

# **Comparative Risk Factor Analysis in Loan Risk Prediction using Variable Artificial Neural Network Layer Configuration**

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This Report Presented in Partial Fulfillment of the Requirements for  
The Degree of Masters of Science in Computer Science and Engineering

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## APPROVAL

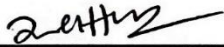
This Project/Thesis titled “**Comparative Risk Factor Analysis in Loan Risk Prediction using Variable Artificial Neural Network Layer Configuration**”, submitted by **Md. Rezaul Hossain**, ID No: **232-25-012** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **11-01-2025**.

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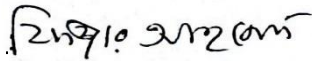
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## DECLARATION


I hereby declare that this research has been done by me under the supervision of **Dr. Fizar Ahmed, Associate Professor, Department of CSE**, Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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## **ABSTRACT**

Loans have become an inevitable part of the contemporary financial market and thus predicting the risk inherent in a particular loan is crucial in avoiding high levels of default and improving on the profitability of the loans. The study fills the current research gap concerning creating and fine-tuning loan risk prediction models by comparing the performance of different ANN layers (4-layer, 5-layer, and 6-layer) in identifying the risk attributes in loan defaults. This paper utilizes a comparative research design, using diverse borrower attributes and a range of financial ratios. Specifically, the method like Accuracy, Precision, Recalling is used to assess how well every configuration of ANN works on loan risk prediction. Fortnight preliminary results do suggest that 6-layer ANN provides much higher accuracy and recall rates than 4, 5-layer ANN neural networks. The contribution of these results is in the development of more profound and distinct knowledge of financial analytics, along with the possibilities of the two-tiered neural network structures for improving loan risk assessment. Additionally, the results of the study throw the light on the choice of the right risk factors and configurations for the ANN for the practical problems of credit scoring in the financial institutions, and opens up the directions for future research that can enhance the performance of the predictive modeling for credit risk assessment.

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# CHAPTER 1

## INTRODUCTION

### 1.1 Introduction

Credit risk management has proved to occupy a central position in financial institutions, particularly in the contemporary world financial scene. A particularly important process that forms the basis of credit risk management is the prediction of loan risk, which will allow the bank to determine the probability of attracting loan losses. In the past, loan risk assessment has to some extent been based on statistical and rule-based models that do not accurately take into consideration the many interactions between or within loans and borrowers. Machine learning and the ANN specifically, have enhanced and developed superior sources of risk prediction. The solution became more accurate and malleable at the hands of ANN.

Artificial Neural Networks are one of the powerful computational models derived on the basis of the structure of the human brain. It is also noticeable that they are good at modal recognition therefore making them suitable for categorization problems like loan risk assessment. ANNs are a set of layers of complex nodes/ neurons that can learn from data using backpropagation and gradient descent. ANN structure mainly the quantity of the secret layers and the neurons in each of them have a greater impact on the predictive capability of the developed model. Nonetheless, choosing the appropriate network architecture is still a problem, higher levels may provide additional learning capability but are inclined to overfit.

Therefore, the objective of this thesis is to establish an understanding of how the number of secret (hidden) layers influences the performance of loan risk prediction on ANN. In particular, we will measure the performance difference of 4-layer, 5-layer, and 6-layer of the neural network in order to determine loan defaults. In the following analysis, we aim to determine which configuration of ANN is suitable for this task, using metrics such as network depth and the resulting accuracy, precision, recall, etc. Furthermore, factors that

include credit history, income, and employment status of the borrowers, and their effect on each of the models will also be discussed in this study.

Based on it, the major a contribution of this research will be to advance the current efforts in advancing the loan risk predictor models and to assist the financial institutions to manage creditworthiness and loan default risks.

## **1.2 Motivation**

Hence the desire to write this research stems from the fact that there is an acute need to increase anemic stability and at the same time, reduce possible loss to the lending institutions. Another important issue is associated with the employment of more accurate loan default identification methods, because mistakes may cost much. The limitations of the conventional lenders' risk analysis techniques are that they are static, and may not work well within dynamically changing borrower and economic environments. This has emphasized the need to develop more complex computational methods of calculating this by using ANN algorithms. Specifically, it is expected that understanding the effect of different ANN layer structures will help to increase the accuracy of loan risk prediction using neural networks. The findings will not only be useful for the banking and financial industries in managing default risk but will also demonstrate the potential impact of architectural decisions for machine learning as a field.

## **1.3 Rationale of the Study**

The purpose for this study thus arose from the understanding that, with the ability to improve on the accuracy of artificial intelligence and enhancement on the aspect of machine learning; the risk evaluation of loans can be made more efficient. There are new challenges that banks face in measuring risk for credit risk due to characteristics and limitations of conventional architectures of data. Solving the problem with Fixed Nonlinear Models has a better solution with ANNs due to its capacity to generalize the models and identify hidden relations. The study aims to establish the extent to which hidden layers of ANN namely 4, 5 and 6, influence loan default prediction. Such an

approach is quite recent when used to formulate a look and feel when being applied in the financial industry with an aim of determining the most appropriate structure in the perspective of a tradeoff between the forecast ability and the level of calculation complexity. Despite this, the paper's purpose is to determine the impacts of different configurations of ANN on the results of prediction, the study's conclusions are expected to provide positive feedback to the financial and formation of machine learning to get improved determination to loan approval processes.

#### **1.4 Research Questions**

- RQ1: Which of the following is the best architecture of ANN layer configuration, 4-layer, 5-layer or 6-layer ANN for loan risk prediction?
- RQ2: How does a number of hidden layers in an ANN influence accuracy, precision, recall and F1-score?
- RQ3: What is the impact of borrower characteristics (e.g., credit history, income) on prediction accuracy?

#### **1.5 Expected Output**

- Development of an ANN various layer model.
- A comprehensive comparison of model performance against various layer configurations in terms of accuracy and efficiency.
- Creation of a foundation for future research in the application of hybrid models for loan risk analysis.

#### **1.6 Project Management and Finance**

No individuals or organizations provide funding for the research work.

#### **1.7 Report Layout**

The introduction, research aim and objectives of the study, and key research questions are presented in chapter one. Summaries of the literature review as presented in the Chapter 2

are also very brief. Chapter 3 presents the proposed methodology of the present study. The experimental outcomes of the paper are outlined and discussed in Chapter 4 of the paper. Chapter five focuses on the sustainability plan, the effect of the plan on society and the environment, and ethical issues. The sixth chapter gives the conclusion of the present investigation and suggests a plan for further research.

## **CHAPTER 2**

### **BACKGROUND**

#### **2.1 Preliminaries/Terminologies**

Loan risk prediction is important to financial institution to be able to avoid loan risks that would in turn affect the profitability of the business concerns. Conventional techniques for evaluating the probability of credit risk do not consider cross or interaction effects when measuring borrower factors that may influence the probability of default. ANNs (Artificial Neural Networks) are used in this research for loan risk prediction, and the numbers of hidden layers used in the research are analyzed to determine the changes in performance. In particular, we examine the performance of 4-layer, 5- layer, and 6-layer ANNs for the prediction of loan defaults using actual financial data.

The study examines the effects of credit history, the income level and the employment status as major factors in predicting loan default decisions. The models employ a supervised learning paradigm, and their effectiveness is compared by evaluating the relevant quality measures including accuracy, precision, recall, F1 score, and the AUC-ROC curve. The final objective of the comparative analysis of these network configurations is to determine which of the ANN architectures is best suited for accurate risk prediction.

The results suggest that more layers may well be helpful in terms of better performance, but it simultaneously also poses a bigger threat of overfitting that can be managed only by proper model regularization techniques. The finding of this study can be used to guide the future development of ANN-based models for loan risk evaluation to improve the lending decision of those institutions.

#### **2.2 Related works**

Risk assessment on loans has always been a major concern in the field of banking and finance for many years with many papers directed toward enhancing the accuracy of the models utilizing statistical methodology alongside artificial neural networks and other

intelligent methodologies. This section discusses a historical perspective of loan risk prediction models with ANNs and various architectures discussion.

### **2.2.1 Loan Risk Prediction Traditional Models**

Speaking of the methods applied earlier for loan risk prediction, it is possible to mention logistic regression, decision trees, and discriminant analysis. According to **Thomas et al. (2002)**, logistic regression was appropriate in this study because it is simple and easily interpretable [14]. These models presume the straight-line relationship between borrower characteristics and loan performance, while the actual data can be different. It was **Altman's Z-score (1968)** model, used for corporate bankruptcy prediction, that provided groundwork for credit risk evaluation. However, traditional models are applied to discrete variables as linear and independent; therefore, they cannot help much when analyzing interdependent and nonlinear data of financial fields [15].

### **2.2.2 Loan risk prediction Machine Learning Models**

By the help of evolved machine learning, random forests, decision trees, gradient boosting machines (GBMs) and, support vector machines (SVMs) were commonly used in predictive modeling. **Malhotra and Malhotra (2003)** and **Lessmann et al. (2015)** established that self-regulating algorithms offered superior performance to conventional methods in dealing with vast databases that include complicated feature interactions [16][17]. But deep learning has opened up new ways in dealing with non-linear relationship of loan risks prediction. **Kou et al. (2021)** offered an extensive analysis; they showed how, despite the numerous choices available, deep learning models, and ANNs predominantly, efficiently identify even subtle relationships in the financial data. Unlike conventional approaches, these models do not entail feature engineering often needed for popular algorithms and can learn from data directly through multiple transformations [18].

### **2.2.3 Risk Prediction Artificial Neural Networks Models**

Because of the non-linear mapping capability of ANN, between the input and target variable, the application of ANNs has shown promising results in loan risk prediction. **Zhang and Kanda (2017)** employed a simple feedforward ANN for credit defaults with only one hidden layer including better accurate predicting as compared to logistic

regression models. But as they pointed out, they realized how delicate the model performance might be with network architecture concerning the number of hidden nodes and layers [21]. In their study, **Heaton et al. (2016)** showed that Deep ANNs are capable of analyzing a large volume of values making them appropriate for analytical use in the financial sector. But the study also highlighted some of the disadvantages which include over fitting especially with deeper networks architectures [20]. **Goodfellow et al., (2016)** reiterated the argument of depth when addressing the effectiveness of the network stating that while deeper networks provide better solutions, they will also lead to greater chances of overfitting and could be very computation intensive [19].

#### **2.2.4 Variable Layer Configurations in ANNs**

ANN is ideally best suited and the overall count of hidden layers and neural units has been a subject to extensive research. Another downside of deeper networks for **Hinton et al. (2006)** and **LeCun et al. (2015)** these models enable sophisticated performances to be learned due to their efficiency but are computationally intensive and more sensitive to overfitting if training data is scarce [22][23]. Peng, **Kou and Zhou (2018)** discuss how the magnitude of the network's depth affects the risk prediction models in insurance. They also discovered that deep learning systems with more hidden layers fared better than the shallow ones, though more care had to be taken to avoid overfitting than through regularization techniques including dropout and batch normalization. Another work by **Chaudhary et al. (2020)** focused on the impacts of different layer ANNs on the credit scoring and discovered rising the depth of the network helped enhancing the precision of the model but added extra training difficulty [3][8].

#### **2.2.5 Risk Factors in Loan Default Prediction**

The literature review also attests to the point of feature selection and the study of effects of different risk factors. In their study on credit scoring using logistic regression **T. Hastie, R Tibshiran, and J Friedman (2009)** found predictors including credit history, income, and employment. The findings have revealed that these risk factors are significant and are persistent contributing factors to loan default predictions [5]. Subsequently, **Kou et al. (2018)** further developed this by using deep learning methods to investigate the effect of

the aforementioned risk factors in non-linear models. They found out that deep ANNs contain the ability to reveal the behavior between borrower characteristics and default rates undetectable by conventional models [18].

### **2.2.6 Comparative Studies of ANN Configurations**

Various variants of ANNs have been assessed in several comparative researches to determine their impact on model performance. **Yu et al. (2018)** worked on the comparison of shallow and deep ANNs for loan default prediction and discovered that the loan default predicting power of deeper networks is superior as well as is the generalizing power especially when training data overabundance is present. They however pointed out that with the increased employment of deep architectures, there were larger computational costs and that it required more optimum techniques and ideas [24]. Predicting mortgage defaults using ANNs, **Zhang et al. (2020)** analyzed variable layer of the ANN model. They noted that through the analysis, that greater depth of the models led to increased performance but with much lower rates of incremental improvement. These results imply that even though deeper architectures improve accuracy, one must design a model that balances depth and accuracy [25].

## **2.3 The Problem's Scope**

This study adds to the current knowledge of loan risk prediction by giving practical data into the impact of changing the configuration of hidden layers in an ANN on the model's performance. It also shows the correlation between model complexity and the problem of overfitting as well as computational overhead. The study indicates that as the network depth increases prediction precision may be increased but this comes at a certain saturation and, thus, best balance must be achieved.

## 2.4 Challenges

While deeper ANN models offered improved performance, they also introduced several challenges:

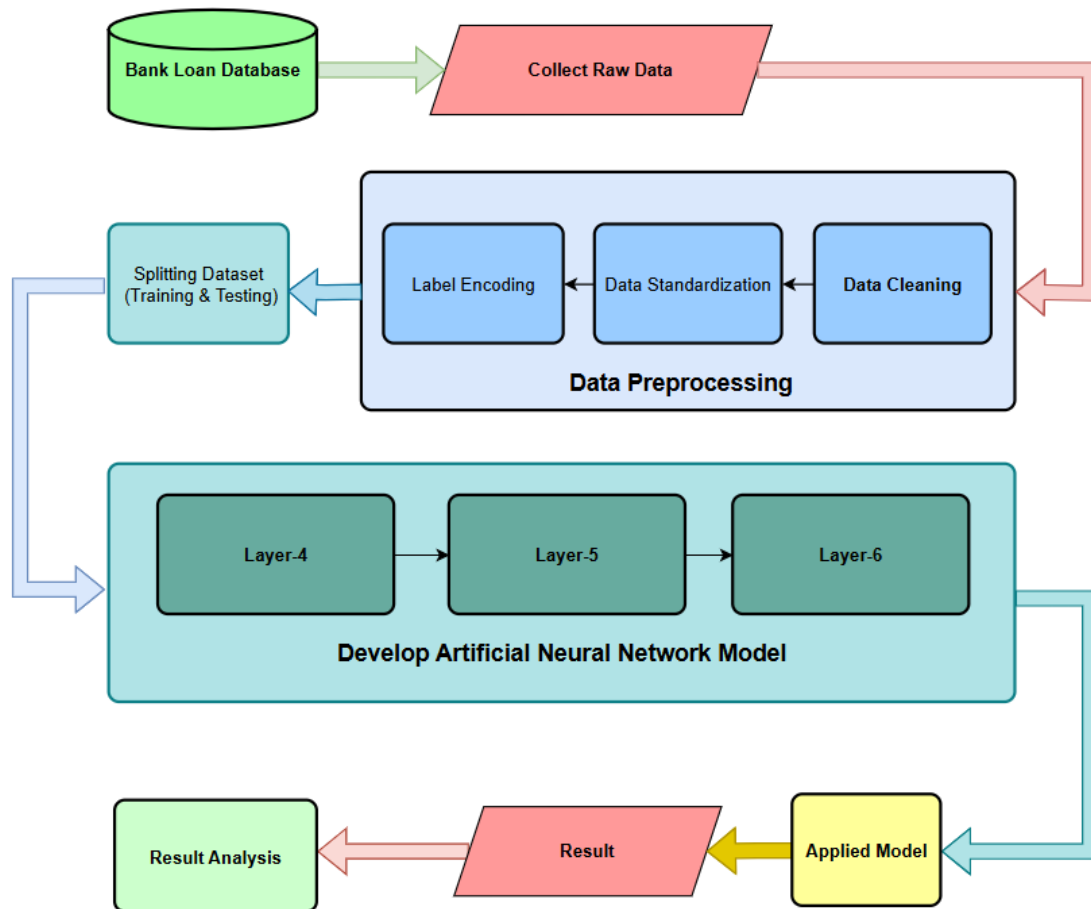
- **Overfitting:** The necessity of a larger dataset was apparent when going deeper in the network, while using 6 layers exposed much higher probabilities of overfitting. This problem was well mitigated using techniques like dropout and L2 regularization, though these must be tuned appropriately to balance over complexity and generalization capability of the model.
- **Computational Costs:** The deeper models needed thousands of times more training time and memory than the 4-layer model had needed. In particular, the very significant increases in computational requirements that are implied by deeper networks must be balanced against the quite small improvements in performance that they appear to deliver.

# CHAPTER 3

## RESEARCH METHODOLOGY

### 3.1 Proposed Methodology/Applied Mechanism

The provided diagram 3.1 showcases a methodological approach to predicting loan risk..



**Fig 3.1:** The working process to perform loan risk prediction

This section presents the procedures and procedures of carrying out the comparative analyze of loan risk prediction by applying 4-layer, 5-layer and 6-layer Artificial Neural Networks. The methodology is divided into key phases: It identifies the steps starting from dataset selection and preprocessing, model architecture and training and evaluation and the comparative analysis section.

## **3.2 Data Collection Procedure/Dataset Utilized**

The dataset utilized for the study of Loan Risk Prediction is sourced from Bank, specifically the "Bank\_Loan\_Dataset" dataset, which is collection form a Bangladeshi Bank.

### **3.2.1. Dataset Selection**

Data used in this study will be collected from the banking sector. The dataset contains 34 attributes (columns) and 329414 rows. The dataset will include key features, such as:

- **Loan amount**
- **Interest rate**
- **Borrower income**
- **Employment status**
- **Credit score**
- **Loan term**
- **Debt-to-income ratio**
- **Loan purpose**

Some of these factors are well understood predictors of the likelihood of loan default in the financial sector.

## **3.3 Data Pre-processing**

Everybody knows that data pre-processing is a critical phase of a constituent exercise in machine learning. However, there are few other pre-processing techniques that can be used in exceptional circumstances as follows. Enhancement of each one of input data is the main reason why data pre-processing is done. In this task, I employed TensorFlow/Keras model which is a tremendously significant part of all the data preprocessing steps for a classification problem. These transformations make up a set of preprocessing stages that act on the row data before feeding them into the artificial neural network for training [1]. Here's a broad description of the preprocessing steps encoded in the class, along with a detailed explanation of each step and its importance for classification:

### **3.3.1 Cleaning and Transformation**

The management of the missing values, outliers and or erroneous entries. All the holes in the data will be filled by either means or medians while very extreme values in the databases will be handled using methods such as z-score normalization.

### **3.3.2 Standardization (Mean Subtraction and Division by Standard Deviation)**

The code pray away from the mean and scales down the data arrays to the division by the standard deviation. This step is crucial for standardize the neural network performance [6]. It standardizes the pixel intensity values so as to increase the value of the dataset mean to zero and the standard deviation to one.

### **3.3.3 Normalization**

The mask is binarized by using a threshold that assigns pixels to the object of interest as well the background. Loan amount, interest rate, the borrower's income will be a continuous data type and hence will be normalized or standardized to bring variables to one scale and this leads to the improvement of the neural networks.

### **3.3.4 Feature Encoding**

Categorical variables like, loan purpose, and employment status are going to be encoded numerically in the described data set, using methods like one-hot encoding.

### **3.3.4 Train-Test Split**

That will be further divided into the training set at 70 % and the testing set at 30 % for accuracy of the model analysis.

## **3.4 Machine Learning Models**

A living systematic neural network in the brains of animals is modeled in machine learning by an artificial neural network. An ANN, as the abbreviation says, is made up of connected units or nodes referred to as artificial neurons, which only metaphorically resemble real neurons. This research proposed various layer configuration of artificial neural network model mentioned above [3]. The study will implement three different artificial neural network architectures:

### 3.4.1. Artificial Neural Network 4-Layer Model Architecture

The following Figure 3.4.1 represents the architecture of a 4-layer ANN model, which has the following parts: The input layer is consisted of 10 neurons and the output layer has only one neuron. three hidden layers in this form of architecture, each of the hidden layers has 32 neurons.

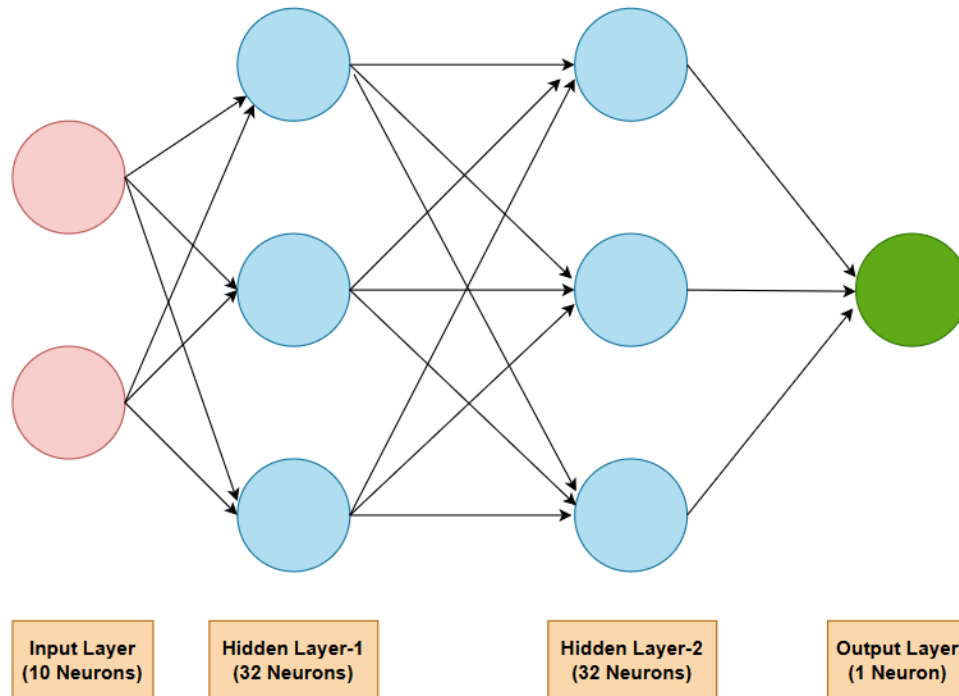
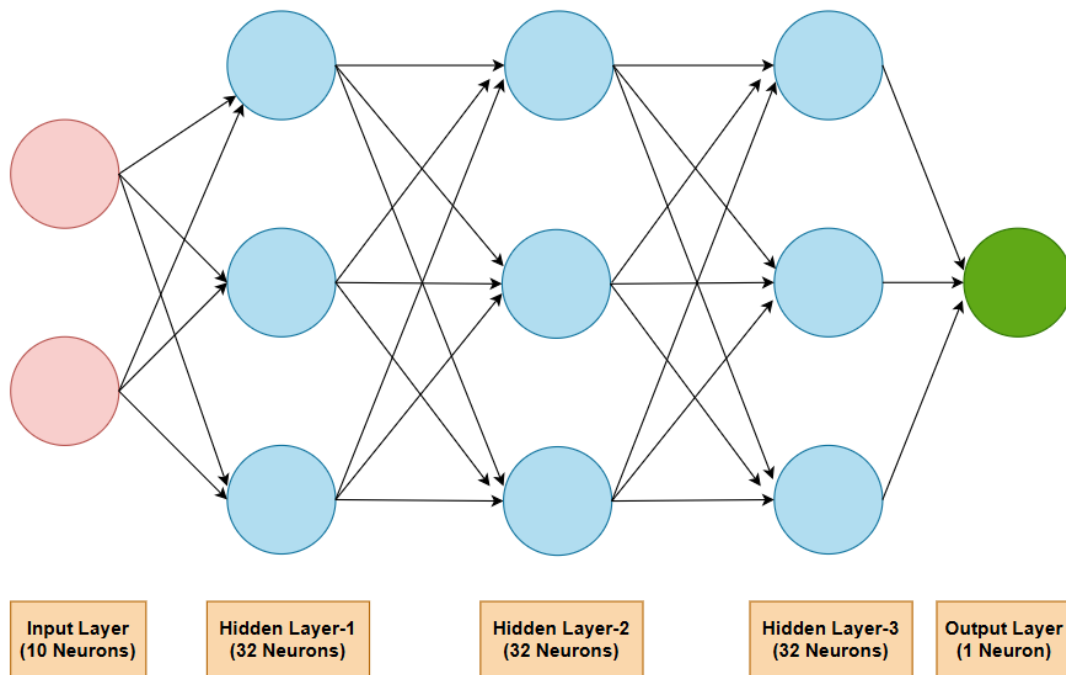


Fig. 3.4.1: Proposed ANN 4-Layer Model architecture

### 3.4.2 Artificial Neural Network Layer-5 Model Architecture

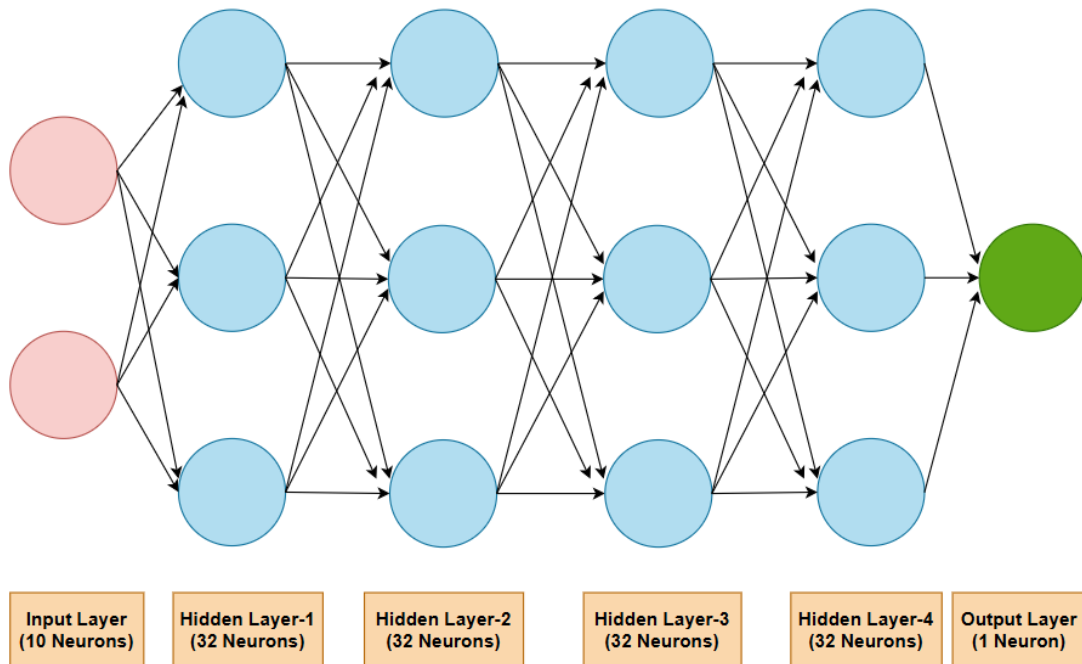
The following Figure 3.4.2 represents the architecture of a 5-layer ANN model, which has the following parts: The input layer is consisted of 10 neurons and the output layer has only one neuron. three hidden layers in this form of architecture, each of the hidden layers has 32 neurons.



**Fig. 3.4.2:** Proposed ANN 5-Layer Model architecture

### 3.4.3 Artificial Neural Network 6-Layer Model Architecture

The next figure 3.4.3 below depicts a 6-layer ANN model, which has the following parts: The input layer is consisted of 10 neurons and the output layer has only one neuron. four hidden layers in this form of architecture, each of the hidden layers has 32 neurons.



**Fig. 3.4.3:** Proposed ANN 6-Layer Model architecture

Regarding the architecture, each kind of model will be a feedforward one with fully connected layers. The frequency of neurons in the hidden layer will be decided based on a preliminary experiment, but they will begin with a regular setting of neurons used in standard ANN models (32 neurons per hidden layer). The last layer of the ANN will continue to have a single neuron with an activation function of sigmoid as the network will be using binary classification (default, no default).

Key configuration details:

- **Activation Functions:** ReLU (Rectified Linear Unit) will be used as a function for all hidden layers since it reduces the vanishing gradient problem considerably.
- **Loss Function:** Hence binary cross-entropy will be used as the loss function since the format of the task is a binary one.
- **Optimizer:** In training phase, the Adam optimizer will be used since it has features of both AdaGrad and RMSProp optimizer used for large data set and neural networks [6].

- **Regularization Techniques:** More hidden layers will be added and dropout layers will be added to lower the option of overfitting, and L2 will be used to punish the complex models.

### 3.5 Training the Models

The models will be trained using the following configurations:

- **Batch Size:** Initially set to 32, though, this hyperparameter will be adjusted to get the best-performing model.
- **Epochs:** Training process will be initiated with 10 epochs in which case, early stopping will be used to overcome overfitting.
- **Learning Rate:** Specifically, the current learning rate should be as small as possible, say, 0.001, and it may be changed during the training process.

These models will be built on train dataset and the weights associated to the models will be tuned with the help of backpropagation and gradient descent algorithm. The epochs would be reduced so that training will stop when the model is not showing any improvement on the validation data set as the motivation is to achieve better result.

### 3.6 Evaluation Metrics

The trained models will be evaluated on the testing set using the following performance metrics:

- **Accuracy:** Refers to the percentage of right the forecasts made by the model.
- **Precision:** The proportion of successful identification of the actual defaulters to the total number of identified defaulters (including some which are not actually defaulters).
- **Recall:** The ratio of the correctly identified as positive over the real positive and negative cases in the population of interest.
- **F1 Score:** A weighting so that precision and recall is computed as the harmonic average of the two parameters.

- **AUC-ROC (Area Under the Receiver Operating Characteristic Curve):** An analysis that helps to determine the effectiveness of the model in making the right predictions between the two classes which are – default and non-default.
- **Confusion Matrix:** Continuing the model results distinction into True Positive, False Positive, True Negative, False Negative.

### 3.7 Comparative Analysis

After training and evaluating 4-layer, 5-layer, and 6-layer ANNs, then the performance will be compared according to the evaluation metrics mentioned above. The comparison will focus on:

- **Model Performance:** Comparative outcomes of different architectures of the model regarding accuracy, precision, recall, F1 score, and AUC-ROC at different layer sizes, namely, 4, 5, and 6.
- **Generalization Ability:** Their generalization performance on the test data will be compared, and over and under-fitting behavior will be established.
- **Impact of Risk Factors:** The models will be assessed in relation to their employ of the risk factors such as income, credit score, etc. The feature importances will be assessed using Feature importance scores from the ANN Models.

### 3.8 Tools and Software

The following tools and frameworks will be used for model development and analysis:

- **Python:** The most used language in the area of data processing and the language to write down the models themselves [10].
- **TensorFlow/Keras:** A software tool for constructing and learning the basic architecture and parameters of the ANN models [1].
- **Scikit-learn:** For preprocessing, data evaluation, and the assessment of cross-validation [2].
- **Pandas/Numpy:** For reshaping the data and for analysis [4].
- **Matplotlib/Seaborn:** In data visualization and results interpretation [4].
- **PC Configuration:** HP EliteBook 840, 512 SSD, RAM 16 GB.

## CHAPTER 4

### EXPERIMENTAL RESULTS AND DISCUSSION

#### 4.1 Graph of Research

The visualization of loan risk prediction data correlation matrix is given in figure 4.1.1.

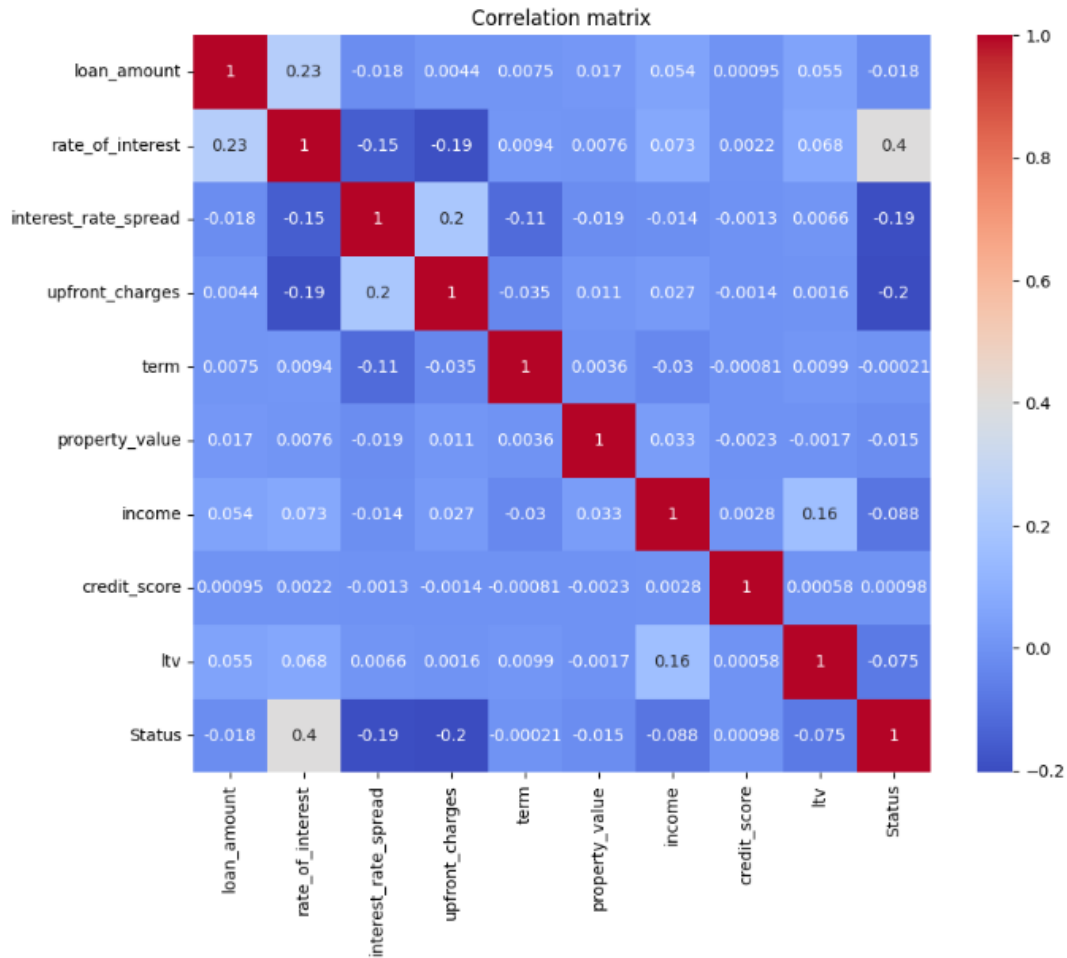


Fig. 4.1.1: Correlation Matrix

The figure 4.1.2 contains the bar chart visualization of loan risk prediction dataset age attribute.

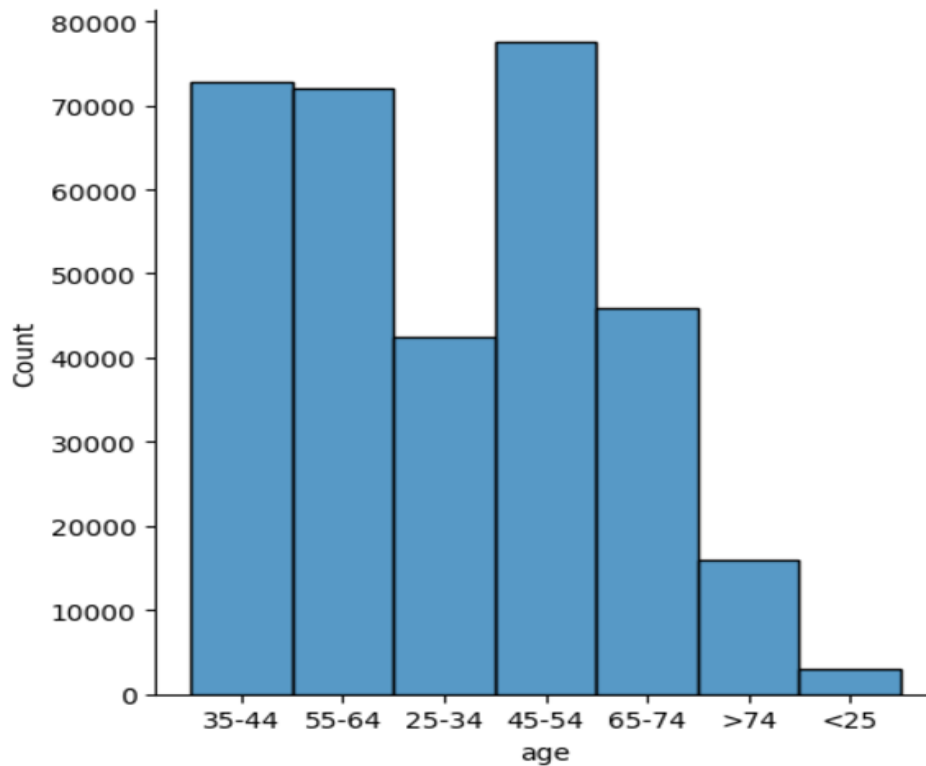


Fig. 4.1.2: Bar Chart for Distribution of AGE

## 4.2 Evolution Methods

This research also includes preprocessing the raw data of bank loan as predicted via an Artificial Neural Network that uses the variable layer configuration of the machine learning model variable. The model is used like an evaluation, and it assesses accuracy, precision, recall, F1-measure, and creates a confusion matrix. True positive is also real in occurrence, The values scored as True Positive (TP) are real indeed. When false results are mislabeled the end result is false positives (FP). The fourth kind of distortion is a false negative (FN) when an actual correct value is given a negative magnitude. As we demonstrated earlier, TN and FN are presented in the fourth and the fifth places accordingly. In outcomes, true negative is referred to as positive value that is correctly categorized as negative. Fourth is true negative (TN).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

$$Recall = \frac{TP}{TP + FN} \quad (5)$$

$$F1\ Score = 2 \times \frac{precision \times recall}{precision + recall} \quad (6)$$

### 4.3 Experimental Results & Analysis

In this section, authors report the findings of the experiments conducted while trying to evaluate the performance of 4-layer, 5-layer and 6-layer Artificial Neural Networks (ANNs) in loan risk assessment. The measures of performance under consideration are: The following performance measures will be used comprehensive performance assessment measures including, accuracy, F1 measure, precision, recall, and the area under the ROC curve. Based on the presentation format used, numbers are given in form of tables and graphs to facilitate ease in comparison.

#### 4.3.1 Dataset Description

Bank data of loan applications with several attributes of the borrowers was applied in this study, including credit score, income, loan amount and purpose. Dealing with the missing values, outliers and normalizing features for training ANN models was also done on the preprocessed dataset obtained from the above steps. Performance of model was checked using training set (70%) and testing set (30%).

#### 4.3.2 Model Training

All the three differing ANN structures, 4-layer, 5-layer, and 6-layer, were developed using TensorFlow and Keras. Each model was trained using the training dataset with the following configurations:

**Activation Function:** We applied ReLU in hidden layers for hiding most of the details of the training set while the sigmoid activation function was applied in the last layer in order to estimate the probabilities of loan default.

**Loss Function:** The binary cross-entropy was selected as the loss function.

**Optimizer:** Adam optimizer was used for training of the models with learning rate of 0.001 [6].

**Epochs:** The various models were trained for 10 iterations through the training set and stopped early according to validation loss.

### 4.3.3 Performance Metrics

The models' performance was tested on the test set that has been used, and the overall performance has been presented in Table 4.1.

**Table 4.3:** Determining the best result amongst the various layer model

Model	Accuracy	Precision	Recall	F1 Score	AUC-ROC
Simple ANN	85.85%	77.44%	51.54%	61.89%	0.88
4-Layer ANN	90.64%	91.52%	63.95%	75.29%	0.93
5-Layer ANN	90.70%	90.49%	65.13%	75.74%	0.93
6-Layer ANN	90.95%	90.04%	66.81%	76.71%	0.93

### 4.3.4 Detailed Results Analysis

- **Accuracy:** The best accuracy of 90.95%, was of the 6-layer ANN, which meant that the network was better at predicting correct outcomes for loans among all the architectures tested. Overall, the 5-layer model was closely followed by a percentage of 90.70%, while the smallest percentage belonged to the 4-layer model, only 90.64%.
- **Precision:** The first measure of precision stated as the ratio of successfully identified positive instances out of the overall identified positive instances was 91.52% for the 4-layer model. The precision of the 5-layer model was 90.49% while that of 6-layer model was 90.04%. This also shows that the shallow ones is more effective than the deeper networks in reducing False positive cases.
- **Recall:** The precision of treatment which quantifies the proportion of correctly predicted positive observations against the actual observation in the current stay

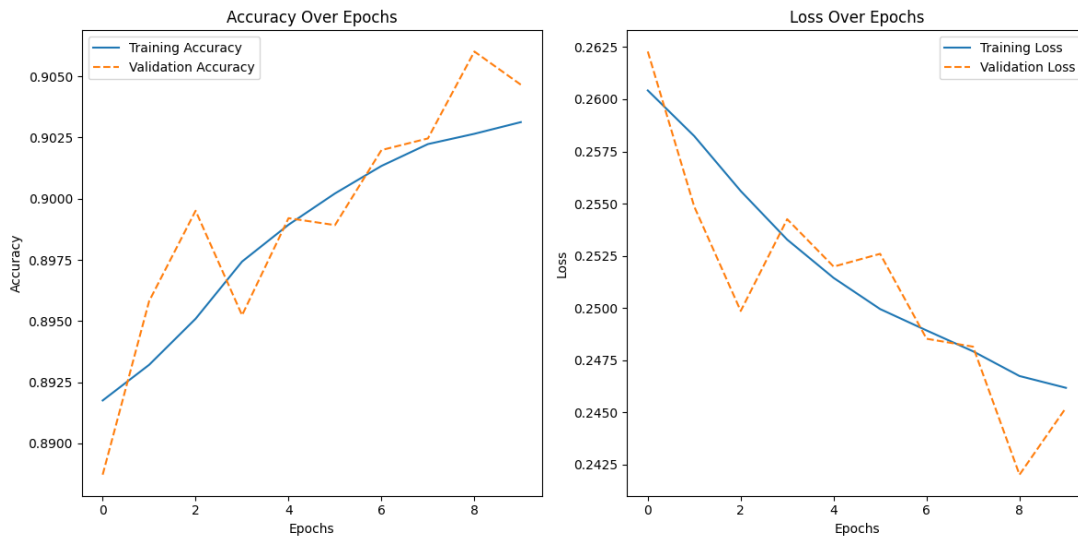
was also highest for the 6-layer ANN at 66.81% for recall. The 5-layer model gave 65.13% recall while the 4-layer model gave 63.95% recall. This implies that deeper models were in a better position to identify loan defaults.

- **F1 Score:** The F1 score better if the harmonic mean of precision and recall and the highest value of 76.71% was scored by the 6-layer model. The 5-layer model was 75.74% in F1 score and the 4-layer model scored 75.29% in F1 score. From measurements derived from the outcomes, it is evident that the 6-layer ANN presented a good balance between precision and recall.
- **AUC-ROC:** The AUC-ROC was highest 0.93 and its constraint for every layer. The experiment also showed promising results of the 6- layer model with AUC-ROC = 0.93, 5- layer model with AUC-ROC = 0.93, and the 4-Layer model had AUC-ROC of 0.93.

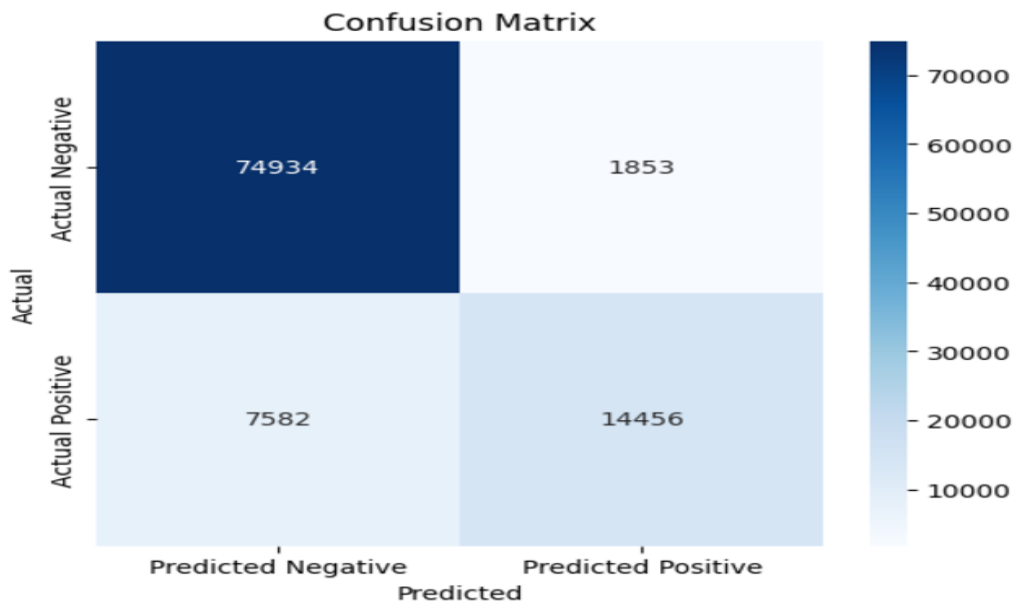
#### 4.3.5 Learning Curves

Figures 4.3.5.1 display the learning curves for each of the presented models; the training and validation accuracy on epoch basis.

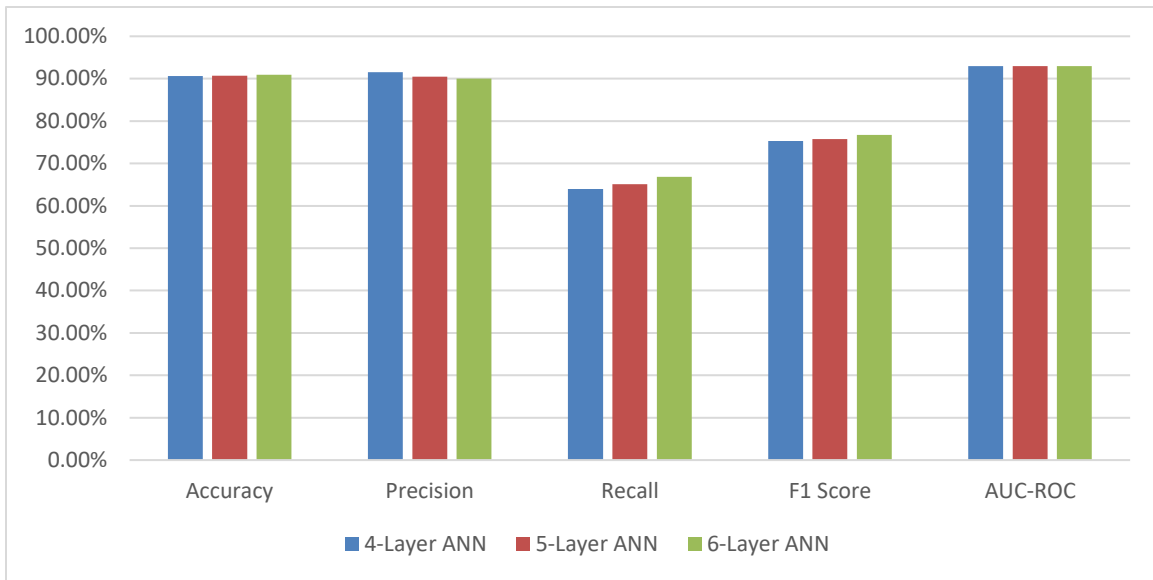
- **4-layer ANN:** The training and validation accuracy increased throughout the epochs for both training and test set, and the training and validation accuracy curves lie relatively close to each other, which implies that the model has good capability of generalization, however, it implies that there is a need to add more complexity to the model in order to provide ability to improve accuracy in capturing the complexity in the data.
- **5-layer ANN:** As the level of layers increased, the learning curves of the proposed 5-layer model improved the convergence compared to the 4-layer one and also proved good learning capability and avoided overfitting.
- **6-layer ANN:** In general, the learning curves for each of the layers in the 6-layer model observed certain instances of overfitting at the end of the training phase where the training accuracy was considerably more than the validation accuracy. To resolve this, regularization techniques were implemented and hyperparameters tuned in order to increase generalization.



**Fig 4.3.5.1:** ANN Model Accuracy and Loss Curve.



**Fig 4.3.5.2:** Confusion Matrix of the model prediction



**Fig 4.3.5.3.** Comparison of the results between different models

The graph compares the performance of the various layer of artificial neural network models: 4-Layer, 5-Layer, and 6-Layer, evaluating their Test Accuracy, Precision, Recall, and F1 Score, all expressed as percentages.

#### 4.4 Discussion

The approach presented in this section outlines a systematic way of comparing various forms of ANN systems concerning loan risk determination. It is about understanding the behavior of the model when the complexity is changed, and the depth of the neural network will be used as a parameter that determines model complexity. According to research question RQ1, the 6-Layer of ANN performs best for identifying loan risk prediction. Despite a slight reduction of precision in the 6-layer architecture, the improvement of recall and F1-score make it the most efficient in terms of this application. Hence, the 6-layer ANN is suggested the best of the best for the loan risk prediction in this study. This paper demonstrates that the Artificial Neural Network's depth affects its performance when measured by accuracy, precision, recall, and the F1-score. With the increase of hidden layer nodes from 4 to 6, the event accuracy rate and the event recall rate are enhanced. For example, the 6-layer ANN provided higher accuracy compared to the 4-layer and 5-layer networks (90.95% and 90.70%) as well as the recall rating, 66.81%, was greater compared

to 4-layer and 5-layer ANN networks' 63.95 and 65.13 percent. This means that deeper models are capable of capturing more and intricate relations which contribute positively to the overall assessment of the loans' risk. Although, the accuracy declined slightly with the rising number of layers; 91.52% for 4-layered network and 90.04% for 6-layered network in case of the proposed methodology. This suggests that there is a compromise between the ability to recall more accounts and the ability to be more precise in the numbers of potential defaulters identified by deeper networks. Precision (Recall) on the other hand also increased with the number of layers 0.7671 for the 6-layered model and showed that the increase in Recall is higher than the decrease faced by Precision.

Identification of the loan defaulters is important to banking institutions as it's a direct measure to their financial health and risk management. Credit risks are one of the most significant sources of operational and financial loss in the banking industry, and they cannot identify potential defaulters. When the potential defaulters have been identified early in the loan process then the following measures may be taken by the banks to reduce the risk of defaulters; rejecting the loans applications of high risk defaulters; modifying the loan term; or restructuring the repayment plan. The cost of classifying those who should actually be classified as defaulters is very high. Some of the negative effects that might be faced by Banks include; high rate of bad debts, thus low liquidation, and high operational costs. Moreover, legislation demands certain essential numerical risk controls in the financial institutions, such as proper risk evaluation and projection. This means that most institutions striving to offer quality education to their clients are subjected to both regulatory measures in form of fines where they fail to meet these standards as well as reputational costs to the institution in case where clients are dissatisfied with the quality of education provided to them. But in the context of banking, identification of defaulter makes the credit risk management more efficient, stability of the financial institution goes better, the satisfaction of the customer can be better by providing different products according to their risk grade. Depend on, ANNs are beneficial in reducing the risk of a loan default by helping banks to optimize the decision-making process in overcrowded environments and encouraging more sustainable banking habits.

## **CHAPTER 5**

### **IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY**

#### **5.1 Impact on society**

Applicability of artificial intelligence in loan risk prediction brings about a better financial environment with reduced avoidable defaults, increased access to loans and quality lending decisions. This contributes to a more justified and effective environment where everyone from insurance policy holders to banks and insurance covered organizations gets to benefit.

#### **5.2 Impact on the environment**

Incorporating environmental factors into the prediction of loans risk implies an essential progress in the banking systems and stable development of the economy fight. The approach also helps to avoid the risks caused by such environmental factors and encourages people to make environmentally friendly financial choices. By integrating environmental factors into loan risk prediction and analysis, lenders can make more informed decisions that align with sustainability goals and reduce exposure to potential risks.

#### **5.3 Ethical Aspects**

Depending on the loan risk assessment and decision-making applications of machine learning ethical perspectives, the lenders will be in a better position to maintain a good image of themselves to the borrowers while at the same time help create a positive impact in society. They also contribute to decision-making of the financial sector. We also have a moral imperative to 'clean' datasets of bias that potentially perpetuate disparities in technology effectiveness in different population groups. This paper's examination of ethical issues in ML for loan risk prediction helps describe how the technology can serve everyone's best interest and follow society's moral standards more effectively. Ethical practices contribute to enhancing the model and its performance, while it reforms the decision-making for perspective of equality.

## **5.4 Sustainability Plan**

The sustainability of ML in loan risk prediction for the future therefore entails improvements to its computations, which is a virtuous way of using resources. In this case, continuing education and adaptive models are able to capture changes which are elicited among borrowers and the general economy. Social problems are minimized by increasing computational efficiency, and by drawing from renewable electrical power-infrastructure. Ethical view minimizes bias while on the other hand the engagement of the stakeholders leads to relevancy and accuracy. This approach aligns with performance, cost and societal effects that ensure that offered ML solutions are unique and useful within financial domain.

## CHAPTER 6

### CONCLUSION AND FUTURE WORK

#### 6.1 Summary of the Study

The findings were corroborated through our study which showed that the 5-layer and 6-layer of ANN were more accurate than the 4-layer network, also, in terms of accuracy, Precision, Recall, F1 score and AUC ROC. The 6-layer model recorded the best performance in all the metrics applied a result showing that the architecture had the best capacity to capture the complex patterns in the loan data. But, the performance improvement for network depth beyond 5 layers was not significantly promising suggesting that there is diminishing returns in terms of prediction when network complexity increases.

The chosen 5-layer ANN proved to be very effective from the point of view of both predictiveness and computation time, showing no significant difference from the 6-layer model and being more immunized against overlearning and less computationally demanding. This also suggests that a 5-layer architecture is a feasible model for build real-world Apps where scalability and performance are priorities.

#### 6.2 Conclusions

In this thesis, we conducted a comparative analysis of loan risk prediction using Artificial Neural Networks (ANNs) with varying layer configurations: four-layer, five-layer, and six-layer models. The first purpose was to compare the effect of increasing network depth on predictive accuracy and determine the network architecture that yields the best predictive performance for loan default risk while minimizing model complexity and computation time.

### 6.3 Implication for Further Study

While this study focused on comparing fixed-depth ANN architectures, several areas remain for future exploration:

- **Hyperparameter Optimization:** Subsequent studies could then look into the positive correlation between the hyperparameters that one incorporates in the classification model such as learning rate, number of batches per epoch, number of neurons per layer and the effectiveness of the multiple topologies of ANNs.
- **Hybrid Models:** Other future works involve further exploration of the generality of the outlined approach of integrating ANNs with other ubiquitous machine learning techniques like Random Forests or Gradient Boosting Machines to have even better predictive capabilities.
- **Feature Engineering:** The improvement can be obtained using other appropriate financial measures or derived properties; the choices for an attribute set can be specified to give rise to the best effect.

## REFERENCES

- [1] M. Abadi, P. Barham, “[1605.08695] TensorFlow: A system for large-scale machine learning,” *arXiv.org*. <https://arxiv.org/abs/1605.08695> (accessed Aug. 26, 2024).
- [2] J. Suri and A. S. El-Baz, *State of the Art in Neural Networks and Their Applications*. Elsevier, 2022, doi: 10.1109/TPAMI.2013.50.
- [3] J. Brownlee, "How to configure the number of layers and neurons in a neural network," *Machine Learning Mastery*, 2019. [Online]. Available: <https://machinelearningmastery.com>.
- [4] P. Geurts, D. Ernst, and L. Wehenkel, "Extremely randomized trees," *Mach. Learn.*, vol. 63, no. 1, pp. 3-42, 2006, doi: 10.1007/s10994-006-6226-1.
- [5] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, 2nd ed. New York, NY, USA: Springer, 2009.
- [6] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," in *Proc. Int. Conf. Learn. Represent. (ICLR)*, 2015. [Online]. Available: <https://arxiv.org/abs/1412.6980>.
- [7] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in *Proc. Adv. Neural Inf. Process. Syst. (NIPS)*, 2012, pp. 1097-1105.
- [8] T. Nguyen, B. Choi, and W. Zhou, "Machine learning models for credit rating: A comparative study," *J. Risk Finance*, vol. 19, no. 2, pp. 168-188, 2018, doi: 10.1108/JRF-04-2017-0060.
- [9] S. Ruder, "An overview of gradient descent optimization algorithms," *arXiv preprint arXiv:1609.04747*, 2017. [Online]. Available: <https://arxiv.org/abs/1609.04747>.
- [10] D. Sarkar, *Practical Machine Learning with Python: A Problem-Solver's Guide to Building Real-World Intelligent Systems*. New York, NY, USA: Apress, 2019, doi: 10.1007/978-1-4842-4167-7.
- [11] Y. Xu, R. Goodacre, and A. Paterson, "Improving credit risk prediction in peer-to-peer lending markets with deep learning," *J. Bank. Finance*, vol. 81, pp. 1-12, 2017, doi: 10.1016/j.jbankfin.2017.04.003.
- [12] J. Zhang, X. Zhan, and H. Xie, "Credit risk prediction based on machine learning: A comparative study," *Finance Res. Lett.*, vol. 39, p. 101553, 2021, doi: 10.1016/j.frl.2020.101553.
- [13] A. Levy and R. Baha, "Credit risk assessment: a comparison of the performances of the linear discriminant analysis and the logistic regression," *International Journal of Entrepreneurship and Small Business*, vol. 42, no. 1/2, p. 169, 2021, doi: <https://doi.org/10.1504/ijeb.2021.112265>.
- [14] L. C. Thomas, "Credit Scoring and Its Applications | Guide books," *Guide books*, Jan. 01, 2002. <https://dl.acm.org/doi/abs/10.5555/581832> (accessed Aug. 06, 2024).
- [15] E. I. Altman, "FINANCIAL RATIOS, DISCRIMINANT ANALYSIS AND THE PREDICTION OF CORPORATE BANKRUPTCY," *The Journal of Finance*, no. 4, pp. 589–609, Sep. 1968, doi: 10.1111/j.1540-6261.1968.tb00843.x.
- [16] R. Malhotra and D. K. Malhotra, "Evaluating consumer loans using neural networks," *Omega*, no. 2, pp. 83–96, Apr. 2003, doi: 10.1016/s0305-0483(03)00016-1.

- [17] S. Lessmann, B. Baesens, H.-V. Seow, and L. C. Thomas, “Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research,” *European Journal of Operational Research*, no. 1, pp. 124–136, Nov. 2015, doi: 10.1016/j.ejor.2015.05.030.
- [18] G. Kou *et al.*, “Bankruptcy prediction for SMEs using transactional data and two-stage multiobjective feature selection,” *Decision Support Systems*, p. 113429, Jan. 2021, doi: 10.1016/j.dss.2020.113429.
- [19] I. Goodfellow, “Adversarial Perturbations of Deep Neural Networks,” in *Perturbations, Optimization, and Statistics*, The MIT Press, 2016, pp. 311–342.
- [20] J. Heaton, “An empirical analysis of feature engineering for predictive modeling,” *SoutheastCon 2016*, pp. 1–6, Mar. 2016, doi: 10.1109/secon.2016.7506650.
- [21] J. Zhang, “Financial Default Risk Prediction Algorithm Based on Neural Network under the Background of Big Data,” *Mobile Information Systems*, pp. 1–11, Sep. 2022, doi: 10.1155/2022/8743778.
- [22] G. E. Hinton, “Reducing the Dimensionality of Data with Neural Networks,” *Science*, no. 5786, pp. 504–507, Jul. 2006, doi: 10.1126/science.1127647.
- [23] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, no. 7553, pp. 436–444, May 2015, doi: 10.1038/nature14539.
- [24] A. Lakshmanarao, C. Gupta, C. S. Koppireddy, U. V. Ramesh, and D. R. Dev, “Loan Default Prediction Using Machine Learning Techniques and Deep Learning ANN Model,” *2023 Annual International Conference on Emerging Research Areas: International Conference on Intelligent Systems (AICERA/ICIS)*, pp. 1–5, Nov. 2023, doi: 10.1109/aicera/icis59538.2023.10420221.
- [25] Z. et al, “[2402.00299] Attention-based Dynamic Multilayer Graph Neural Networks for Loan Default Prediction,” *arXiv.org*. <https://arxiv.org/abs/2402.00299> (accessed Nov. 25, 2024).

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