance loan default prediction accuracy. Leveraging a dataset of 148,670 loan records with 37 features from Nigerian banks, the model integrates ANN's ability to capture complex patterns with LSTM's proficiency in processing sequential data. Performance evaluation using accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC) demonstrates the hybrid model's superiority over traditional approaches. The ANN-LSTM model achieved 99.7% accuracy and 100% AUC, significantly outperforming Naive Bayes and Logistic Regression models. These results suggest that the proposed hybrid approach can substantially improve risk assessment and decision-making processes in Nigerian banks, potentially reducing loan default rates and enhancing overall financial stability.

Keywords: Loan Defaults, ANN-LSTM, Predictive Models, Machine Learning, Financial Risk Management

1. INTRODUCTION

The Nigerian banking sector faces a critical challenge in the form of escalating loan defaults, which significantly threaten financial stability and profitability. This issue has been exacerbated by the rapid expansion of credit lending and increased competition from emerging credit firms (Anand et al., 2022). Non-performing loans (NPLs), typically identified when payments are overdue by at least 90 days, have forced banks to undertake substantial write-offs, adversely affecting their financial health and operational stability (Abimbola, 2020; Albanesi & Vamossy, 2019).

To address this pressing concern, recent research has explored various machine learning methodologies for enhancing loan default prediction. Studies have demonstrated the effectiveness of algorithms such as XGBoost, AdaBoost, and J48 Decision Tree in predicting loan defaults and managing credit risks (Zhou, 2023; Lai, 2020; Alaba et al., 2021). Additionally, deep learning techniques, including deep neural networks and Bayesian deep learning models, have shown promise in achieving high prediction accuracies (Jumaa et al., 2023; Liu et al., 2023; Dendramis et al., 2020).

However, existing approaches often struggle to capture both complex non-linear relationships and temporal dependencies inherent in financial data. This limitation presents a significant research gap in the field of loan default prediction, particularly in the context of Nigerian banks.

To address this gap, this study proposes a hybrid Artificial Neural Network-Long Short-Term Memory (ANN-LSTM) model. This innovative approach aims to enhance predictive accuracy by combining the ANN's ability to identify intricate patterns with the LSTM's proficiency in modeling sequential information. The primary objective of this research is to develop a more robust and accurate loan default prediction model tailored to the Nigerian banking sector, thereby contributing to improved financial risk management and decision-making processes.

By leveraging the strengths of both ANN and LSTM architectures, this study seeks to provide a powerful tool for Nigerian banks to identify high-risk borrowers, minimize potential losses, and ultimately enhance the stability of the financial sector. The proposed hybrid model represents a significant advancement in the application of machine learning techniques to financial risk assessment, with potential implications for the broader field of credit risk management.

2 RELATED WORK

2.1 Traditional Machine Learning Approaches to Loan Default Prediction

Numerous studies have explored various traditional machine learning models for predicting loan defaults. Yang (2024) found logistic regression to be the most effective for Australian mortgage data, citing its interpretability and ability to capture linear relationships between predictors and loan approval. Conversely, Zhou (2023) reported superior performance from XGBoost when applied to a large dataset from The Grant Group of Companies. Hahami & Piper (2022) conducted a meta-analysis comparing logistic regression and random forest models, concluding that random forest outperformed in predicting loan default probability.

Shankaragowda & Nagashree (2023) explored the K-nearest neighbors (KNN) algorithm, emphasizing the importance of feature engineering in developing accurate predictive models. Alaba et al. (2021) compared J48 Decision Tree, BayesNet, and Naïve Bayes algorithms using Nigerian banking data, finding the J48 Decision Tree to be the most efficient. Lai (2020) conducted a comparative study of XGBoost and AdaBoost, providing insights into their relative performance in loan default prediction.

These studies consistently identified factors such as debt-to-income ratio, loan-to-value ratio, credit history, and demographic information as significant predictors of default risk. The research highlights the ongoing relevance of traditional machine learning approaches in credit risk assessment.

2.2 Advanced Machine Learning and Deep Learning Techniques

Recent research has leveraged more sophisticated approaches for credit risk modeling. Jumaa et al. (2023) achieved 95.2% accuracy using a deep learning model on UAE banking data. Liu et al. (2023) developed a Bayesian deep learning model, attaining over 96% accuracy on the Lending Club dataset, significantly outperforming traditional models. Dendramis et al. (2020) presented a multilayer ANN method for small business loan default prediction, demonstrating significant gains, particularly in short-term horizons and in reducing Type I misclassification errors.

2.3 Hybrid and Innovative Approaches

Hybrid and innovative models have shown promise in enhancing predictive accuracy while addressing specific challenges. Dong (2022) explored LightGBM, achieving an AUC of 0.73 for online loan defaults. Shingi (2020) proposed a federated learning approach, incorporating SMOTE to handle imbalanced data, thus addressing data privacy concerns and class imbalance issues simultaneously.

This reviewed studies primarily focus on traditional machine learning, standalone deep learning approaches, and specific advanced techniques. However, there is limited study of research into comprehensive hybrid deep learning models that leverage both the interpretability and the complex pattern recognition capabilities of deep learning, particularly in combining artificial neural networks with long short-term memory (LSTM) networks for loan default prediction. Hence, this study.

3. METHODOLOGY

3.1 Data Collection

This study utilized a comprehensive dataset comprising 148,670 loan records with 37 features, obtained from https://www.kaggle.com/datasets/yasserh/loan-default-dataset. The dataset encompasses a wide range of borrower characteristics and loan attributes, providing a robust foundation for model development. Key variables include; Demographic information: Gender, age; Loan details: loan_amount, loan_type, loan_purpose, term; Financial indicators: Credit_Score, income, LTV (Loan-to-Value ratio), dtir1 (Debt-to-Income ratio); Property information: property_value, construction_type, occupancy_type; Application specifics: submission_of_application, approv_in_adv; Geographic data: Region; The target variable, 'Status', indicates whether a loan application was approved (1) or rejected (0).

Data acquisition and preliminary analysis were conducted using Python 3.x within the Google Colab environment, leveraging libraries such as pandas for data manipulation and matplotlib for initial visualizations. This cloud-based platform facilitated collaborative data exploration and ensured reproducibility of results. The dataset's diverse features allow for a comprehensive analysis of factors influencing loan default risk, enabling the development of a nuanced predictive model tailored to the Nigerian banking context.

Table 1: Description of Identified Variables for Loan Default Prediction

Variable	Description	Data Type	Sample Value
ID	Unique identifier for each loan application.	int64	24890
Year	Year in which the loan application was processed.	int64	2019
loan_limit	The loan limit category for the application.	object	Cf
Gender	Gender of the primary applicant.	object	Sex Not Available
approv_in_adv	Whether the loan was approved in advance.	object	Nopre
loan_type	Type of loan applied for.	object	type1
loan_purpose	Purpose of the loan.	object	p1
Credit_Worthiness	Credit worthiness category of the applicant.	object	l1
open_credit	Whether the applicant has open credit.	object	Nopc
business_or_commercial	Whether the loan is for business or commercial use.	object	nob/c
loan_amount	Amount of the loan applied for.	int64	116500
rate_of_interest	Interest rate for the loan.	float64	
Interest_rate_spread	Spread of the interest rate over the base rate.	float64	
Upfront_charges	Upfront charges applicable for the loan.	float64	
Term	Term of the loan in years.	float64	360
Neg_ammortization	Whether the loan allows negative amortization.	object	not_neg
interest_only	Whether the loan has an interest-only payment option.	object	not_int
lump_sum_payment	Whether the loan allows a lump-sum payment.	object	not_lpsm
property_value	Value of the property for which the loan is applied.	float64	118000
construction_type	Type of construction of the property.	object	Sb
occupancy_type	Occupancy type of the property.	object	Pr
Secured_by	Type of security for the loan.	object	Home
total_units	Total number of units in the property.	object	1U
Income	Income of the applicant.	float64	1740
credit_type	Type of credit used for the loan.	object	EXP
Credit_Score	Credit score of the applicant.	int64	758

co-applicant_credit_type	Credit type of the co-applicant.	object	CIB
Age	Age of the primary applicant.	object	25-34
submission_of_application	Mode of submission of the application.	object	to_inst
LTV	Loan-to-Value ratio.	float64	98.72881356
Region	Region where the property is located.	object	South
Security_Type	Type of security for the loan.	object	direct
Status	Status of the loan application (approved or rejected).	int64	1
dtir1	Debt-to-income ratio of the applicant.	float64	45

3.2 Data Pre-processing

To prepare the dataset for the loan default prediction model, we implemented a comprehensive pre-processing pipeline using Python 3.x in Google Colab. The process encompassed the following key steps:

1) **Data Cleaning**:
   - Handled missing values using appropriate imputation techniques (e.g., mean for numerical features, mode for categorical features)
   - Removed duplicate entries to ensure data integrity
2) **Encoding Categorical Variables:**
   - Employed one-hot encoding for nominal categorical variables (e.g., Gender, loan_type, Region)
   - Applied ordinal encoding for ordered categorical variables (e.g., Credit_Worthiness, age)
3) **Feature Scaling:**
   - Normalized numerical features (e.g., loan_amount, income, Credit_Score) using Min-Max scaling to ensure uniform scale across variables
4) **Feature Engineering:**
   - Created interaction terms for potentially related features (e.g., LTV ratio and Credit_Score)
   - Derived new features such as debt-to-income ratio from existing variables
5) **Handling Class Imbalance:**
- Addressed potential imbalance in the target variable (Status) using Synthetic Minority Oversampling Technique (SMOTE)
6) **Feature Selection:**
- Utilized correlation analysis and feature importance techniques to identify the most relevant predictors
7) **Data Partitioning:**
- Split the preprocessed dataset into training (80%) and testing (20%) sets, ensuring stratification based on the target variable

This preprocessing methodology was implemented using pandas for data manipulation, scikit-learn for encoding and scaling, and imbalanced-learn for SMOTE. The resulting cleaned and transformed dataset served as the foundation for subsequent model development and evaluation.

3.3 Formulation of Hybrid ANN-LSTM Model

To enhance loan default prediction accuracy, we developed a novel hybrid model combining Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks. This architecture was implemented using TensorFlow and Keras in a Google Colab environment. The model formulation process encompassed the following key steps:

a) **ANN Component**:

- Designed a feedforward neural network to capture complex non-linear relationships in static features.
- Implemented multiple dense layers with ReLU activation functions
- Applied dropout for regularization to prevent overfitting

b) LSTM Component:

- Constructed an LSTM network to process sequential data and capture temporal dependencies
- Utilized bidirectional LSTM layers to analyze the input sequence in both forward and backward directions
- Incorporated attention mechanisms to focus on the most relevant time steps

c) Hybrid Architecture:

- Concatenated the outputs of the ANN and LSTM components
- Added dense layers for final prediction, with a sigmoid activation function in the output layer

d) Model Compilation:

- Employed binary cross-entropy as the loss function
- Utilized Adam optimizer for efficient stochastic optimization
- Monitored accuracy and Area Under the ROC Curve (AUC) as performance metrics

e) Hyperparameter Tuning:

- Conducted grid search to optimize key parameters such as learning rate, number of layers, and nodes per layer
- Implemented early stopping to prevent overfitting during training

f) Model Training:

- Trained the hybrid model using the preprocessed dataset with a batch size of 32 and 100 epochs
- Employed k-fold cross-validation (k=5) to ensure robust performance estimation

This hybrid ANN-LSTM architecture leverages the strengths of both neural network types, enabling the model to capture both static patterns and temporal dynamics in loan default prediction. The implementation in Google Colab facilitated efficient model development and iteration, leveraging GPU acceleration for enhanced computational performance.

3.4 Evaluation

To rigorously assess the performance of our hybrid ANN-LSTM model for loan default prediction, we implemented a comprehensive evaluation framework using Python in Google Colab. The evaluation methodology encompassed the following key components:

1) **Performance Metrics:**
   - Accuracy: Measured overall correctness of predictions
   - Precision and Recall: Assessed model's ability to identify true positives while minimizing false positives
   - F1-Score: Calculated harmonic mean of precision and recall
   - Area Under the Receiver Operating Characteristic Curve (AUC-ROC): Evaluated model's discriminative ability across various thresholds
2) **Comparative Analysis:**

Benchmarked the hybrid model against traditional machine learning algorithms (e.g., Logistic Regression, Random Forest) and standalone ANN and LSTM models

3) **Confusion Matrix:**

Generated and analyzed confusion matrices to visualize true positives, true negatives, false positives, and false negatives

I leveraged scikit-learn for implementing traditional models and evaluation metrics, while TensorFlow and Keras facilitated the evaluation of neural network components. Matplotlib and Seaborn were utilized for visualization of results. This comprehensive evaluation framework enabled a thorough assessment of the hybrid ANN-LSTM model's efficacy in predicting loan defaults within the Nigerian banking context.

4 RESULTS AND DISCUSSION

This section presents the comprehensive findings of our loan default prediction study, employing a hybrid Artificial Neural Network-Long Short-Term Memory (ANN-LSTM) model. We begin by examining the dataset's attribute distributions and addressing missing data through judicious imputation techniques. Categorical variables were encoded to facilitate deep learning modeling. The hybrid ANN-LSTM model was developed and benchmarked against traditional algorithms, including Naive Bayes and Logistic Regression.

Model performance was rigorously evaluated using a suite of metrics: accuracy, F1 score, recall, precision, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). Confusion matrices provided further insight into model behavior. This comprehensive evaluation framework enabled the identification of the most effective algorithm and feature combination for robust loan default prediction in Nigerian banks.

4.1 Statistical Summary and Distribution Analysis of Dataset for Loan Default Prediction Accuracy

The dataset for loan default prediction comprises 148,670 records across 11 key numerical features. This comprehensive analysis provides insights into the distribution and characteristics of these features:

1. **Loan Amount**: The average loan amount is ₦331,117.70, with a standard deviation of ₦183,909.30. The distribution is right-skewed, ranging from ₦16,500 to ₦3,576,500, indicating significant variability in loan sizes.

2. **Interest Rates:** The mean interest rate is 4.05%, with a relatively low standard deviation of 0.56%. Rates range from 0% to 8%, suggesting diverse lending terms

3. **Interest Rate Spread**: With a mean of 0.44% and standard deviation of 0.51%, this feature shows considerable variation in risk premiums applied to loans.

4. **Upfront Charges**: Average upfront charges are ₦3,224.99, with a high standard deviation of ₦3,251.12, indicating wide variability in initial loan costs.

5. **Loan Term:** The majority of loans have a 360-month (30-year) term, as evidenced by the median and 75th percentile. The mean of 335.14 months suggests some shorter-term loans in the dataset.

6 **Property Value**: The mean property value is ₦497,893.50, with a substantial standard deviation of ₦359,935.30, reflecting diverse real estate markets.

7. **Income:** Applicant incomes average ₦6,957.34 monthly, with a high standard deviation of ₦6,496.59, indicating significant income disparity among applicants

8 **Credit Score**: The mean credit score is 699.79, with scores ranging from 500 to 900, suggesting a varied creditworthiness profile among applicants.

9 **Loan-to-Value Ratio (LTV):** The average LTV is 72.75%, with a wide range from 0.97% to 7,831.25%, indicating diverse lending risk profiles.

10 **Debt-to-Income Ratio (DTIR**): The mean DTIR is 37.73%, with a standard deviation of 10.55%, suggesting varied financial obligations among applicants.

11 Loan Status: The target variable shows that 25% of loans in the dataset defaulted, indicating a class imbalance that will need to be addressed in the modeling phase.

This statistical summary reveals significant variability across all features, underscoring the complexity of loan default prediction. The presence of outliers, particularly in LTV and income, suggests the need for robust preprocessing techniques. The class imbalance in the target variable (Status) highlights the importance of employing appropriate modeling strategies to ensure accurate prediction of the minority class (defaulted loans).

4.2 Correlation Analysis and Feature Importance

The correlation heatmap Figure 1 reveals significant relationships within the loan default dataset, crucial for predictive modeling. Credit_Score demonstrates a strong negative correlation with default occurrences, emphasizing its importance in creditworthiness assessment. Debt-to-Income Ratio (dtir1) and Loan-to-Value (LTV) ratios positively correlate with default risk, indicating the impact of leverage and debt burden. Notable correlations between property_value and loan_amount suggest the role of collateral in lending decisions. These intricate relationships provide insights for refining the ANN-LSTM model's predictive capabilities, potentially enhancing risk assessment precision in financial institutions. By leveraging these correlations, the model can capture nuances in the lending landscape, potentially improving the accuracy and sophistication of credit risk evaluation.

4.3 Evaluation of the Experiments and Validation of Predictive Accuracy Model for Loan Defaults

a. Evaluation of ANN-LSTM using Performance Metrics for Loan Defaults Prediction Accuracy

The values from figure 3 of confusion matrix are used to calculate the precision, recall, F1 score, and accuracy, showing the mathematical expressions and providing the answers in percentages.

a) From the confusion matrix:

True Negative (TN) = 17340; True Positive (TP) = 5642; False Negative (FN) = 21; False Positive (FP) = 36

Now, calculations for each metric:

1. Precision:

Precision = TP / (TP + FP) = 5642 / (5642 + 36) = 5642 / 5678 = 0.9937 or 99.37%

2. Recall:

Recall = TP / (TP + FN) = 5642 / (5642 + 21) = 5642 / 5663 = 0.9963 or 99.63%

3. F1 Score:

F1 = 2 * (Precision * Recall) / (Precision + Recall) = 2 * (0.9937 * 0.9963) / (0.9937 + 0.9963) = 2 * 0.9900 / 1.9900 = 0.9950 or 99.50%

4. Accuracy:

Accuracy = (TP + TN) / (TP + TN + FP + FN) = (5642 + 17340) / (5642 + 17340 + 36 + 21) = 22982 / 23039 = 0.9975 or 99.75%

The ANN-LSTM model demonstrates exceptional performance in predicting loan defaults, as evidenced by the confusion matrix and derived metrics. The model achieves an impressive accuracy of 99.75%, indicating its high overall correctness in classifying both default and non-default cases. The precision of 99.37% reflects the model's ability to minimize false positives, crucial for maintaining lender confidence and resource allocation efficiency. The recall of 99.63% showcases the model's strength in identifying actual defaults, which is vital for risk management. The F1 score of 99.50% represents a balanced harmony between precision and recall, confirming the model's robust performance across different evaluation criteria.

These metrics collectively suggest that the ANN-LSTM model excels in distinguishing between default and non-default loans with high reliability. The near-perfect scores across all metrics indicate that the model has successfully captured the complex patterns and relationships within the loan data, resulting in minimal misclassifications. This performance level is particularly noteworthy given the often-imbalanced nature of loan default datasets.

b. Evaluation of Naives Bayes using Performance Metrics for Loan Defaults Prediction Accuracy

The performance of the Naive Bayes model in predicting loan defaults was rigorously evaluated using the confusion matrix (Figure 7) and the Area Under the Curve (AUC) score. The confusion matrix provides a clear illustration of the model's classification accuracy and its ability to differentiate between defaulting and non-defaulting loans.

The results indicate that the model correctly predicted non-defaults (True Negatives) in 19,845 cases and defaults (True Positives) in 7,175 cases. However, there were 2,649 instances where the model incorrectly predicted defaults (False Positives) and 65 instances where it failed to identify defaults (False Negatives). These results demonstrate the model's substantial accuracy in predicting true defaults, while also highlighting a moderate rate of misclassification, particularly in terms of false positives (incorrectly predicted defaults).

Additionally, the model achieved an AUC score of 97%, reflecting its excellent overall ability to discriminate between the default and non-default classes across various threshold settings. This high AUC score confirms the model's effectiveness in managing imbalanced datasets typical of loan default scenarios, where actual defaults are relatively low compared to non-defaults.

In conclusion, the Naive Bayes model exhibits robust predictive performance with a significant capability to effectively identify loan defaulters. However, attention must be given to the relatively high number of false positives, which could lead to unnecessary interventions for predicted defaults. This evaluation supports the model's practical applicability, where early and accurate detection of potential loan defaults is crucial for risk management and decision-making processes in financial institutions.

c. Evaluation of Logistic Regression using Performance Metrics for Loan Defaults Prediction Accuracy

The evaluation metrics for a logistic regression model predicting loan defaults using a confusion matrix, illustrating the model's predictions versus the actual values. The large value (22,720) along the diagonal indicates the number of true negatives, where the model correctly predicted non-defaulters. However, the off-diagonal elements (1,037 and 3,352) represent misclassifications, with 1,037 false negatives (actual defaulters predicted as non-defaulters) and 3,352 false positives (non-defaulters predicted as defaulters).

The Receiver Operating Characteristic (ROC) curve, which plots the true positive rate against the false positive rate at various classification thresholds shows the area under the curve (AUC) is 0.94, indicating a high degree of separability between the two classes. An AUC of 0.94 suggests that the model has excellent discriminative ability in distinguishing between defaulters and non-defaulters.

These evaluation metrics provide valuable insights into the logistic regression model's performance in predicting loan defaults. The confusion matrix highlights the specific types of errors made by the model, while the ROC curve and AUC score offer an overall assessment of the model's discriminative power. Such quantitative measures are crucial for evaluating and refining predictive models in the domain of loan default risk assessment.

4.4 Results and Discussion of Model Performance for Loan Default Prediction Accuracy

The validation of predictive models for loan defaults was comprehensively assessed using the performance metrics of accuracy, precision, F1 score, recall, and AUC score, as summarized in the accompanying figure 5. This analysis involved three models: ANN-LSTM, Naive Bayes, and Logistic Regression, each evaluated to determine their efficacy in predicting loan defaults.

ANN-LSTM emerged as the most effective model, showcasing exemplary performance across all metrics. It achieved an accuracy of 99.7%, precision of 99%, F1 score of 100%, recall of 99%, and an AUC score of 100%. These results indicate that the ANN-LSTM model excels in both identifying true defaults and avoiding false positives, making it an optimal choice for environments where the cost of a prediction error is high.

Naive Bayes, while demonstrating good recall at 99%, exhibited lower precision at 73%, resulting in an F1 score of 84% and an AUC score of 97%. This suggests that while the model is effective in identifying the most true defaults, it also misclassifies a significant number of non-defaults as defaults. Such characteristics might suit scenarios where missing a default is more detrimental than false alarms.

Logistic Regression showed the weakest performance among the three, with an accuracy of 87.3%, precision of 68.97%, F1 score of 77.25%, recall of 87.78%, and an AUC score of 94%. These figures reveal that while the model reasonably identifies defaulting and non-defaulting loans, it struggles with a higher rate of both false positives and false negatives compared to the other models.

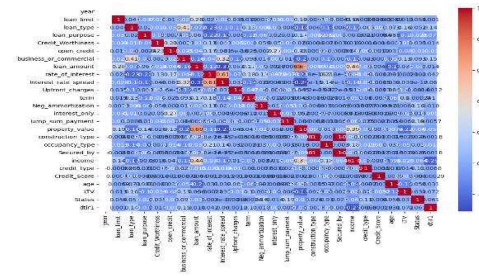
The bar chart vividly underscores these points by visually comparing the performance across all models and metrics, clearly highlighting the superior predictive power of the ANN-LSTM model. This visualization not only corroborates the numerical data from the table but also enhances the understanding of each model’s strengths and limitations in practical applications.

In conclusion, the ANN-LSTM model’s robustness makes it highly suitable for financial institutions aiming to reduce loan default risks through predictive analytics. Institutions might consider using Naive Bayes for its high recall in scenarios were failing to predict a default has severe consequences. However, Logistic Regression, despite its limitations, could still be utilized in less critical applications where model transparency and interpretability are required. This comparative analysis provides a nuanced understanding that can guide the strategic deployment of these models based on specific operational needs and risk tolerance.

Table 2: Statistical Summary of Features for ANN-LSTM Loan Default Prediction Accuracy

Feature	Count	Mean	Std	Min	25%	50%	75%	Max
loan_amount	148,670	331,117.70	183,909.30	16,500	196,500	296,500	436,500	3,576,500
rate_of_interest	112,231	4.05	0.56	0	3.63	3.99	4.38	8
Interest_rate_spread	112,031	0.44	0.51	-3.64	0.08	0.39	0.78	3.36
Upfront_charges	109,028	3,224.99	3,251.12	0	581.49	2,596.45	4,812.50	60,000.00
Term	148,629	335.14	58.41	96	360	360	360	360

property_value	133,572	497,893.50	359,935.30	8,000.00	268,000.00	418,000.00	628,000.00	16,508,000.00
Income	139,520	6,957.34	6,496.59	0	3,720.00	5,760.00	8,520.00	578,580.00
Credit_Score	148,670	699.79	115.88	500	599	699	800	900
LTV	133,572	72.75	39.97	0.97	60.47	75.14	86.18	7,831.25
dtir1	124,549	37.73	10.55	5	31	39	45	61
Status	148,670	0.25	0.43	0	0	0	0	1



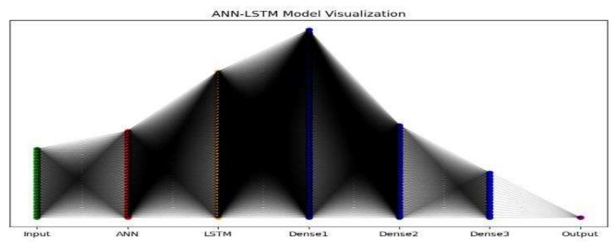


Figure 2: ANN-LSTM Architecture

Figure 1: Confusion Matrix for Loan Default

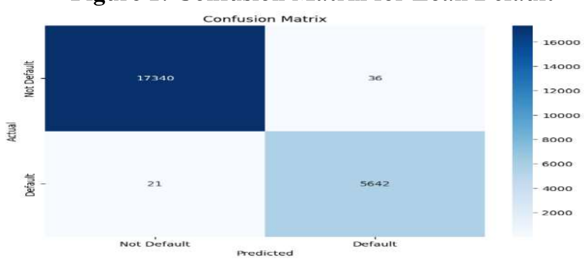


Figure 3: ANN-LSTM Confusion Matrix

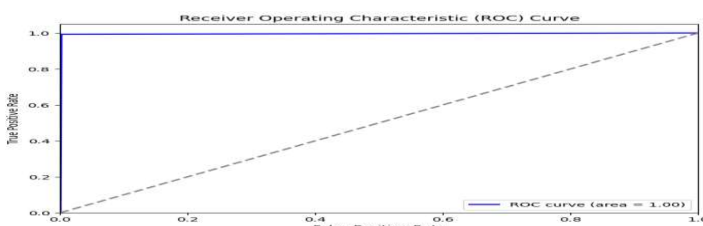


Figure 4: Area under ROC curve (AUC) for ANN-LSTM Loan Defaults

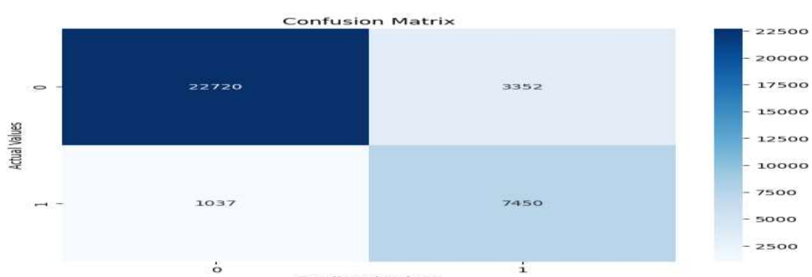


Figure 5: Logistics Regression Confusion Matrix

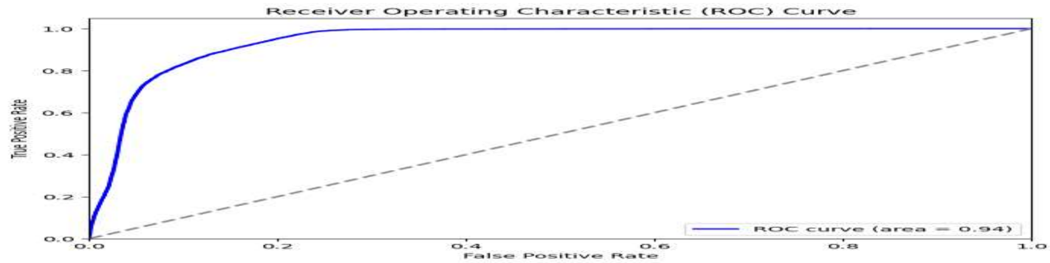


Figure 6: Area under ROC curve (AUC) for Logistics Loan Defaults

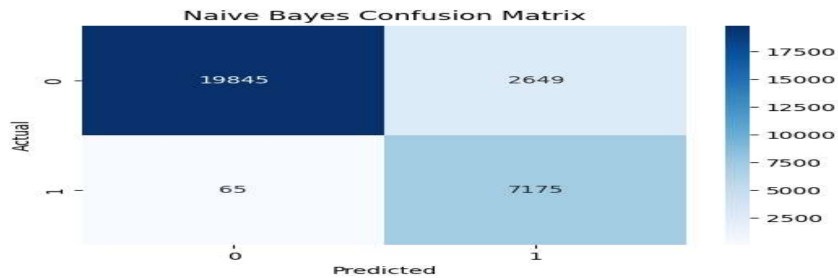


Figure 7: Naïve Bayes Confusion Matrix

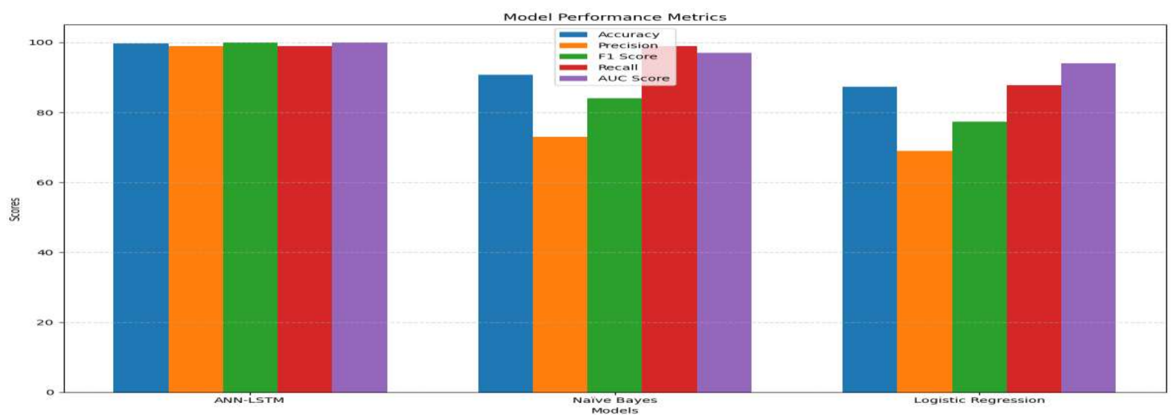


Figure 8: **Comparative Performance Metrics of Predictive Models for Loan Default Prediction Accuracy**

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This study demonstrates the superior performance of a hybrid ANN-LSTM model in predicting loan defaults within the Nigerian banking sector. The model achieved remarkable accuracy (99.7%), precision (99%), recall (99%), F1 score (100%), and AUC score (100%), significantly outperforming traditional approaches such as Naive Bayes and Logistic Regression. These results underscore the model's robust capability to capture both complex non-linear relationships and temporal dependencies inherent in loan data.

The hybrid architecture's success lies in its ability to leverage the strengths of both Artificial Neural Networks and Long Short-Term Memory networks, resulting in a more nuanced and accurate prediction mechanism. This advancement represents a significant contribution to the field of credit risk assessment, offering financial institutions a powerful tool for identifying high-risk borrowers and minimizing potential losses.

The study's findings have important implications for risk management practices in Nigerian banks, potentially leading to more informed lending decisions, reduced default rates, and enhanced overall financial stability. By demonstrating the efficacy of advanced machine learning techniques in the context of the Nigerian banking system, this research paves the way for broader adoption of AI-driven risk assessment tools in emerging markets.

5.2 Recommendation

Based on the compelling results of this study, we strongly recommend the implementation of the ANN-LSTM hybrid model in Nigerian banking institutions for loan default prediction. To ensure successful adoption and maximize the model's potential, a gradual integration approach is advisable, where banks initially implement the model alongside existing risk assessment methods. This will allow for a comparative analysis and smooth transition. Continuous monitoring and refinement of the model's performance in real-world scenarios is crucial to enable ongoing adaptation to evolving economic conditions and borrower behaviors.

Financial institutions should prioritize the collection and maintenance of high-quality, comprehensive loan data to further improve the model's predictive accuracy. Additionally, investing in training programs to equip relevant personnel with the skills necessary to interpret and act upon the model's outputs effectively is essential. It is imperative to develop clear guidelines for the ethical use of AI in lending decisions, ensuring fairness and transparency in the application of the model.

Finally, working closely with regulatory bodies is necessary to ensure the model's implementation aligns with existing financial regulations and risk management frameworks. By adopting these recommendations, Nigerian banks can harness the full potential of the ANN-LSTM model, leading to more robust risk management practices and a more stable financial sector.

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