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Credit Card Customer Prospect Prediction Using Neural Network Algorithm

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Abstract**—***The use of credit cards is common in everyday life, both for personal and business purposes. Credit cards make it easier for cardholders to make purchases that cannot be paid for with cash, but also come with the risks associated with borrowing money. In the banking and financial industry, credit card issuers need information about the prospects for borrowing from prospective cardholders in order to determine suitable candidates and minimize the risk of bad credit. Measurement of credit card customer prospects is influenced by several attributes, such as income, finances, type of work, and age. Understanding credit card prospects is very important for credit card issuers in making decisions and creating effective business strategies. Therefore, it is important for credit card issuing companies to predict the prospects of prospective cardholder customers. This research will focus more on the classification of customer credit card lending interests which will later become credit card customer prospects with several different attributes such as sources of income, product credit, account activity, and average account balance. The problem in this study is that there is no precise predictive model in predicting the prospects of credit card customers. The method used in this study is CRISP-DM (Cross-Industry Standard Process for Data Mining) by comparing Logistic Regression algorithms, K-Nearest Neighbor, Decision Tree (C.45), and Neural Networks. The results of this study indicate that the highest correlation to borrowing (is_lead) is Credit_Product or customers with current status crediting a product with a value of 0.57. The results of this study also show that the highest accuracy and AUC values are obtained by the Neural Network algorithm with a value of 86.19% accuracy and 0.75 for the AUC value. This indicates that the performance of the Neural Network algorithm is better than the other three algorithms in classifying credit card lending intentions.*

Keywords**—***Data Mining, Logistic Regression, K-Nearest Neighbor, Decision Tree (C.45), Neural Network, Credit Card Lead Prediction.*

I. Introduction

Credit granting is carried out by identifying and assessing factors that influence credit risk. Loss of income and threats to profitability are important considerations when granting credit. Factors influencing credit risk include the debtor's failure to pay claims, which the debtor will incur if they fail to fulfill their payment obligations, and the amount lost due to such risk or default (Menarianti, 2015).

Credit card use has become commonplace in everyday life, for both personal and business purposes. Therefore, it is crucial for credit card issuers to predict the prospects of potential credit card customers. By identifying the right customers or prospective cardholders, the company's sales department can easily offer credit card applications, thereby increasing work efficiency.

According to several studies, artificial neural networks can process data effectively to predict the probability of credit card customer default and provide the highest accuracy (Pasha et al., 2017). This study will attempt to prove that artificial neural networks can also better predict credit card application interest, which was previously widely used for predicting credit failure or credit approval. Credit card prospect prediction algorithms can use several techniques such as regression analysis, Decision Tree, or Neural Network. Comparisons between these algorithms can be made based on the level of accuracy, processing speed, and ease of interpretation of the results. Comparing credit card prospect prediction algorithms is important to help companies determine the most appropriate algorithm to use in predicting credit card prospect.

This research problem focuses on the challenge of predicting credit card customer prospects, which currently lacks an appropriate model. The research is limited to the use of a public dataset from Kaggle entitled Credit Card Lead Prediction, which represents the needs of banks in implementing credit card cross-selling strategies to existing customers with the aim of identifying customers with high interest. The research problem formulation is how to build a prediction model for customer interest in credit card applications, while the research objective is to design a prediction model by creating a Neural Network with optimal performance. The expected benefit of this research is the provision of a prediction model that makes it easier for credit card issuers to find potential customer information, as well as being a reference in the development of similar prediction methods in the future.

II. Literature Review

An easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it.

A. Credit

Credit is the provision of funds for borrowing and lending transactions with the approval and agreement between a bank or financial institution and its customer, requiring the borrower to repay the funds within a specified time. The development of credit cards has been a significant step forward. In 1730, the first credit card was issued as a plastic card. In recent years, lenders in Singapore have experienced a credit card debt crisis, and credit card fraud is expected to

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peak in the third quarter of 2006. Taiwanese banks have issued cash advances and credit cards to unqualified applicants. The crisis has affected consumer confidence in the financial sector and posed significant challenges for banks and cardholders. Fraud is a common term, and data mining encompasses many techniques involved in studying accessible data and extracting valuable information.

B. *Data Mining*

Data mining is defined as the process of extracting data using statistical, mathematical, and artificial intelligence techniques to extract and identify useful information from disparate databases. Data mining is commonly known as Knowledge Discovery in Databases (KDD). The name data mining stems from the similarity between finding valuable information in a large database and mining a mountain to find something of value. Both require sifting through large volumes of documents or intelligently investigating where the so-called value lies. Data mining is at the heart of the Knowledge Discovery Database (KDD) process. KDD is an organized process for identifying valid, novel, useful, and understandable patterns from large and complex data sets. KDD consists of nine stages, here is a brief explanation of the steps in KDD: (Han and Kamber, 2006).

1. Establishing an understanding of the application domain. This stage defines the goals of the end users and the departments involved in implementing KDD.
2. Selecting and creating the datasets on which the knowledge discovery process will be conducted. This is where the data to be used for the KDD process is determined. Discover available data, obtain necessary additional data, and integrate all data for KDD into a single dataset, including the attributes required for the KDD process.
3. During preprocessing and cleaning, data reliability is improved. This includes data removal, such as managing incomplete data and removing noise or outliers.
4. Data Transformation: At this stage, data is refined using attribute transformation and dimensionality reduction methods.
5. Selecting the appropriate data mining task: At this stage, the type of data mining to be used is determined, whether classification, regression, or clustering, depending on the KDD objective and the previous step.
6. Selecting a Data Mining Algorithm: At this stage, the most suitable algorithm for finding patterns is selected.
7. Using the Data Mining Algorithm: At this stage, the data mining algorithm defined in the previous step is implemented.
8. Evaluation: At this stage, the obtained samples are evaluated and translated.
9. Using the Acquired Knowledge: At this stage, the knowledge has entered another system, activated the system, and measured its results.

C. *Data Mining Classification Algorithm*

Classification is the process of discovering a model (or function) that distinguishes and describes classes of data or concepts, with the aim of predicting the class of objects whose class labels are unknown. Data classification consists of two steps. The first is the learning (training) phase, where a classification algorithm is created to analyze the training data and then represent it in the form of classification rules. The second is the classification phase, where test data is used to estimate the accuracy of the classification rules. The classification process is based on four components: (Siswopranoto, 2018).

1. Class, a categorical dependent variable that represents the "label" assigned to an object. Examples: heart disease risk, credit risk, customer loyalty, earthquake type.
2. Predicator, an independent variable represented by a characteristic (attribute) of the data. Examples: smoking, alcohol consumption, blood pressure, savings, assets, salary.
3. Training dataset, a data set containing values from the two components above, used to determine the appropriate class based on the predictor.
4. Testing dataset, contains new data to be classified by the created model, and the classification accuracy is evaluated.

D. *Data Distribution Parameters*

There are two types of data required: training data and testing data. Training data is the data used to train the model to recognize the desired pattern. Testing data is the data used to verify the results of the training. In research, training and testing data are generally divided into 60% (training): 40% (testing), 70% (training): 30% (testing), 80% (training): 20% (testing). These percentages are based on the general rule of thumb (Rahmawati, Larasati, and Marsono, 2021).

E. *Logistic Regression*

Logistic Regression is a classification method in statistical machine learning and is also a supervised learning method. This method has superior performance when handling large-scale data and is the most commonly used method in data mining. Besides its use in data mining, it can also be used in medicine and the social sciences. For example, in the medical world, Logistic Regression can be used to assist in important decision-making (Puttra and Azhar, 2021).

F. *k-Nearest Neighbor (k-NN)*

The k-nearest neighbor (k-NN or KNN) algorithm is an object classification method based on learning from data closest to the object. K-Nearest Neighbor is based on the concept of "learning by analogy." Training data is described by n-dimensional numeric attributes. Each learning data represents a point, denoted c, in n-dimensional space. If a data query with an unknown label is entered, k-Nearest Neighbor will search for the k training data closest to the query data in n-dimensional space. The distance between the query data and the training data is calculated by measuring the distance between the point representing the query data and all points representing the training data using the Euclidean distance formula. During the training phase, this algorithm only stores the feature vector and classifies the training data samples. During the classification phase, similar characteristics are calculated for the experimental data (classification unknown). (Siswopranoto, 2018).

G. Decision Tree (C4.5 Algorithm)

The C4.5 algorithm is used to classify data using decision tree techniques. The C4.5 algorithm is an extension of the ID3 algorithm and utilizes decision tree principles. The C4.5 algorithm can process both numeric and discrete data, handle missing attribute values, generate easily interpretable rules, and perform among the fastest compared to other algorithms. The basic idea of this algorithm is to create a decision tree based on selecting the attribute with the highest priority, or what can be called the highest gain value, based on the attribute's entropy value as the classification attribute axis. The tree's branches are then recursively expanded until the entire tree is formed. According to the IGI Global (International Publisher of Progressive Academic) dictionary, entropy is the amount of irrelevant data that contributes to the information in a data set. Gain is information obtained from changes in entropy in a data set, either through observation or inferred by participating in a data set (Amir and Abijono, 2018).

H. Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) operate on a principle similar to that of nerve cells, with parts that function to process information. These parts are connected to similar parts through a network that functions as a series of inputs and outputs. These input and output functions are similar to the functions of neurites and dendrites in human nerve cells. Therefore, an ANN can be defined as a distributed, parallel information processing structure consisting of processing elements connected by connections. Each processing element has a single output connection that branches out to a desired number of collateral connections. The output of these processing elements can be the result of data processing, which can be a mathematical equation, a function, or a method. The processing of each processing element must be completely local, meaning the output depends only on the input value at the time the data is obtained locally. The output depends only on the current input value obtained through the connection and the value stored in local memory. ANN is a parallel, distributed process that has the ability to store knowledge gained from learning and keep it available for use (Sugiyarto and Gata, 2019).

The network training process is greatly influenced by the number of hidden layers and neurons in the training process. Uzair and Jamil in their research summarized and proved that increasing the number of neurons in the hidden layer, as well as increasing the number of hidden layers, can increase the accuracy of the training process. However, this will affect the complexity of the process. The Neural network training process slows down if a large number of hidden layers are used. So, if the problem criterion is to obtain better accuracy, then a large number of hidden layers is the most suitable solution, but if time complexity is the main factor of an application, then a large number of hidden layers will not work in that type of application. Also, an unnecessary increase in neurons or layers will cause overfitting problems. That is why it is important before designing a Neural network, a sample training database must be analyzed so that the estimated number of neurons and hidden layers can be guessed correctly. (Uzair and Jamil., 2020). Some references for the use of hidden layers are in table 1.

TABLE 1. Hidden layer parameter

Source	Hidden Layer Parameter
(Rustam, et al., 2020)	3,5 4,6 5,7 6,8
(Maulana, et al., 2021)	5 5,3 8,6 8,6,4 10,8,5
(Josephine, et al., 2021)	12,12,8 32,24,12,8 64,64,32,24,12,8

I. Evaluation and Validation

To test the model, this study used the cross-validation, confusion matrix, and ROC (Receiver Operating Characteristic) curve methods.

1. Cross-validation is a standard test performed to predict the error rate. The training data is randomly divided into several equal parts, then the error rate is calculated part by part. The average of all error rates is then calculated to obtain the overall error rate. (Siswopranoto, 2018)
2. Confusion Matrix, this method uses a matrix table. if the data set consists of only two classes, one class is considered positive and the other negative (Bramer, 2007).

TABLE 2. Confusion matrix model

True Classification	Classified as	
	+	-
+	*True Positives*	*False Positives*
-	*False Negatives*	*True Negatives*

Formula:

Sensitivity = TP/P (1)

Specificity = TN/N (2)

Precision = TP/(TP+FP) (3)

Accuracy =Sensitivity + Specificity (4)

Legend:

TP = True Positives

TN = True Negatives

P = Positive Records

N = Negative Records

FP = False Positives

3. The ROC curve shows accuracy and visually compares classifications. The ROC expresses a confusion matrix. The ROC is a two-dimensional graph with false positives as horizontal lines and true positives as vertical lines. The area under the curve (AUC) is calculated to measure the difference in performance of the methods used. AUC. (Siswopranoto, 2018).

$$\emptyset^r = \frac{1}{mn}\sum_{i=1}^{n} \quad \sum_{i=1}^{n} \varphi(xi^r, xj^r) \qquad (5)$$

$$\varphi(X,Y) = \begin{cases} 1 & Y < X \\ \frac{1}{2} & Y = X \\ 0 & Y > X \end{cases} \quad (6)$$

Legend:
Ø^r = Empty Set
K = Number of classification algorithms compared
X = Positive output
Y = Negative output

For data mining classification, AUC values can be divided into several groups (Gorunescu, 2011).
a) 0.90-1.00 = Excellent Classification
b) 0.80-0.90 = Good Classification
c) 0.70-0.80 = Fair Classification
d) 0.60-0.70 = Poor Classification
e) 0.50-0.60 = Failure

III. Research Methods

A research method is a method or technique used by researchers to collect, analyze, and interpret data to answer research questions or hypotheses. The method chosen for this study, CRISP-DM (Cross-Industry Standard Process for Data Mining) shown in figure 1 was chosen because it has several advantages, including:

1. Flexibility: CRISP-DM can be used in various types of data mining projects, including for business and research purposes.
2. Focus on process stages: This method is structured and clear in every stage of the data mining process, from understanding the business to evaluating the results.
3. Application of best practices: CRISP-DM is an industry standard commonly used by many organizations and companies, so it has been tested and implemented by many practitioners.
4. Iterative process: This method supports an iterative approach, enabling data mining teams to develop better models through an iterative process.
5. Well-documented: CRISP-DM provides comprehensive and structured documentation for each stage of the process, making it easier for the team to monitor the project and revisit each stage as needed.

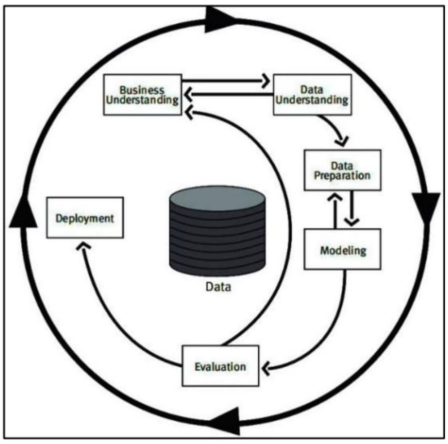


Figure 1. CRISP-DM methodology (Chapman, 2000:10)

A. Business Understanding

Some of the steps taken at this stage include understanding the needs and objectives from a business perspective. At this stage, researchers attempt to understand the business object being studied and align it with the research objectives by developing a robust model. The business understanding stages are explained as follows:

1. Identification
   Identification is derived from the research problem being conducted. This identification explains the need for a bank to find information on attributes that influence customer intentions to apply for a credit card, as well as an appropriate model for predicting credit card customer prospects. The research results will then be used to offer credit card applications to potential customers who are directly interested in borrowing a credit card, making the offer process more time-efficient and effective.
2. Aligning with Objectives
   Adjusting with objectives is derived from the identification conducted, so that this research has a precise and definite direction. The research objective addresses the existing problem: to create a predictive model for customer intention to apply for a credit card using the Neural Network algorithm with the best performance.
3. Implementation of Initial Strategy
   The implementation of the initial strategy is derived from the objectives and previous research literature review. The initial strategy involves comparing the Logistic Regression, K-Nearest Neighbor, Decision Tree (C.45), and Neural Network algorithm models that have the highest accuracy in predicting customer interest.

B. Data Understanding

This stage begins with data collection, data description, and data quality evaluation. Data Understanding in this study is divided into initial data search, data collection, and attribute selection.

1. Initial Data Selection
   The initial data selection in this study used purposive sampling, a sampling technique frequently used in research. The word "purposive" literally means "intentionally." Simply put, purposive sampling means taking a sample intentionally. Purposive sampling is a sampling technique that involves selecting respondents carefully selected by the researcher based on specific characteristics (Nasution, 2009).
   Based on the sample selection method, bank data was used to classify customer interest in credit card applications. The data selected was public data collected from the website www.kaggle.com for the period of May 2021 regarding the classification of customer interest in credit card applications.
2. Data Collection
   The data collection process in this study used a non-participant observation data collection method. The

researcher did not conduct direct observations but instead collected all observational data from a dataset. This method was carried out by collecting available data. The data collected consisted of bank customer data on credit card application interest from the website www.kaggle.com, comprising 245,725 training data and 105,312 model test data. The research employed information and data collection methods derived from scientific papers such as theses, journals, and books.

TABLE 3. Data attributes

Attribute	
ID	Identifiers
Gender	Customer gender
Age	Customer Age (in Years)
Region_Code	Region code
Occupation	Customer occupation type
Channel_Code	Customer acquisition channel code (encoded)
Vintage	Customer Vintage (in Months)
Credit_Product	If Customer Has an Active Credit Product (Mortgage, Personal Loan, Credit Card, etc.)
Avg_Account_Balance	Average Customer Account Balance in the Last 12 Months
Is_Active	If Customer Has Been Active in the Last 3 Months
Is_Lead	Application interest (target)

C. Data Preparation

This stage involves constructing the final dataset from the raw data. Several steps will be taken, including data cleaning, data selection, and data transformation to serve as input for the modeling phase. In this process, researchers select the data to be used. The following actions will be taken.

1. Changing data types,
2. Deleting blank data or labeling it,
3. Deleting duplicate data.

D. Modeling

System modeling is performed by creating a model for each algorithm in predicting credit card prospects using the selected methodology. Before the modeling process is carried out, researchers will compare data set parameters to determine the parameters for each algorithm. This modeling will determine the accuracy of each model, including Logistic Regression, K-Nearest Neighbor, Decision Tree (C.45), and Neural Network. The algorithm modeling process carried out in this study includes several stages, as follows.

1. Comparing data parameters for each algorithm to find the best parameters with the highest accuracy value.
2. Modeling each algorithm based on the best parameters allows for selecting the best algorithm for implementation in the system.
3. Finding the best modeling method or settings to improve the accuracy of the selected model.

E. Evaluation

Result testing is the process of evaluating a system's performance by testing it against specified specifications. The goal is to identify errors or failures in the system before it is launched into production. This research will test the selected algorithm model. The evaluation process uses a confusion matrix, accuracy values, and ROC diagrams for the selected algorithm model.

F. Deployment

In the Deployment stage, researchers will develop a system based on the selected model and produce a thesis research report and journal article based on all the research stages. The system will be developed by adhering to system development standards: input, process, and output. The system created will be a simple system explaining the implementation of the selected model in predicting customer interest in credit card applications.

IV. RESULT AND DISCUSSION

A. Modeling

Modeling was performed to classify data, thus ensuring accuracy for each model. The models used included Logistic Regression, K-Nearest Neighbor, Decision Tree (C.45), and Neural Network algorithms to predict credit card prospects. Modeling was performed by training machine learning with training data and testing the results using testing data. Before modeling, a comparison was conducted between data divisions to determine the best accuracy for each parameter used in the model. The parameter dataset comparison is shown in table 4.

TABLE 4. Parameter dataset comparison

Parameter	Logistic Regression	K-Nearest Neighbor	Decision Tree (C.45)	Neural Network
70:30	0.84734	0.84881	0.84663	0.8555
80:20	**0.84741**	0.84912	**0.84673**	0.85522
90:10	0.84699	0.84937	0.84648	**0.85792**
10 Fold CV	0.84664	**0.84939**	0.84672	0.8559

The parameter dataset comparison revealed that the highest accuracy was achieved by Logistic Regression, which splits the training and testing data 80:20, K-Nearest Neighbor using 10-fold cross-validation, Decision Tree (C.45) with an 80:20 split between the training and testing data, and Neural Network with a 90:10 split between the training and testing data. The results of this parameter comparison will be modeled to determine the Confusion Matrix, accuracy, and Receiver Operating Characteristic (ROC) values with the Area Under Curve (AUC) level. This is done to observe and compare the predicted results with the actual classification process.

The comparison process explains the comparison of each model or algorithm that has been processed to predict credit card application intentions. The comparisons include the accuracy and AUC values of the Logistic Regression, K-Nearest Neighbor, Decision Tree (C.45), and Neural Network algorithms. The comparison values for each algorithm are as follows.

TABLE 5. Comparison of algorithm modeling

Algorithm	Accuracy	AUC
Logistic Regression	84.67%	0,73
K-Nearest Neighbor	85.95%	0,75
Decision Tree (C.45)	84.67%	0,70
Neural Network	86.19%	0,75

Based on the comparison results in Table 5, the AUC values for the Logistic Regression and Decision Tree (C.45) algorithms are the same at 0.73, with the accuracy value of the Decision Tree (C.45) algorithm being slightly higher than that of the Logistic Regression algorithm. The highest accuracy and AUC values were obtained by the Neural Network algorithm with 86.19% accuracy and 0.75 for the AUC value. This indicates that the Neural Network algorithm performs better than the other three algorithms in classifying credit card application intention predictions. The next best algorithm was the K-Nearest Neighbor algorithm with 85.95% accuracy and 0.75 for the AUC value. This indicates that the K-Nearest Neighbor algorithm also performs better classification than the other two algorithms.

Before designing a system, it is important to clearly understand the methods, activities, and hidden layers used in Neural Network modeling. This allows for a clear and better understanding of the methods, activities, and layers for use in system design. This Neural Network modeling utilizes the Sklearn Python library, which utilizes backpropagation to minimize errors in the network's output. The Neural Network in the Sklearn Python library uses backpropagation to find the best weights to achieve the highest accuracy. A comparison of the methods, activities, and hidden layers is as follows.

TABLE 6. Comparison of methods, activities, and number of hidden layers

Activation, Solver	Hidden layer					
	5,7	**6,8**	**8,6,4**	**10,8,5**	**12,12,8**	**32,24,12,8**
Activation='Relu', Solver='Adam'	0.85211	0.85338	0.85220	0.86253	0.86257	0.86131
Activation='Relu', Solver='Sgd',	0.85187	0.84813	0.84825	0.85272	0.85232	0.86184
Activation='Relu', Solver='Lbfgs'	0.84967	0.84918	0.85093	0.84963	0.85248	0.85053
Activation='Identity', Solver='Adam'	0.84906	0.84695	0.84886	0.84792	0.84809	0.84882
Activation='Identity', Solver='Sgd'	0.84825	0.84723	0.84817	0.84878	0.84849	0.84857
Activation='Identity', Solver='Lbfgs'	0.84910	0.84922	0.84914	0.84922	0.84922	0.84922
Activation='Logistic', Solver='Adam'	0.85431	0.85333	0.85976	0.85533	**0.86318**	0.86274
Activation='Logistic', Solver='Sgd'	0.85325	0.85199	0.76279	0.76279	0.76279	0.76279
Activation='Logistic', Solver='Lbfgs'	0.85346	0.85126	0.85390	0.85533	0.85407	0.76279
Activation='Tanh', Solver='Adam'	0.85415	0.86127	0.86111	0.86241	**0.86314**	0.86151
Activation='Tanh', Solver='Sgd'	0.85285	0.84813	0.85289	0.85203	0.85395	0.86156
Activation='Tanh', Solver='Lbfgs'	0.85342	0.85301	0.85350	0.85329	0.85936	0.85928

The comparison results in Table 4.3 show that the Neural Network in the Sklearn Python library uses the 'adam' method and 'logistic' activation, with three hidden layers. The first and second hidden layers have 12 neurons, and the third hidden layer has 8 neurons. From the parameter settings, the highest accuracy value is obtained, namely 0.86318 or 86.32%. This means that the system modeling design will use the adam method, logistic activation, and 3 hidden layers 12,12,8. In the next position, the highest accuracy value can be achieved by using the adam method, tanh activation, and 3 hidden layers with the first and second layers having 12 neurons, and the third hidden layer is 8 neurons. This means that the adam method, tanh activation, and 3 hidden layers 12,12,8 can also be used as a reference for system modeling.

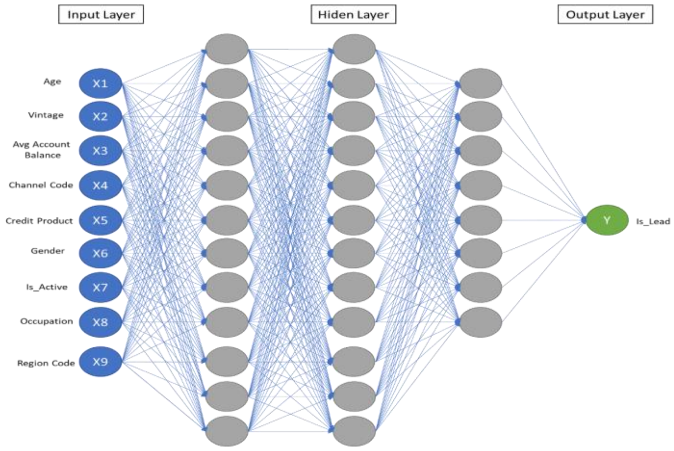


Figure 2. Neural network architecture for predicting credit card application intention

Figure 2 shows the architecture of the designed Neural Network system, which has nine input layers: Age, Vintage, Avg Account Balance, Channel Code, Credit Product, Gender, Is_Active, Occupation, and Region Code. It has three hidden layers, with the first and second layers containing 12 neurons, and the third layer containing 8 neurons. The output layer is Is_Lead, or the customer's intention to borrow a credit card. The input layer is used as input data to be processed by the Neural Network system, which is then connected or processed within the hidden layer to find the best process for achieving the highest accuracy in predicting credit card application intention, which is then used as the output layer. The system design does not specify specific weights for each input variable and hidden layer; this is because the system uses backpropagation to find the optimal weights while minimizing errors in the network's output.

B. Evaluation

The evaluation stage is carried out to measure the prediction results of the selected model, namely the Neural Network. Measurements are conducted on 10% of the total training data for testing. The evaluation is conducted by examining the accuracy value of the designed system and a Confusion Matrix to compare the original values from the classification process. The Confusion Matrix and accuracy results are shown below.

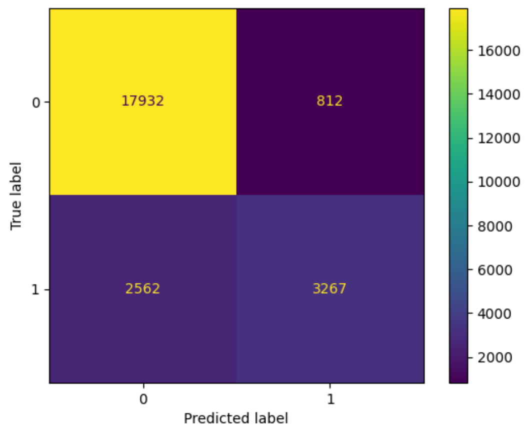
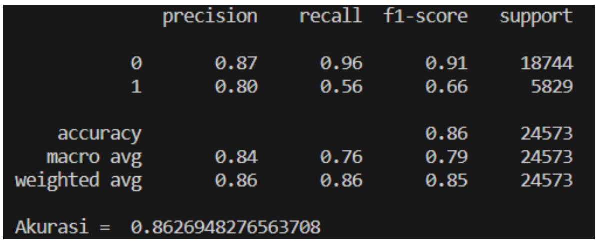


Figure 3. Confusion matrix for selected model evaluation

Figure 3 shows the results of the Neural Network modeling evaluation conducted with a 90:10 ratio using the Adam method, logistic activation, and 3 hidden layers 12,12,8. The True Positives value was 17932, False Positives 812, False Negatives 2562, and True Negatives 3267 in the Confusion matrix test conducted. This means that out of 18744 customers who did not intend to borrow a credit card, there were 2562 who were predicted to intend to borrow a credit card. It also means that out of 5829 customers who intended to borrow a credit card, there were 812 who were predicted not to intend to borrow a credit card.



	precision	recall	f1-score	support
0	0.87	0.96	0.91	18744
1	0.80	0.56	0.66	5829
accuracy			0.86	24573
macro avg	0.84	0.76	0.79	24573
weighted avg	0.86	0.86	0.85	24573

Akurasi = 0.8626948276563708

Figure 4. Relevance and accuracy of the selected model evaluation

Figure 4 relevance of data evaluation tested on the selected Neural Network model designed is known to have a precision value that can be said to be very relevant in the classification, namely 0.87 or 87% in the precision of customers who are not interested and 0.80 or 80% precision of customers who are interested. While the recall value is very relevant to the data value of customers who do not intend to borrow a credit card, namely 0.96 or 96% and medium relevance to customers who intend to borrow a credit card with a value of 0.56 or 56%. In harmony or f1-score the relevance relationship between precision and recall can be said to be very good at a value of 0 or customers who intend to borrow a credit card 0.91 or 91%, and can be said to be good at a value of 1 or customers who intend to borrow a credit card 0.66 or 66%. For the average macro precision (macro avg) value which is 0.84 or 84% and the average weighted avg value of 0.86 or 86%, this states that the precision performance value in the Neural Network algorithm is very good. For the average macro recall value (macro avg) which is 0.76 or 76% and the average weighted avg value of 0.86 or 86%, this also states that the recall performance value in the Neural Network system design is very good. For the average macro (macro avg) f1-score value or an indication of harmony between precision and recall which is 0.79 or 79% and the average weighted avg value of 0.85 or 85%, this also states that the f1-score performance value in the Neural Network system design is very good. The accuracy produced for the Neural Network system design is 0.86269 or 86.27%, this means that the classification carried out is very good.

Figure 5 on the ROC curve produced by the evaluation of the Neural Network model shows an AUC value of 0.76 with a direction away from the middle red line of the curve, this can be concluded that the performance of the Neural Network algorithm in the Sklearn python library with the 'adam' method, 'logistic' activation, with 3 hidden layers 12,12,8 can predict all test data fairly or Fair Classification. The Neural Network algorithm in predicting credit card interest can be concluded to be good enough to be used as a prediction model, this can be proven by a fairly good accuracy of 86.27%, and an ROC curve that moves away from the center line of the curve with an AUC level value of 0.76.

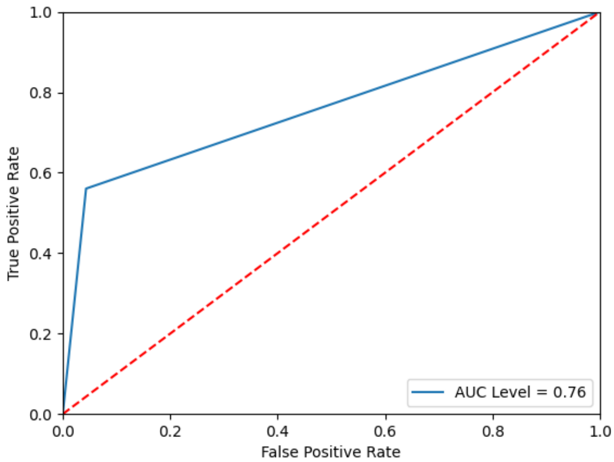


Figure 5. ROC evaluation of selected models

V. CONCLUSION

Based on the results of the algorithm comparison, it is known that the highest accuracy and AUC values are obtained by the Neural Network algorithm with a value of 86.19% accuracy and 0.75 for the AUC value. This indicates that the performance of the Neural Network algorithm is better than the other three algorithms in classifying the prediction of credit card application intentions. The comparison results obtained by designing a Neural Network model in the Sklearn python library with the 'adam' method, 'logistic' activation, with 3 hidden layers with the first and second layers having 12 neurons and the last layer having 8 neurons. The model evaluation accuracy value is 0.86269 or 86.27%. This means that the design of a very good system modeling is done using the adam method, logistic activation, and 3 hidden layers with 12,12,8.

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