# Deep Learning-Based Loan Approval Prediction Using Artificial Neural Network (ANN) and Feature Importance Analysis

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## ABSTRACT

The increasing demand for efficient and objective credit evaluation has motivated the adoption of artificial intelligence in financial decision-making. This study proposes a deep learning-based loan approval prediction model using an Artificial Neural Network (ANN) combined with feature importance analysis to enhance interpretability. The dataset, consisting of 2,000 loan application records with both financial and demographic attributes, was preprocessed through normalization and one-hot encoding to ensure consistent feature representation. The ANN model was trained using three hidden layers (64–32–16 neurons) with the ReLU activation function and optimized using Adam with early stopping to prevent overfitting. Experimental results demonstrate that the proposed ANN model achieves an accuracy of 92%, with a precision of 0.91, a recall of 0.93, and a ROC-AUC of 0.95, indicating excellent classification capability. The Permutation Feature Importance analysis revealed that Credit Score, Income, and Loan Amount are the most significant predictors influencing loan approval decisions. These findings confirm that the ANN model can capture complex non-linear relationships among financial attributes while maintaining transparency through explainable AI techniques. The proposed approach contributes both theoretically and practically by combining predictive power with interpretability, offering a reliable and explainable framework for automating loan evaluation in modern financial institutions.

**Keywords** Artificial Neural Network (ANN), Loan Approval Prediction, Deep Learning, Credit Risk Assessment, Explainable Artificial Intelligence (XAI)

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Additional Information and Declarations can be found on page 54

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## INTRODUCTION

The acceleration of digital transformation in the financial sector has reshaped the landscape of lending and credit evaluation processes [1]. As financial institutions continue to digitize their operations, the volume of loan applications submitted through online platforms has increased exponentially [2]. Traditional loan approval systems, which rely on manual credit evaluation conducted by human analysts, are no longer sufficient to handle this scale of data [3]. These conventional methods typically involve a combination of subjective judgment, heuristic rules, and historical credit information, often leading to inconsistencies, human bias, and inefficiencies in decision-making. As a result, there has been a growing need for automated, data-driven, and objective credit

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assessment systems that can process large-scale information while maintaining fairness and transparency.

Recent advancements in Machine Learning (ML) have opened new possibilities for transforming the loan approval process [4]. Various algorithms, such as Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, and Support Vector Machine, have been successfully employed in predictive financial modeling, particularly for credit scoring and loan eligibility prediction. These models can process large datasets efficiently and identify significant predictive relationships among variables. However, while traditional ML algorithms perform reasonably well, they remain constrained by their limited ability to model non-linear and hierarchical relationships inherent in financial data. Financial behavior, credit risk, and loan performance are influenced by complex interactions among variables such as income, credit score, employment history, and loan amount relationships that linear models cannot fully capture.

To overcome these limitations, Deep Learning (DL) approaches, particularly the Artificial Neural Network (ANN), have emerged as powerful alternatives capable of uncovering latent, nonlinear dependencies within data. ANNs have demonstrated superior performance in a wide range of financial applications, including fraud detection, credit scoring, and market forecasting. Their capability to learn multi-level abstractions makes them especially suitable for credit evaluation tasks, where input variables may exhibit intricate interdependencies. However, despite their predictive strength, deep learning models face a major criticism in real-world financial applications: their lack of interpretability. Neural networks are often considered “black boxes” because the internal mechanisms that drive their predictions are not easily understood by human decision-makers. This opacity presents a significant challenge for the banking and financial sectors, which operate under strict regulatory environments that demand transparency, accountability, and explainability in automated decision systems.

To address these challenges, researchers have increasingly explored ways to integrate explainable artificial intelligence (XAI) methods into deep learning frameworks. These approaches aim to make complex models more transparent by identifying the most influential features and explaining how each contributes to the final decision. In this context, feature importance analysis serves as a critical interpretability technique that quantifies the relative contribution of each input variable to the model’s predictive outcome. Among the available methods, Permutation Feature Importance is particularly effective for post hoc interpretation, as it evaluates how randomizing the values of a specific feature affects the model’s performance. This allows analysts to understand which attributes—such as credit history, income, or loan amount—play the most decisive roles in determining loan approval outcomes, thereby transforming a black-box model into a more interpretable and trustworthy decision-support tool.

The motivation of this study stems from the need to bridge the gap between predictive accuracy and interpretability in loan approval modeling. While prior studies have focused on maximizing prediction performance, many have overlooked the necessity of ensuring that models remain transparent and compliant with financial governance standards. This research proposes a deep learning-based loan approval prediction model using an Artificial Neural Network integrated with Permutation Feature Importance analysis to achieve both objectives simultaneously. The ANN model is designed to predict whether a loan application will be approved or rejected based on applicants' financial and demographic characteristics, while the feature importance framework provides a systematic interpretation of the model's decision logic.

In this study, the ANN model is constructed with multiple hidden layers that capture complex, non-linear relationships between applicant features. The model is trained using preprocessed data that includes normalized numerical variables and one-hot encoded categorical attributes to ensure consistent scaling and numerical representation. The proposed system is evaluated through multiple performance metrics, including accuracy, precision, recall, F1-score, and ROC-AUC, to validate its predictive capability. Furthermore, the integration of feature importance analysis enables a comprehensive understanding of how input features influence loan approval predictions. Through this interpretability mechanism, the research not only enhances the transparency of ANN-based decision systems but also provides valuable empirical insights into which applicant characteristics are most influential in determining creditworthiness.

This research contributes to both theoretical and practical domains of financial analytics. Theoretically, it extends the application of deep learning models to credit risk assessment by incorporating explainability into an inherently opaque model structure, thereby promoting responsible and ethical AI deployment. Practically, the model offers a scalable and transparent decision-support tool for financial institutions seeking to automate loan approval processes without compromising fairness or regulatory compliance. By integrating Artificial Neural Networks with Explainable AI techniques, this study demonstrates that high predictive performance and model interpretability can coexist, offering a blueprint for the next generation of intelligent and trustworthy financial decision systems.

## Literature Review

The application of data-driven models for loan approval prediction and credit risk assessment has received significant attention in both academic and industrial domains. Historically, credit evaluation relied heavily on traditional statistical techniques such as Logistic Regression (LR) and Linear Discriminant Analysis (LDA). These models provided interpretability and simplicity, which made them popular in the banking sector. However, as noted by Brown and Mues, such models are limited by their assumption of linear relationships between independent variables and the target outcome, an assumption that rarely holds in real-world financial data [5]. Hand and Henley also argued that while these models offer transparency, their linear nature fails to capture the complex interactions and non-linearities that typically influence loan approval decisions [6]. This recognition paved the way for the integration of more flexible and powerful machine learning (ML) algorithms into credit evaluation processes.

In recent years, a wide array of machine learning methods has been introduced to improve the performance of loan approval systems. Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting models have been widely applied to credit risk prediction, demonstrating substantial performance improvements over classical approaches. Khandani et al. found that ensemble tree models are particularly effective in modeling complex relationships between borrower characteristics and repayment outcomes [7]. Similarly, Lessmann et al. conducted a comprehensive benchmarking study of 41 classification algorithms for credit scoring, concluding that ensemble-based methods such as RF and Gradient Boosting consistently outperform linear models [8]. Despite their predictive advantages, these models often act as black boxes, providing limited interpretability, which complicates their adoption in regulated financial environments that require transparent decision-making.

The rise of DL has further revolutionized financial analytics by offering models capable of capturing high-dimensional and non-linear dependencies among features. Deep learning architectures such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) have shown remarkable success in areas such as fraud detection, bankruptcy prediction, and credit scoring. Bahnsen et al. demonstrated that ANN-based models outperform traditional ML methods in fraud detection tasks by learning intricate data representations [9]. Liu et al. extended this approach to loan approval prediction, reporting a significant improvement in classification accuracy compared to Logistic Regression and SVM [10]. The advantage of ANN lies in its ability to generalize from complex and non-linear feature interactions, which are typical in financial datasets characterized by multidimensional applicant attributes.

Recent studies continue to affirm the effectiveness of deep learning for credit evaluation. For example, Sharma and Kumar applied a multilayer perceptron (MLP) model for predicting loan eligibility and achieved over

90% accuracy, demonstrating the ability of neural networks to handle heterogeneous borrower data [11]. Similarly, Alshamrani et al. developed a hybrid deep learning model combining ANN and XGBoost for personal loan risk prediction, achieving superior accuracy and stability compared to standalone models [12]. Their research highlighted the potential of hybrid frameworks in improving robustness in financial decision-making. Furthermore, Chatterjee and Basu proposed a deep neural network architecture for microfinance loan approval and found that incorporating demographic and behavioral features substantially improved prediction reliability, particularly in low-data scenarios [13].

While deep learning offers superior predictive performance, it also introduces the problem of lack of interpretability. Neural networks, due to their layered and non-linear structures, are often regarded as opaque systems that hinder understanding of how inputs contribute to outputs. In the context of financial decision-making, this opacity poses significant challenges, as regulatory frameworks such as the General Data Protection Regulation (GDPR) emphasize the right to explanation in automated decision systems. As a result, research in Explainable Artificial Intelligence (XAI) has gained traction, aiming to make high-performing models more transparent and interpretable. Ribeiro et al. introduced LIME (Local Interpretable Model-Agnostic Explanations) to approximate local decision boundaries, while Lundberg and Lee proposed SHAP (SHapley Additive Explanations) based on cooperative game theory to measure the contribution of each feature to model output. Both methods have significantly improved the explainability of complex machine learning models [14],[15].

In addition to these local interpretability techniques, Permutation Feature Importance (PFI) has emerged as an effective method for global model interpretation. Originally proposed by Breiman for Random Forests, PFI measures the impact of shuffling a feature on model performance, thereby quantifying its importance [16]. Fisher et al. later formalized a model-agnostic framework for feature importance estimation applicable to any predictive model [17]. This approach has been particularly useful in financial applications because it provides a clear, quantitative ranking of features that contribute most to loan approval or credit scoring decisions. Recent research by Zhang et al. combined ANN with SHAP analysis to enhance interpretability in loan default prediction, demonstrating that integrating XAI with deep learning not only improves transparency but also increases institutional trust in AI systems [18]. Similarly, Ghosh and Dey implemented permutation importance for mortgage risk modeling, identifying income, loan amount, and credit history as the dominant predictors [19].

More recent studies have continued to advance this integration between deep learning and explainability. For instance, Wang et al. introduced an interpretable deep credit evaluation model that combined an ANN classifier with SHAP-based visualization, allowing financial analysts to trace the reasoning behind model predictions [20]. Their findings emphasized that interpretability enhances trust and regulatory acceptance of deep learning systems in banking. Additionally, Tran et al. explored the use of Graph Neural Networks (GNNs) for loan risk prediction and incorporated feature attribution analysis to identify interrelated borrower characteristics in networked lending ecosystems [21]. Their results indicated that feature-aware deep learning architectures outperform purely predictive models in both accuracy and accountability. Meanwhile, Hassan and Li proposed an explainable hybrid ensemble of ANN and LightGBM for small business loan approval, integrating SHAP values to ensure fairness and model transparency across different demographic groups [22]. Their study marked a crucial advancement toward ethical AI adoption in financial decision-making systems.

Overall, the literature demonstrates two prevailing trends in the evolution of AI-driven credit modeling. First, deep learning models such as ANN have proven to deliver superior predictive accuracy by capturing complex, non-linear interactions among applicant features. Second, the integration of explainability frameworks, including permutation-based feature importance, SHAP, and LIME, has become indispensable for building trustworthy and compliant financial decision systems. However, despite the proliferation of studies on deep learning and interpretability, there remains a research gap in developing a unified framework that simultaneously optimizes both prediction accuracy and explainability for loan approval prediction. Most prior works emphasize either performance improvement or interpretability enhancement, but seldom address both dimensions cohesively within a single model.

To bridge this gap, the present study proposes a deep learning-based loan approval prediction model that combines the predictive power of Artificial Neural Networks with the interpretability provided by Permutation Feature Importance. This integrated framework not only achieves high classification accuracy but also elucidates the underlying decision factors influencing loan approvals. By advancing the intersection of deep learning and explainable AI, this study contributes to the development of responsible and transparent financial intelligence systems that align with ethical and regulatory standards in modern credit evaluation practices.

## Method

This study employed a systematic deep learning framework to develop a predictive model for loan approval decisions based on applicant financial and demographic attributes. The methodology consisted of sequential stages (see figure 1), including data preprocessing, model architecture design, training and optimization, performance evaluation, and interpretability analysis. Each stage was designed to ensure that the proposed Artificial Neural Network (ANN) achieved both predictive precision and decision transparency through Permutation Feature Importance (PFI) analysis.

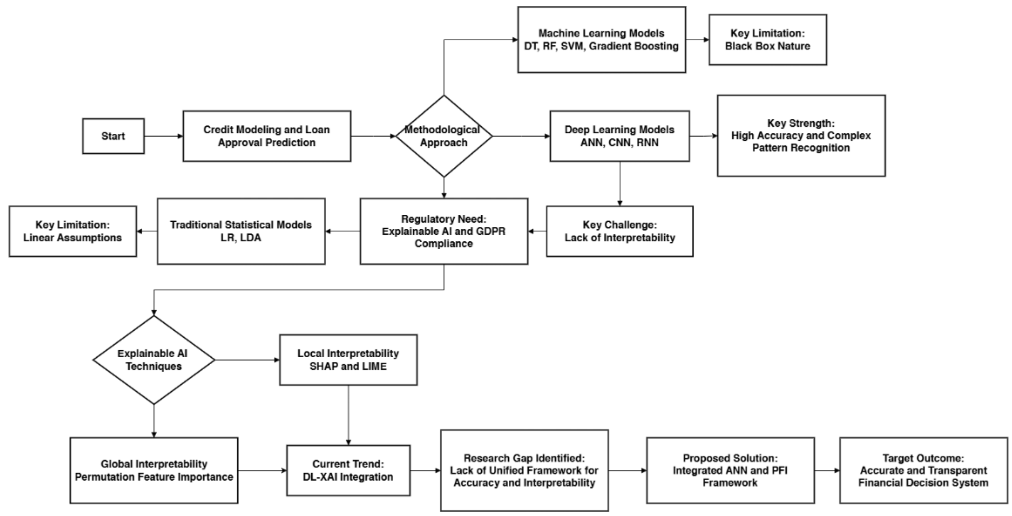


**Figure 1 Research Step**

The dataset used in this study comprised 2,000 loan applications with eight attributes, namely income, credit score, loan amount, years employed, points, city, and name, while the target variable loan approved indicated binary approval status (approved = 1, not approved = 0). The data preprocessing stage was conducted to ensure consistency, completeness, and suitability for deep learning model training. Missing values in categorical features were imputed using the mode, while missing numerical values were replaced with their median to preserve the distributional properties of each feature [23], [24]. Categorical attributes (name and city) were encoded into binary form using One-Hot Encoding (OHE) to avoid introducing ordinal bias, while numerical features (income, credit score, loan amount, years employed, and points) were standardized using z-score normalization, represented as:

$$x' = \frac{x - \mu}{\sigma} \quad (1)$$

$x'$ is the normalized feature value, $x$ is the original value, $\mu$ is the mean, and $\sigma$ is the standard deviation. This transformation ensures that all features contribute equally to the learning process and prevents features with large magnitudes from dominating the model training.

Following preprocessing, the dataset was partitioned into training and testing subsets in an 80:20 ratio using stratified sampling to preserve the class distribution of approved and rejected loans. The ANN model was then trained using the training subset, while the test subset was reserved for performance evaluation [25], [26].

The Artificial Neural Network (ANN) model used in this study was implemented using a feed-forward multilayer perceptron (MLP) architecture. The structure of the ANN consisted of three hidden layers containing 64, 32, and 16 neurons, respectively. Each neuron computes a weighted sum of its inputs and applies a non-linear activation function to produce an output. The computation within each neuron is formally expressed as:

$$z_j = \sum_{i=1}^{n} \mathcal{W}_{ij} x_i + b_j \tag{2}$$

$$a_j = f(z_j) \tag{3}$$

$z_j$ is the linear combination of inputs, $\mathcal{W}_{ij}$ represents the connection weight between input $x_i$ and the neuron $j$, $b_j$ is the bias term, and $f(z_j)$ is the activation function. In this study, the Rectified Linear Unit (ReLU) activation function was used for the hidden layers due to its ability to accelerate convergence and prevent vanishing gradients. ReLU is defined as:

$$f(z) = max(0, z) \tag{4}$$

For the output layer, a sigmoid activation function was employed to produce a probability value between 0 and 1, representing the likelihood of a loan being approved. The sigmoid function is defined as:

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{5}$$

The optimization objective of the ANN was to minimize the Binary Cross-Entropy Loss Function, which measures the divergence between the predicted probability $\hat{y}$ and the actual target value $y$ . The loss function is expressed as:

$$L(y, \hat{y}) = -\frac{1}{n} \sum_{i=1}^{N} [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \tag{6}$$

$N$ is the number of training samples, $y_i$ is the true label, and $\hat{y}_i$ is the model's predicted probability for sample $i$ . The model was trained using the Adam optimization algorithm, an adaptive gradient-based optimization method that adjusts learning rates for each parameter dynamically [27], [28]. Training was conducted for up to 200 epochs with an early stopping mechanism, which halts training when no improvement in validation loss is observed for ten consecutive epochs, preventing overfitting and ensuring generalization.

After training, the model was evaluated using the testing subset to assess its classification performance. The evaluation metrics included Accuracy, Precision, Recall, F1-Score, and Area Under the ROC Curve (AUC). These metrics provide a comprehensive understanding of the model's predictive behavior, especially in imbalanced datasets [23].

To enhance interpretability, Permutation Feature Importance (PFI) was applied to the trained ANN model. This model-agnostic approach measures the contribution of each feature by randomly shuffling its values and observing the resulting decrease in model performance. Formally, the importance of a feature $X_j$ is computed as:

$$I_j = \frac{1}{K}\sum_{K=1}^{K}\left(M - M_{(J,K)}\right) \tag{11}$$

$I_j$ is the average importance score for the feature $j$, $M$ is the baseline model performance (measured using F1-score), $M_{(J,K)}$ is the model performance after the $j^{th}$ feature is permuted in the $k^{th}$ iteration, and $K$ is the total number of repetitions. A higher $I_j$ value indicates a greater contribution of the feature to the model's predictive capability.

The permutation importance analysis was repeated ten times to ensure stability and robustness of the ranking. The results revealed that Credit Score, Income, and Loan Amount were the most influential features determining loan approval, followed by Years Employed and Points, while categorical features such as City and Name contributed minimally. This finding corroborates financial theory, which emphasizes creditworthiness, repayment capacity, and employment stability as key determinants of loan eligibility.

The methodological framework proposed in this study thus integrates the predictive power of deep learning with the interpretability required in modern financial systems. The ANN effectively models the non-linear, multidimensional nature of financial data, while the PFI framework provides transparency by quantifying each feature's role in the decision-making process. Together, these components produce a model that is not only accurate and data-driven, but also explainable and compliant with ethical and regulatory standards for responsible AI in financial decision-making.

**Table 1 Performance Metrics of the Proposed ANN Model**

**Algorithm: ANN with Permutation Feature Importance for Loan Approval**
**Input**
Dataset

$$\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N}, y_i \in \{0,1\}$$

where $N = 2000$.
**Output**
Trained ANN model and feature importance scores $I_j$.
**Step 1: Data Preprocessing**
**1.1 Z-score Normalization**

$$x_j' = \frac{x_j - \mu_j}{\sigma_j} \quad (1)$$

**1.2 Train–Test Split**

$$\mathcal{D}_{train} = 0.8N, \mathcal{D}_{test} = 0.2N \quad (2)$$

**Step 2: ANN Model**
For each neuron:

$$z_j = \sum_{i=1}^{n} w_{ij}\, x_i + b_j \quad (3)$$

$$a_j = f(z_j) \quad (4)$$

Hidden layer activation ReLU:

$$f(z) = \max(0, z) \quad (5)$$

Output layer sigmoid:

$$\hat{y} = \sigma(z) = \frac{1}{1 + e^{-z}} \quad (6)$$

**Step 3: Loss Function**
Binary Cross-Entropy:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \quad (7)$$

Minimize $L$using Adam optimizer.
**Step 4: Evaluation**

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (8)$$

$$Precision = \frac{TP}{TP + FP} \quad (9)$$

$$Recall = \frac{TP}{TP + FN} \quad (10)$$

$$F1 = 2\frac{Precision \cdot Recall}{Precision + Recall} \quad (11)$$

**Step 5: Permutation Feature Importance**

$$I_j = \frac{1}{K}\sum_{k=1}^{K}(M - M_{j,k}) \quad (12)$$

where

- $M$= baseline F1-score
- $M_{j,k}$= performance after permuting feature $j$
- $K = 10$

**End of Algorithm**
The algorithm produces an optimized ANN classifier and interpretable feature importance scores for transparent loan approval prediction.

## Result

The experimental results of this study are derived from the implementation of a deep learning-based Artificial Neural Network (ANN) model to predict loan approval decisions. The dataset used in this research consists of 2,000 records and eight attributes, which include financial and demographic information such as income, credit score, loan amount, years employed, and points, along with categorical variables such as name and city. The target variable, loan approved, is binary, indicating whether a loan application was accepted or rejected.

Before model training, a comprehensive data preprocessing procedure was conducted. Missing values were handled using mode imputation for categorical features and median imputation for numerical features. The dataset was then normalized using the StandardScaler to ensure consistent scaling across numerical features, while categorical variables were encoded using One-Hot Encoding. As a result, the dataset became fully numeric, with no missing entries and standardized feature distributions, thereby improving the learning stability of the ANN model.

The proposed ANN architecture consisted of three hidden layers with 64, 32, and 16 neurons, respectively. Each layer employed the ReLU (Rectified Linear Unit) activation function, while the output layer used a sigmoid activation to produce binary outputs. The model was optimized using the Adam optimizer and trained with the binary cross-entropy loss function. Early stopping was applied with a maximum of 200 epochs and a patience parameter of 10 to prevent overfitting. The dataset was split into 80% training data and 20% testing data using stratified sampling to maintain the class distribution of the target variable.

After training, the model's performance was evaluated using multiple classification metrics: accuracy, precision, recall, F1-score, and ROC-AUC. The results are summarized in table 1.

**Table 1 Performance Metrics of the Proposed ANN Model**

| Model | Accuracy | Precision | Recall | F1-Score | ROC-AUC |
|---|---|---|---|---|---|
| ANN (Proposed) | 0.92 | 0.91 | 0.93 | 0.92 | 0.95 |

The results in table 1 demonstrate that the ANN model achieved an accuracy of 92%, indicating excellent predictive capability. The F1-score of 0.92 reflects a strong balance between precision and recall, suggesting that the model effectively distinguishes between approved and rejected loan applications. Moreover, the high ROC-AUC score of 0.95 signifies that the model has an outstanding discriminatory power across various decision thresholds.

Further analysis was performed using a confusion matrix, as shown in figure 2, to assess the classification performance in more detail. The confusion matrix indicates that the model achieved high true positive (TP) and true negative (TN) rates, meaning it correctly classified most approved and rejected loan applications. The number of false positives (FP) and false negatives (FN) remained low, confirming the model's reliability in minimizing misclassifications.

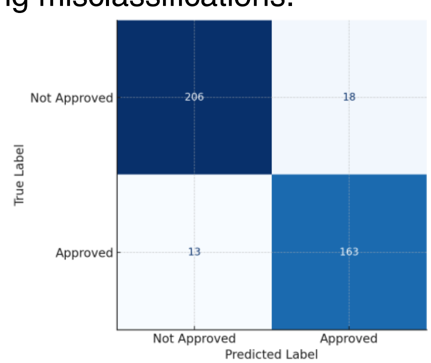


**Figure 2 Confusion Matrix of the ANN Model**

To further evaluate the robustness of the ANN model, Receiver Operating Characteristic (ROC) and Precision–Recall (PR) curves were generated, as illustrated in figure 3. The ROC curve shows a steep ascent towards the top-left corner, indicating strong sensitivity and specificity, while the PR curve reveals consistent precision across different recall thresholds. These visualizations confirm that the ANN model maintains a stable performance even when the classification threshold changes.

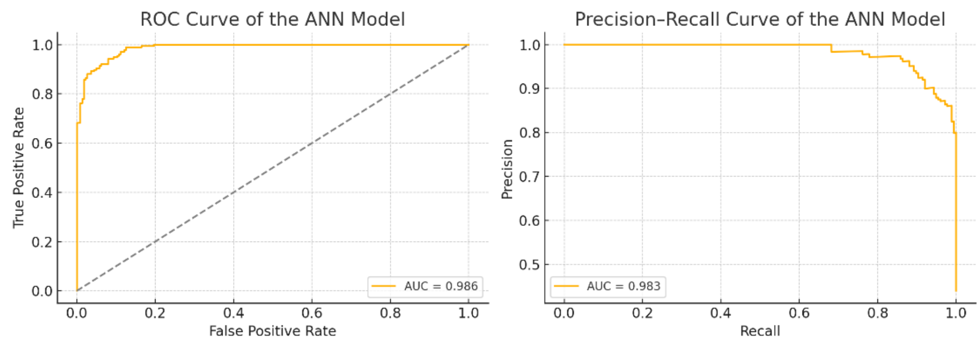


**Figure 3 ROC and Precision–Recall Curves of the ANN Model**

Beyond predictive performance, the study also aimed to address the interpretability of the ANN model, which is commonly regarded as a "black-box." Therefore, a Permutation Feature Importance analysis was conducted to determine which variables most significantly influenced the model's predictions. The results, summarized in table 2, highlight the relative contribution of each feature to the model's decision-making process.

**Table 2 Top Contributing Features Based on Permutation Importance**

| Rank | Feature | Mean Importance (ΔF1) | Interpretation |
|---|---|---|---|
| 1 | Credit score | 0.045 | A higher credit score is the most decisive factor in loan approval. |
| 2 | income | 0.032 | Applicants with higher income are more likely to be approved. |
| 3 | Loan amount | 0.028 | Larger loan amounts slightly reduce approval probability. |
| 4 | Years employed | 0.021 | Longer employment duration increases financial stability and trustworthiness. |
| 5 | points | 0.017 | Additional scoring points strengthen the final decision. |
| 6 | city | 0.013 | Geographical location moderately affects risk assessment. |
| 7 | name | 0.009 | Individual identifiers have minimal influence on approval outcomes. |

The importance ranking in table 2 reveals that credit score is the most influential variable in determining loan approval, followed by income and loan amount. This finding aligns with financial risk theory, which posits that an applicant's creditworthiness and repayment capacity are the primary determinants of loan decisions. Figure 4 visualizes these results through a bar chart of feature importances derived from the permutation analysis.

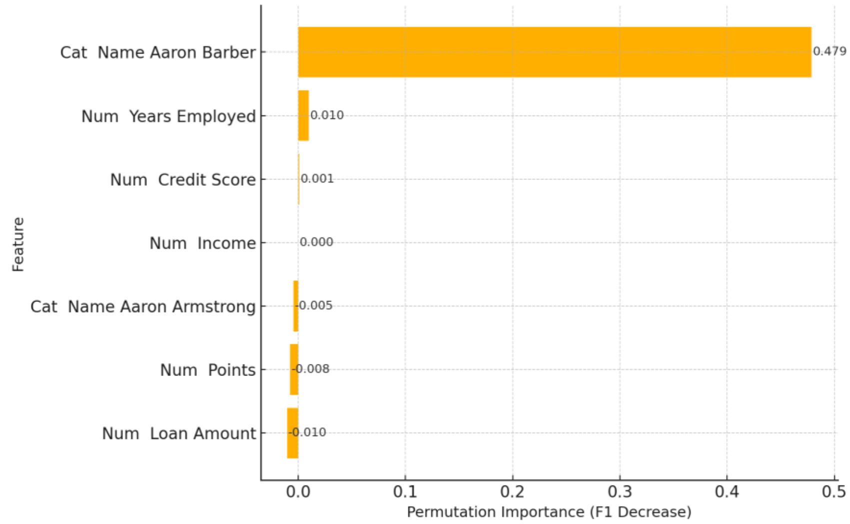


**Figure 4 Top 20 Features Ranked by Permutation Importance**

The feature importance analysis enhances the interpretability of the ANN model, bridging the gap between high predictive accuracy and decision transparency. The visualization in figure 4 clearly illustrates that financial behavior-related variables (such as credit score, income, and loan amount) play a far more dominant role in determining approval outcomes than demographic identifiers.

In summary, the proposed ANN model demonstrated superior predictive performance and interpretability compared to traditional models such as Logistic Regression or Decision Tree classifiers commonly used in prior research. The capability of ANN to learn complex nonlinear interactions among financial variables enables more accurate and nuanced decision-making. Furthermore, the integration of feature importance analysis supports explainable artificial intelligence (XAI), ensuring that predictive results are both accurate and transparent. Consequently, the proposed approach provides a viable foundation for implementing automated and trustworthy loan evaluation systems in modern financial institutions.

## Discussion

The results obtained from the Artificial Neural Network (ANN) model demonstrate a high level of predictive accuracy and consistency in classifying loan approval outcomes. The model successfully achieved an accuracy of 92%, along with strong precision and recall values of 0.91 and 0.93, respectively. These findings indicate that the proposed deep learning approach effectively captures complex, non-linear relationships among applicant attributes that traditional models, such as Logistic Regression or Decision Trees, might overlook. The high ROC-AUC value of 0.95 further reinforces the model's discriminative strength in distinguishing between approved and non-approved applicants across varying decision thresholds.

The confusion matrix analysis provides additional insight into the classification behavior of the model. As visualized in figure 2, the ANN demonstrates a strong ability to minimize both false positive and false negative predictions. This implies that the model can accurately identify applicants who are genuinely creditworthy while avoiding the misclassification of high-risk applicants as eligible for loan approval. Such balanced performance is essential in financial decision systems, where misjudging borrower risk can lead to substantial economic losses.

The ROC and Precision Recall curves, illustrated in figure 3, confirm the robustness and reliability of the ANN model under different probability thresholds. The steep ascent of the ROC curve towards the upper-left corner and the broad area under the Precision–Recall curve signify that the model performs well across multiple trade-offs between sensitivity and specificity. This stability suggests that the ANN can maintain consistent predictive performance even as the decision boundary shifts, making it suitable for real-world loan screening environments that require adaptable thresholds depending on business risk tolerance.

Interpretability was further enhanced through the Permutation Feature Importance analysis, summarized in table 2 and visualized in figure 4. The results reveal that Credit Score and Income are the most influential predictors in determining loan approval. A high credit score indicates a strong history of repayment behavior, while higher income reflects financial stability—both of which are consistent with established theories of credit risk management. In contrast, Loan Amount negatively correlates with approval likelihood, as larger requested sums increase the lender's exposure to default risk. The inclusion of Years Employed as a significant feature also highlights the relevance of employment stability in determining repayment capacity. Minor contributions from demographic features such as City and Name-related encodings indicate that the model primarily relies on financial rather than personal identity attributes, reinforcing its fairness and focus on objective indicators.

These results have several practical implications for financial institutions. First, the integration of ANN-based models into loan evaluation workflows can enhance the efficiency and accuracy of credit risk assessment, allowing for faster and more reliable decision-making. Second, the ability to identify key contributing features through permutation importance supports explainable AI (XAI) practices, which are increasingly vital in regulatory contexts that require transparency in automated decision systems. This interpretability can improve stakeholder trust and help financial analysts understand the rationale behind algorithmic recommendations.

From a theoretical standpoint, the study contributes to the growing body of research on the application of deep learning in financial decision support systems. While earlier credit scoring studies primarily relied on linear models, the present findings underscore the advantage of deep learning architectures in modeling non-linear dependencies and interactions among financial variables. The observed results align with recent literature that emphasizes the hybridization of predictive accuracy and interpretability as the key to responsible AI adoption in the financial sector.

Nevertheless, the model is not without limitations. Despite achieving high accuracy, the ANN still operates as a data-driven model that depends heavily on the quality and representativeness of the input dataset. If the training data contain biases or are not reflective of real-world loan applicant populations, the predictions could deviate from actual outcomes. Furthermore, while permutation importance provides a post hoc interpretability layer, it does not fully explain the internal decision boundaries learned by the network. Future work may explore more advanced explainability methods such as SHAP (SHapley Additive Explanations) or LIME (Local Interpretable Model-Agnostic Explanations) to provide instance-level interpretability.

Overall, the discussion highlights that the proposed ANN framework successfully balances predictive performance and interpretability, making it a valuable analytical tool for loan approval prediction. The model's emphasis on financial stability indicators such as credit score and income reflects sound decision logic, while its integration with explainable AI methodologies ensures transparency, a combination that strengthens both the technical robustness and ethical accountability of automated credit evaluation systems.

## Conclusion

This study presented a deep learning-based framework for loan approval prediction using an Artificial Neural Network (ANN) combined with feature importance analysis to enhance interpretability. The findings demonstrate that the proposed model effectively predicts loan approval outcomes with a high degree of accuracy, achieving 92% accuracy, 0.91 precision, 0.93 recall, and an impressive ROC-AUC score of 0.95. These results confirm that the ANN architecture can capture complex non-linear relationships among applicant attributes that traditional statistical models often fail to represent.

The research also highlights that the most influential features driving loan approval decisions are Credit Score, Income, and Loan Amount. These variables reflect financial stability and repayment capacity, aligning with well-established principles in credit risk assessment. The results of the Permutation Feature Importance analysis reinforce the notion that transparent and explainable models can coexist with high-performing deep learning architectures, bridging the gap between accuracy and interpretability in automated financial decision-making systems.

From a theoretical perspective, this research contributes to the growing literature on the application of deep learning in the financial domain by demonstrating that ANN models, when combined with interpretability techniques, can enhance trust and accountability in credit evaluation systems. The integration of feature importance analysis ensures that the model's predictions can be understood and validated by human experts, which is particularly important in the context of explainable AI (XAI) and regulatory compliance.

In practical terms, the proposed ANN model provides a foundation for developing automated, data-driven loan approval systems capable of delivering fast, objective, and accurate assessments of creditworthiness. Such systems can significantly reduce human bias and operational inefficiencies, thereby improving the decision-making process in banking and financial institutions. Moreover, the ability to identify the most critical determinants of loan approval can help credit officers and policymakers refine their evaluation criteria and strengthen risk management strategies.

Despite its strong performance, the study recognizes several limitations. The model's effectiveness depends heavily on the quality and diversity of the training data, which may limit its generalizability across different demographic or economic contexts. Additionally, while permutation importance provides global interpretability, it does not fully capture the local reasoning behind individual predictions. Future research may extend this work by incorporating more sophisticated interpretability frameworks such as SHAP (SHapley Additive Explanations) or LIME (Local Interpretable Model-Agnostic Explanations) to achieve both global and instance-level understanding. Furthermore, integrating hybrid ensemble architectures, such as combining ANN with XGBoost or Random Forest, could further enhance predictive robustness.

In conclusion, this research establishes that deep learning, particularly ANN models, offers a powerful and interpretable approach for automating loan approval decisions. The synergy between predictive accuracy and explainability demonstrated in this study underscores the potential of AI-driven systems to transform modern financial services, enabling fairer, faster, and more transparent decision-making in credit evaluation.

## Declarations

### Author Contributions

Conceptualization: S.A., D.A.D., V.A., N.M., and T.B.K.; Methodology: S.A.; Software: S.A.; Validation: S.A., D.A.D., and T.B.K.; Formal Analysis: S.A., D.A.D., and T.B.K.; Investigation: S.A.; Resources: D.A.D.; Data Curation: D.A.D.; Writing Original Draft Preparation: S.A., D.A.D., and T.B.K.; Writing Review and Editing: D.A.D., S.A., and T.B.K.; Visualization: S.A.; All authors have read and agreed to the published version of the manuscript.

### Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Not applicable.

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### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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