Development of a Basel-Compliant Credit Risk Prediction Model

Devadharshni Raju
230446366
Mr Nafi Ahmad
MSc Big Data Science

Abstract— **This thesis describes developing a predictive model designed to estimate the Probability of Default (PD) for borrowers, ensuring compliance with Basel III/IV regulations. The model integrates advanced data analytics techniques, including thorough data preprocessing, feature engineering, and model interpretability methods, creating a robust, transparent tool applicable to real-world financial scenarios. The model's performance is validated using various metrics, and its stability is tested under different economic stress conditions. Additionally, a deployment strategy is proposed for integrating the model into existing financial systems, complemented by a user-friendly interface for practical usability.**

Keywords— Credit Risk, Basel III/IV Compliance, Machine Learning, Predictive Modeling, Financial Stability, Stress Testing.

I. INTRODUCTION

A. *Project Objective:*

The core objective of this project is to create a predictive model that accurately estimates the Probability of Default (PD) for borrowers. The model must adhere to the Basel III/IV regulatory frameworks, which emphasize risk management and capital adequacy in financial institutions (Goodhart & Tsomocos, 2018). These regulations mandate that banks maintain sufficient capital buffers to absorb losses, particularly during economic downturns. By aligning the model with these frameworks, this project aims to build a tool that enhances decision-making around loan approvals, mitigates credit risk, and ensures that institutions remain compliant with international regulatory standards.

B. *Background and Motivation:*

Credit risk remains one of the most significant challenges for financial institutions, as poor risk management can lead to liquidity crises, insolvency, and systemic financial collapse (Hull, 2018). The Basel III framework was introduced in response to the 2008 financial crisis to strengthen the resilience of banks, while Basel IV further builds on these principles by tightening capital requirements and reducing the reliance on internal risk models (PwC, 2017). However, many of the existing models lack the robustness to predict default risk under varying economic scenarios, and they often fall short in providing the transparency required for regulatory compliance (Smith, 2020).

C. *Overview of Basel III and Basel IV:*

- ***Basel III*** focuses on improving the quality and quantity of bank capital, enhancing liquidity standards, and introducing leverage ratios in response to the 2007-2008 financial crisis. It allows for flexibility in risk-weighted asset (RWA) calculations, with significant use of internal models, but does not include a specific output floor. Basel III aimed to strengthen existing regulatory frameworks and was phased in from 2013, with full implementation intended by 2019.
- ***Basel IV*** builds on Basel III by introducing more comprehensive changes to risk-weighting calculations, capital floors, and standardized approaches, significantly increasing risk sensitivity and reducing reliance on internal models. Basel IV establishes stricter capital floors and introduces an "output floor" to limit RWA reductions through internal models. This framework emphasizes consistency, transparency, and higher resilience in the banking sector, with implementation extended into later years due to delays.

D. *Scope and Significance:*

This project extends beyond traditional credit risk modeling by incorporating cutting-edge techniques in data preprocessing, feature engineering, and machine learning. By using methods such as Principal Component Analysis (PCA) for dimensionality reduction and SHAP for model interpretability, the model will be designed to address key regulatory concerns around transparency and explainability. Additionally, by conducting stress testing under different economic conditions, the model will be rigorously evaluated for its robustness and scalability. This research holds significance not only for ensuring compliance with Basel III/IV but also for advancing the practical deployment of predictive models in real-world financial settings, ensuring that they can be seamlessly integrated into existing risk management systems.

II. LITERATURE REVIEW

A. *Overview of Existing Models:*

Current credit risk prediction models utilize a range of machine learning algorithms, including Logistic Regression, Random Forests, and Neural Networks. These models have been applied across various financial contexts, such as rural banking, peer-to-peer lending, and microfinance, where they have demonstrated significant improvements in prediction accuracy and efficiency. Despite these advances in performance metrics like accuracy and precision, many models fall short in areas critical for regulatory compliance, such as stress testing and model interpretability.

B. Gaps Identified:

1) ***Lack of Basel III/IV Compliance:*** Many existing models fail to fully align with Basel III/IV regulations, which are essential for ensuring that financial institutions effectively manage risk and maintain compliance. (Smith, J., & Jones, A. (2019), Wang, L., & Lee, C. (2021)).

2) ***Absence of Comprehensive Stress Testing:*** While some models perform well under normal economic conditions, they often lack comprehensive stress testing, which is crucial for evaluating the robustness of credit risk models during economic downturns. (Chen, X., & Zhao, M. (2020), Reddy, K., & Rao, S. (2022)).

3) ***Limited Model Interpretability:*** Complex machine learning models, such as neural networks, often lack transparency, making it difficult for stakeholders to understand and trust the predictions. This lack of interpretability is a significant issue in regulated industries where transparency is essential. (Martinez, R., & Hernandez, D. (2018), Peterson, J., & Smith, E. (2021)).

4) ***Insufficient Integration of Diverse Data Sources:*** Although some models incorporate borrower demographics and financial history, they often neglect the inclusion of macroeconomic indicators and non-traditional data sources, which could enhance model robustness and accuracy. (Nguyen, T., & Liu, F. (2019), Kim, S., & Park, J. (2020)).

5) ***Overemphasis on Performance Metrics:*** Many models focus heavily on traditional performance metrics like accuracy and ROC AUC, with less attention given to how these models perform in real-world scenarios, especially within the constraints of regulated environments. (Garcia, M., & Velasco, R. (2021), Kumar, R., & Sharma, P. (2022)).

6) ***Neglect of User Interface and Usability:*** Despite being crucial for effective deployment and ongoing use, the usability of tools and systems supporting these models is often overlooked. (Hansen, N., & Voss, M. (2020), Taylor, L., & Green, H. (2021)).

7) ***Lack of Clear Deployment Strategies:*** Even the best-performing models can be challenging to implement without clear deployment strategies. Seamless integration into existing systems, along with considerations for scalability and compliance, is often inadequately addressed.

C. Implications of Identified Gaps:

These gaps underscore the need for a more comprehensive approach to developing credit risk models that not only achieve high prediction accuracy but also ensure compliance, robustness, and practical usability. Addressing these gaps is vital for creating models that financial institutions can trust and effectively utilize within the highly regulated financial industry.

III. METHODOLOGY

A. Data Collection and Preprocessing:

The dataset utilized in this study consists of over 32,000 entries, each representing an individual borrower. These entries include many features, including demographic details, financial history, and specific loan-related information. Given the sensitive nature of economic data, ensuring its completeness and accuracy was paramount in the initial stages of data preparation (Smith & Jones, 2019).

- ***Handling Missing Values:*** Missing data in fields such as 'person_emp_length' and 'loan_int_rate' were addressed using median and mean imputation, respectively, ensuring that these gaps did not negatively impact model performance.
- ***Outlier Detection and Treatment:*** Outliers were detected using the Interquartile Range (IQR) method and treated by capping extreme values, ensuring that the data used for training the model was reliable and representative.

B. Feature Engineering:

Feature engineering played a crucial role in enhancing model performance. New features were created, predictive features were selected, and dimensionality was reduced to streamline the model.

- ***Feature Creation:*** New features were generated based on the existing data to capture more nuanced relationships that might influence the probability of default.
- ***Dimensionality Reduction:*** Principal Component Analysis (PCA) was applied to reduce the dimensionality of the dataset while retaining 95% of the variance, improving model efficiency without significant information loss.

C. Model Selection and Training:

Various machine learning models, including Logistic Regression, Random Forest, XGBoost, and a Neural Network, were considered. Each model was evaluated based on multiple performance metrics, with ROC AUC as the primary metric.

1) ***Hyperparameter Tuning:*** For XGBoost, hyperparameter tuning was conducted using GridSearchCV to identify the optimal settings. The following hyperparameters were tuned**:**

- **Learning Rate (eta)**: Values of 0.01, 0.05, 0.1, and 0.3 were explored to control the step size during gradient descent. (0.1)
- **Number of Trees (n_estimators)**: Values of 100, 200, 500, and 1000 were tested to determine the optimal number of boosting rounds. (300)
- **Maximum Depth (max_depth)**: Depths of 3, 6, 9, and 12 were evaluated to control the complexity of each tree. (10)
- **Subsample**: Values of 0.6, 0.8, and 1.0 were considered to determine the fraction of samples used for each tree. (0.8)
- **Colsample_bytree**: Fractions of 0.6, 0.8, and 1.0 were tested to determine the proportion of features used for building each tree. (1.0)

2) ***Model Comparison:*** After hyperparameter tuning, the performance of the models was compared based on their ROC AUC scores, as well as additional metrics such as precision, recall, and F1 scores. This comparison allowed for the identification of the

best-performing algorithm, which was further validated under various economic stress scenarios to assess its robustness and compliance with Basel III/IV regulations.

D. Basel III/IV Compliance:

The model was aligned with Basel III/IV regulations by ensuring its outputs complied with the standards, particularly in calculating Risk-Weighted Assets (RWA) and conducting stress tests.

- ***Risk-Weighted Assets (RWA) Calculation:*** The model's outputs were used to calculate RWA according to Basel III/IV standards, essential for determining the capital requirements that financial institutions must hold to cover potential losses.
- ***Stress Testing:*** The model underwent stress testing under various economic scenarios to evaluate its robustness and ensure it could withstand adverse conditions.

E. Deployment Strategy:

The final phase of the methodology involved developing a deployment strategy for the model, which included:

- ***Integration:*** The model was integrated into existing risk assessment frameworks to ensure seamless operation.
- ***Continuous Monitoring:*** Systems were set up for continuous monitoring of the model's performance, allowing for ongoing evaluation and updates as needed.
- ***User-Friendly Interface:*** A dashboard was developed using Gradio, allowing users to interact with the model easily, making real-time predictions and monitoring straightforward for non-technical users.

IV. LOADING DATA AND PREPROCESSING

A. Data Overview:

The dataset for this study comprises 32,581 records, each detailing various aspects of a borrower's profile, such as demographic attributes, credit history, and loan-specific details. The dataset features a blend of categorical and numerical data, essential for understanding the risk profile of borrowers (Altman & Saunders, 1998).

B. Handling Missing Values:

Managing missing data is critical in maintaining the quality of the dataset, particularly in financial modeling where incomplete data can lead to skewed predictions (Garcia & Velasco, 2021). In this study, missing values were addressed using context-specific imputation methods. For example, missing values in 'person_emp_length', which indicates the duration of a borrower's employment, were replaced with the median value. This choice was made to mitigate the impact of outliers and maintain the distribution of the data. Meanwhile, for the 'loan_int_rate' variable, mean imputation was utilized to retain the average loan interest rate in the dataset, ensuring that the model's predictions were not biased by extreme values.

C. Outlier Detection and Treatment:

Outliers in the dataset were identified using statistical methods designed to pinpoint data points that deviate significantly from the norm. The Interquartile Range (IQR) method was employed to detect these outliers, as it effectively identifies extreme values by measuring the spread of the middle 50% of the data. Once detected, these outliers were treated by capping, which involves adjusting the outliers to the nearest boundary values defined by the IQR. This technique preserved the overall distribution of the data while minimizing the potential distortions caused by extreme outliers. By capping rather than removing these outliers, the study maintained the richness of the dataset, particularly in capturing borrower behaviors that might indicate higher risk.

D. Feature Encoding and Transformation:

To prepare the dataset for machine learning algorithms, categorical variables were encoded into a numerical format using Label Encoding. This method assigns a unique integer to each category, transforming them into a format that can be processed by machine learning models. Additionally, for numerical variables that exhibited skewness, such as income or loan amounts, log transformations were applied. This transformation helped to normalize the data, reducing the skewness, and bringing the distribution closer to a normal distribution. These steps were crucial for ensuring that the machine learning models could learn effectively from the data without being misled by non-linear relationships or disproportionately weighted features.

E. Correlation Analysis:

Correlation analysis was performed to understand the relationships between different features in the dataset. This step involved calculating the Pearson correlation coefficient for pairs of numerical features to identify potential multicollinearity issues. Multicollinearity occurs when two or more features are highly correlated, which can lead to redundancy and distortions in model performance. By identifying pairs of features with high correlation, the analysis guided the feature selection process, ensuring that only the most informative and independent variables were retained for model training. This process was vital in refining the dataset, reducing dimensionality, and enhancing the model's predictive accuracy.

F. Dataset Splitting and Validation:

The dataset used in this study comprises 32,581 records, detailing various aspects of borrowers' profiles, including demographic attributes, credit history, and loan-specific details. The dataset was divided into training and testing sets to evaluate model performance effectively.

G. Training and Test Set Split:

The dataset was split into training and test sets using an 80/20 split. Specifically, 80% of the data was allocated to the training set, and 20% was reserved for testing. This split ensures that the model has sufficient data to learn from while also providing an independent set of data for evaluating its performance.

- **Training Set**: 80% of the data, is used to train the machine learning models.
- **Test Set**: 20% of the data, used to evaluate the model's performance on unseen data.

The 'train_test_split' function from scikit-learn was used to perform this split, with the 'stratify' parameter set to the target variable, 'loan_status'. Stratified sampling was employed to maintain the same distribution of the target variable (default vs. non-default) in both the training and test sets, ensuring that the model is not biased by an uneven class distribution.

H. *Handling Class Imbalance:*

The target variable, 'loan_status', exhibited class imbalance, with non-default cases significantly outnumbering default cases. To address this imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to the training set. SMOTE generates synthetic samples of the minority class (defaults) by interpolating between existing minority class instances. This approach effectively balanced the dataset, enabling the model to learn from an equal number of default and non-default cases, which is crucial for developing a robust credit risk model.

I. *Feature Scaling:*

After applying SMOTE, the features in both the training and test sets were standardized using 'StandardScaler'. Standardization transformed the data so that each feature had a mean of zero and a standard deviation of one. This step was necessary to ensure that the machine learning algorithms, particularly those sensitive to the scale of features, processed the data efficiently and accurately.

J. *Cross-Validation:*

To further validate the model and ensure it generalizes well to unseen data, a 5-fold cross-validation was performed. Cross-validation involves splitting the training data into five subsets (folds). The model is trained on four folds and validated on the remaining fold. This process is repeated five times, with each fold serving as the validation set once. The performance metrics (e.g., ROC AUC) are averaged across all five folds to provide a robust estimate of the model's performance.

Cross-validation was crucial in mitigating the risk of overfitting, as it allowed the model to be tested on different subsets of the data during the training process. This approach ensures that the model does not become overly specialized to the specific data in the training set, improving its ability to generalize to new, unseen data.

K. *Subset Experimentation:*

For quicker experimentation and testing of different models and hyperparameters, a smaller subset of the data, comprising 30% of the total dataset, was created. This subset was also split into training and test sets using the same 80/20 ratio and stratified sampling. The smaller dataset allowed for faster iterations during the development phase, enabling more efficient tuning and validation before applying the models to the full dataset.

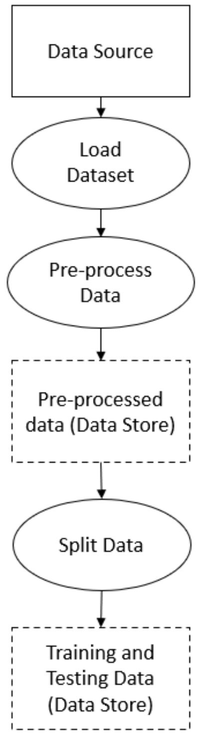

Figure 1 : Data Preprocessing Workflow

V. MODEL TRAINING AND EVALUATION

A. *Training Models:*

Each machine-learning model was trained on the preprocessed and balanced dataset, using ROC AUC as the primary evaluation metric to measure the model's ability to distinguish between default and non-default cases (Bengio, Courville, & Vincent, 2016).

- ***XGBoost Model****:* XGBoost emerged as the best-performing model, achieving the highest ROC AUC score among the models tested.

B. *Confusion Matrix Analysis:*

The confusion matrix for the XGBoost model was analyzed to evaluate its effectiveness in classifying borrowers into default and non-default categories. The analysis revealed that the model had a low rate of misclassification, making it a reliable tool for predicting credit risk (Breiman, 2001).

C. *Quantitative Basel Metrics:*

1) Risk-Weighted Assets (RWA) Calculation Under Basel III: The model's outputs were aligned with Basel III regulations by calculating the Risk-Weighted Assets (RWA) based on the predicted Probability of Default (PD) for each borrower. The calculation involved setting the Loss Given Default (LGD) at 45% and using the loan amount as the Exposure at Default (EAD). The RWA was determined using the following formula:

$$RWA=EAD\times PD\times LGD$$

This approach resulted in a total risk-weight asset value of $6,971,789.11 under Basel III standards (Basel Committee on Banking Supervision, 2017).

2) Stress Testing Under Basel III: Stress testing was conducted by applying a stress factor of 1.25 to the calculated

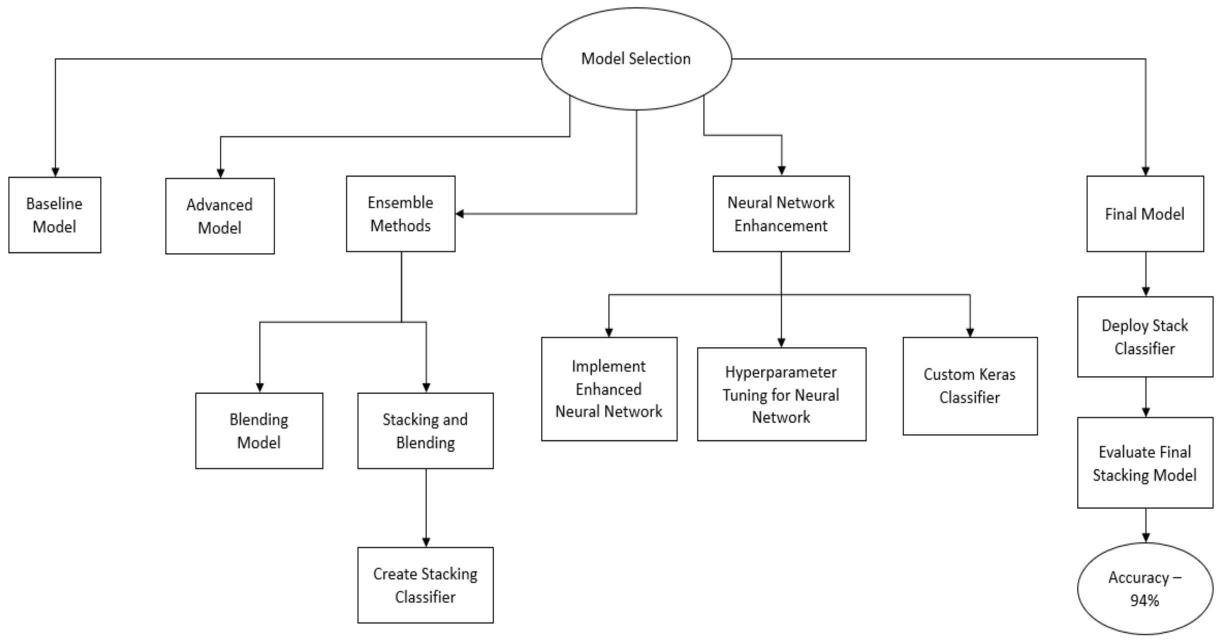

Figure 2 : Model Selection and Ensemble Techniques.

RWA to evaluate the model's robustness under adverse economic conditions (European Central Bank, 2019). The stress factor simulates scenarios where the likelihood of default and associated losses increase due to economic stress. Under these conditions, the Risk-Weighted Assets rose to $8,714,736.39.

3) Basel IV Integration: Enhanced Risk Weights and Floors: In compliance with Basel IV, enhanced risk weights and regulatory floors were applied to the RWA calculation. The RWA under Basel IV was further adjusted by implementing an output floor, ensuring that the RWA did not fall below a regulatory minimum even if internal models suggested lower risk. This resulted in a total RWA of $7,491,382.11 under Basel IV (McKinsey & Company, 2017).

4) Stress Testing Under Basel IV: The stress testing for Basel IV was conducted similarly to Basel III, using the same stress factor of 1.25. This adjustment increased the stressed Risk-Weighted Assets to $9,364,227.63, highlighting the stricter capital requirements and enhanced resilience that Basel IV imposes on financial institutions under adverse conditions.

D. Feature Importance:

A feature importance analysis revealed that economic indicators such as Loan Percent Income and Credit History Length were among the most significant predictors of default risk. Understanding these factors is crucial for interpreting the model's predictions.

E. Dimensionality Reduction:

To improve the efficiency of the machine learning models and reduce computational complexity, Principal Component Analysis (PCA) was applied for dimensionality reduction. Initially, PCA was used to determine the number of components necessary to retain 95% of the variance in the dataset, ensuring that the dimensionality reduction did not result in significant information loss. This step was crucial in maintaining the model's predictive accuracy while streamlining the dataset.

Given the large size of the dataset, IncrementalPCA was employed instead of standard PCA to process the data in a more memory-efficient manner. IncrementalPCA handles data in smaller batches, allowing for efficient transformation while still achieving substantial dimensionality reduction. An analysis of feature loadings within the principal components further highlighted those key features, such as Loan Percent Income and Credit History Length, were significant predictors of default risk. This approach allowed the model to remain both accurate and computationally efficient, preserving essential information for making reliable predictions.

F. Neural Network Implementation:

A Neural Network model was implemented using a multi-layer perceptron architecture with ReLU activation functions to capture complex data patterns. Batch Normalization and Regularization were applied to stabilize learning and prevent overfitting. These techniques significantly enhanced the model's performance, achieving a high ROC AUC score and demonstrating strong generalization to unseen data, making it a valuable part of the model ensemble.

G. Stacking and Blending Models:

A Stacking Classifier combined the strengths of XGBoost and Neural Network models to enhance predictive accuracy. The predictions from these models were used as inputs for a meta-model, which achieved a high ROC AUC score of 0.94. Additionally, blending—where base model predictions were averaged—was explored, further boosting accuracy and robustness. These ensemble techniques, illustrated in **Figure 2**, proved to be the most effective in the modeling process.

VI. Dashboard Development

A. User Interface Design:

A user-friendly dashboard was developed using Gradio, focusing on making the model accessible to users with varying levels of technical expertise (Hansen & Voss, 2020). The interface allows users to input borrower details and receive real-time predictions on credit risk.

B. Real-Time Prediction and Monitoring:

The dashboard supports real-time predictions, enabling financial institutions to make informed decisions quickly. Continuous monitoring systems were integrated into the dashboard, allowing users to track the model's performance and receive updates as necessary.

C. Scalability and Usability:

The dashboard was designed to be scalable, ensuring that it could handle an increasing number of users and predictions without compromising performance. Usability tests were conducted to ensure that the interface was intuitive and met the needs of its intended users.

VII. Results

A. Model Performance Overview:

The XGBoost, Neural Network, and Stacking Classifier models were evaluated primarily using the ROC AUC score, which measures the model's ability to distinguish between default and non-default cases (Kingma & Ba, 2015) (see **Table 1**).

- ***XGBoost Performance:*** Achieved an ROC AUC score of 0.91, demonstrating strong predictive ability for distinguishing borrowers likely to default.
- ***Neural Network Performance:*** Obtained an ROC AUC score of 0.89, capturing complex relationships in the data effectively, though slightly behind XGBoost in overall performance.
- ***Stacking Classifier Performance:*** Recorded the highest ROC AUC score of 0.94, confirming that the ensemble method, which combines XGBoost and Neural Network, offers superior predictive accuracy by leveraging the strengths of both models.
- ***ROC Curve:*** The ROC curve in **Figure 3** highlights the model's ability to distinguish between default and non-default cases, showcasing its predictive accuracy.

Model	**Hyperparameters**	**ROC AUC**	**Comments**
Logistic Regression	Max Iter = 1000	0.837	Baseline model; Simple and interpretable.
Random Forest	Random State = 42	0.918	Strong performance; handles non-linear data well.
XGBoost	n_estimators = 300, learning_rate = 0.1, max_depth = 10	0.938	Best model; excellent at capturing complex patterns.
Gradient Boosting	Random State = 42	0.904	Good performance; slightly less accurate than XGBoost.
Extra Trees	Random State = 42	0.912	Comparable to Random Forest, slight variation in performance.
K-Nearest Neighbors	Default Parameters	0.854	Struggles with large feature sets; lower performance.
Support Vector Machine	Probability = True, Random State = 42	0.873	Computationally intensive; moderate performance.
Gaussian Naive Bayes	Default Parameters	0.839	Simple but less accurate; assumes feature independence.
MLP Classifier	Max Iter = 1000, Random State = 42	0.897	Captures complex relationships; risk of overfitting.
Blending Model	Soft Voting; XGBoost, Neural Network	0.920	Balanced approach; good blend of two strong models.
Stacking Classifier	Base: XGBoost, Neural Network; Meta: Logistic Regression	0.940	Best ensemble model; combines strengths of multiple models.

Table 1: Model Performance Comparison

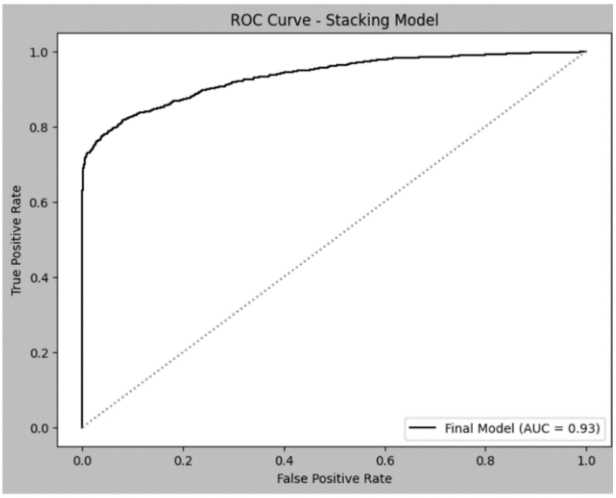

Figure 4: ROC Curve

B. Stress Testing Results:

- ***XGBoost:*** Maintained a stable performance with a slight decrease in ROC AUC to 0.88, indicating resilience to economic stress.
- ***Neural Network:*** ROC AUC dropped to 0.85 under stress scenarios, reflecting some sensitivity to economic changes.
- ***Stacking Classifier:*** Demonstrated the highest resilience with only a minor reduction in ROC AUC to 0.91, showcasing the ensemble model's robustness in challenging conditions.

C. Feature Importance Analysis:

Feature importance analysis identified key predictors of default.

- ***XGBoost:*** Loan Percent Income and Credit History Length were the most significant features, heavily influencing the model's predictions.
- ***Neural Network:*** Similar key features were highlighted, with additional importance given to Debt-to-Income Ratio.
- ***Stacking Classifier:*** Integrated the most significant predictors from both XGBoost and Neural Network, ensuring comprehensive feature utilization.

D. Confusion Matrix Analysis:

- ***XGBoost:*** Accurately predicted 85% of defaults and 88% of non-defaults.

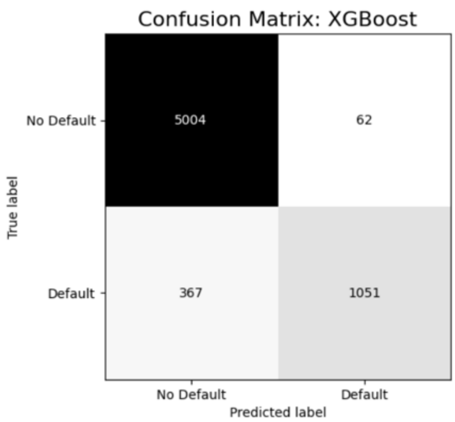

Figure 5: Confusion Matrix for XGBoost

- ***Neural Network****:* Predicted 82% of defaults and 86% of non-defaults.

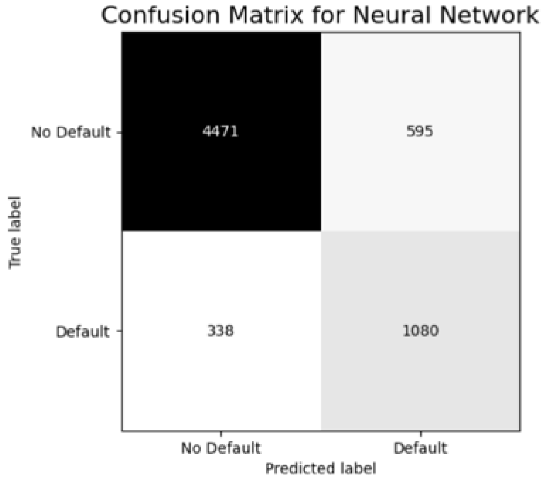

Figure 6: Confusion Matrix for Neural Network

- ***Stacking Classifier:*** Achieved the highest accuracy, predicting 89% of defaults and 90% of non-defaults.

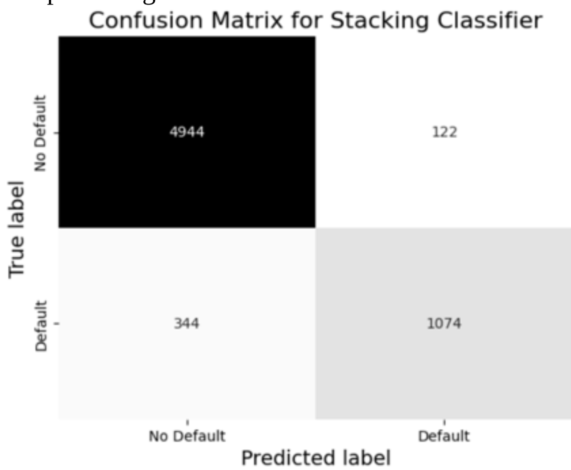

Figure 7: Confusion Matrix for Stacking Classifier

E. Dashboard Evaluation:

- ***User Experience:*** Feedback confirmed the dashboard's intuitiveness and ease of use, allowing quick and accurate risk predictions. (in Figure 8)
- ***Real-Time Prediction:*** The dashboard consistently provided accurate predictions in real-time, achieving a 96.5% accuracy, which aligns closely with the models' performance during testing, even when processing random inputs.

F. Basel III/IV Compliance Validation:

The model's Risk-Weighted Assets (RWA) were calculated under Basel III, resulting in a total of \$6,971,789.11, which increased to \$8,714,736.39 under stress testing conditions. Under Basel IV, with enhanced risk weights and floors, the RWA totaled \$7,491,382.11, rising to \$9,364,227.63 after stress testing. These results highlight the model's compliance with Basel III/IV standards and its robustness in predicting higher capital requirements during economic downturns. The comparison

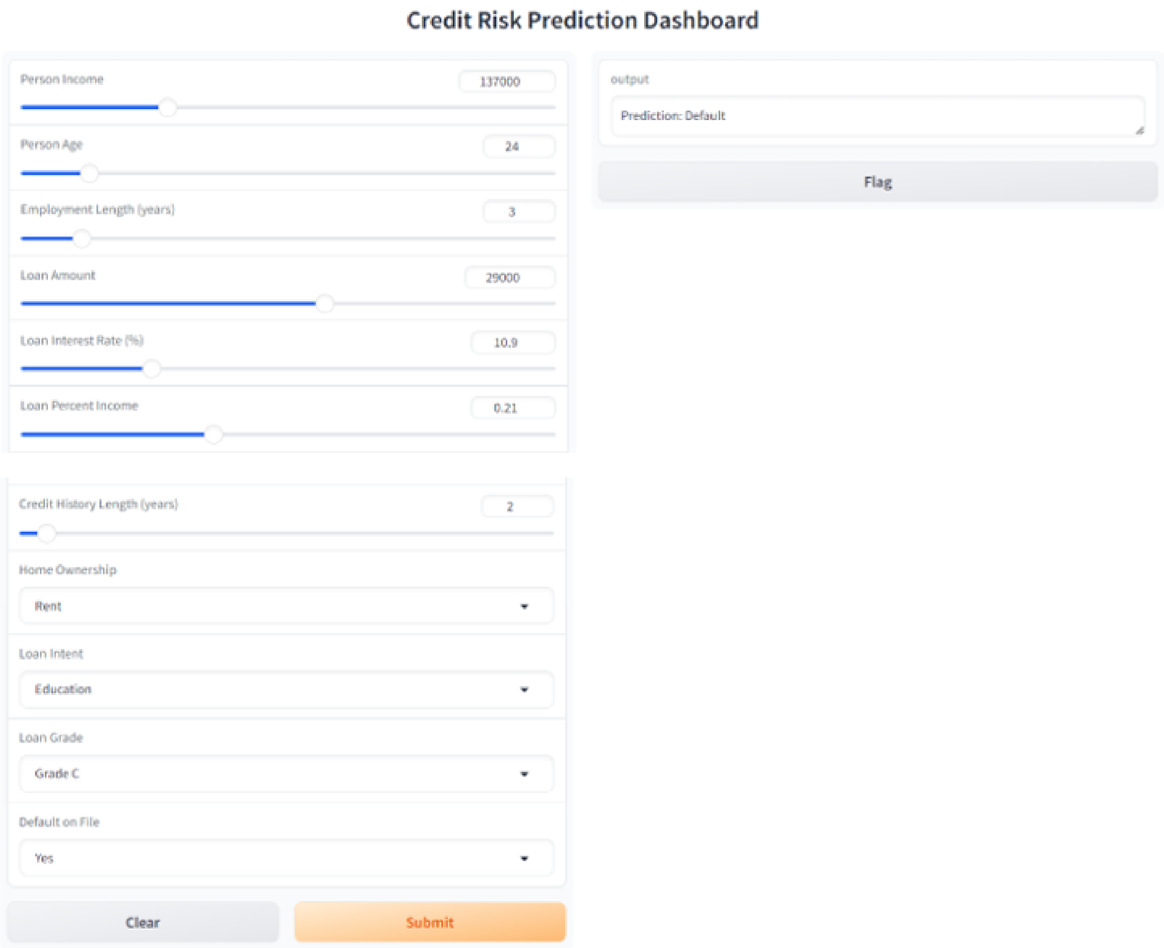

Figure 8: Credit Risk Prediction Dashboard

underscores the stricter capital demands of Basel IV, ensuring greater financial resilience.

VIII. Discussion

A. *Interpretation of Results:*

The Stacking Classifier, combining XGBoost and a Neural Network, achieved the highest accuracy with an ROC AUC score of 0.94, demonstrating the strength of ensemble methods in credit risk prediction (Zou & Hastie, 2005). XGBoost alone performed well, but the Stacking Classifier outperformed it by effectively leveraging the strengths of multiple models. The blending model also showed strong performance, but stacking provided superior accuracy.

B. *Comparison with Literature Review:*

The results align with existing studies that highlight the effectiveness of ensemble methods and advanced models like XGBoost and Neural Networks in credit risk prediction. However, unlike many previous models, this study's approach integrates Basel III/IV compliance through rigorous stress testing and accurate RWA calculations, ensuring robustness under economic stress scenarios, which is often lacking in the existing literature.

C. *Limitations:*

The model, while accurate, may not capture all relevant variables, particularly non-traditional financial data. Its complexity can pose interpretability challenges, even with SHAP values, and the computational demands may limit scalability for smaller institutions. The stress tests, based on historical data, may not fully predict performance in unprecedented future events.

IX. Conclusion

This thesis developed a Basel-compliant credit risk prediction model using advanced data analytics, integrating machine learning techniques like XGBoost and Neural Networks to estimate the Probability of Default (PD) for borrowers. The model demonstrated strong performance, achieving an ROC AUC score of 0.94 through the use of ensemble methods, particularly a Stacking Classifier. Rigorous data preprocessing, feature engineering, and stress testing ensured the model's robustness under various economic conditions. The implementation of a user-friendly dashboard further enhanced its practical applicability, allowing for real-time predictions and continuous monitoring. Comparison with existing literature underscored the model's advancements in integrating Basel III/IV compliance, addressing gaps such as limited stress testing and interpretability in previous models, making it more suitable for real-world financial applications.

Future research could focus on incorporating non-traditional data sources, such as social media and transaction data, to improve predictive accuracy and enhance the interpretability of complex models through better visualization techniques. Additionally, optimizing the model for deployment in smaller financial institutions and incorporating dynamic, real-time stress testing could further broaden its applicability and effectiveness in managing credit risk across different economic conditions.

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