paper427

by Natalita Maulani

Customer Decision Prediction Using Deep Neural Network On Telco Customer Chrun Data

Abstract

Customer churn is the most important problem in the business world, especially in the telecommunications industry because it has a big influence on company profits. Acquiring new customers to a company is much more difficult and more expensive than retaining existing customers. Although machine learning is lacking in a relatively low level of accuracy, the use of appropriate machine learning modeling can help in making predictions, including predicting customer churn. Deep Neural Network (DNN) has been used for churn prediction, but the selection of hyperparameters in modeling requires more time and effort. This makes the process more challenging for less experienced researchers. Therefore, this study proposes the application of the DNN model by testing hyperparameter variations to find a better architecture in predicting customer churn. The hyperparameter variations include 3 variations of the hidden layer, 2 variations of the activation function, namely ReLu and Sigmoid, 5 variations of the optimizer (SGD, Adam, Adagrad, Adadelta, and RMSprop), and 3 variations of learning rate (0.1, 0.01, and 0.001). Experiments show that the DNN algorithm using 3 hidden layers and the right hyperparameter, namely Adadelta optimizer with a learning rate of 0.1 can produce an accuracy performance of 82.73%, better than modeling using K-Nearest Neighbor (K-NN), Random Forest (RF), and Decision Tree (DT) as a comparison algorithm.

Keywords: Customer churn, data mining, machine learning, deep neural network

I. Introduction

Customer churn is the percentage of customers who have stopped or switched to using products/services periodically [1]. The existence of various service providers allows customers to choose the service provider they want and has the right to switch from one service provider to another [2]. Customer churn is the most important problem in the business world because it has a big influence on company profits, especially in the telecommunications industry [3].

Currently, the telecommunications industry is experiencing significant problems related to customer switching due to intense competition and the existence of new, more attractive offers [4]. The telecommunications industry experiences an average annual churn rate of 30-35%, and acquiring new customers is 5-10 times more expensive than retaining existing ones [5]. Therefore, based on observations made by a telecommunications company, getting new customers is much more difficult and more expensive than retaining existing customers [6].

Churn prediction can be used to help companies identify churners early before a customer shifts [7]. Churn prediction can also assist companies in retaining customers and can assist companies in determining the right marketing strategy to increase profits for the company [8]. In predicting churn, it takes a technique to manage data. To find valuable information from the data, a data mining process is applied [9]. Machine learning, part of data mining is a sub-field of artificial intelligence that is widely researched and used in making predictions, including prediction of customer churn [10].

Research related to utilizing machine learning techniques regarding predictive analysis of customer churn in telecommunications services was carried out by [11] using a comparison of 3 machine learning algorithms, namely Deep Neural Network (DNN), Extreme Gradient Boosting (XGBoost), and Random Forest. This study shows that the DNN algorithm gives the best results. In this study, the DNN model only focuses on the use of 4 layers and dropout on each hidden layer. While the research that the author will do is to test the hyperparameter variations in the DNN model including testing the number of hidden layers, variations of the optimizer used, and variations in learning rates.

Research conducted by [3] proposes a predictive approach to large telecommunications data that can be used to develop models that are able to predict, classify, and explain customer churn problems. This study compares several traditional methods. Although the results show that the Random Forest algorithm gets the highest score, in the previous year's research using the DNN method, it obtained a higher accuracy. Churn prediction in the banking sector by testing several hyperparameters on the Deep Neural Network (DNN) algorithm was carried out by [12]. The test hyperparameters include optimizer variation, activation function, and batch size. This study shows that the DNN algorithm can produce significant predictions in churn prediction by using the rectifier configuration in the hidden layer and the sigmoid activation function in the output layer. Despite the promising results, this study reveals that a longitudinal study is needed to test the productivity of experiments using more samples of data collected over a long period from different banks. Research using Exploratory Data Analysis (EDA) on telco customer churn data was carried out by [7]. This study compares 7 machine learning algorithms, namely Naïve Bayes (NB), Generalized Linear Model (GLM), Logistic Regression (LR), Deep Learning (DL), Decision Tree (DT), Random Forest (RF), and Gradient Boosted Tree. (GBT). The results showed that all classifications achieved an accuracy of more than 70% and the GBT algorithm had superior accuracy compared to other algorithms. This research still requires optimization of the method used to produce higher accuracy.

Research conducted by [13] compared the results of testing on customer churn data in the telecommunications industry using the Naive Bayes algorithm with sequential feature selection techniques including Sequential Forward Selection (SFS), Sequential Backward Selection (SBS), Sequential Forward Floating Selection (SFFS) and Sequential Backward Floating Selection (SBFS). Although the feature selection technique was carried out, in this study the accuracy results were still low. Research on prediction of customer churn on telecommunication data was also carried out by [14] using a multi-layered Artificial Neural Network (ANN) algorithm. This research only focuses on one hyperparameter, namely using the Nadam optimizer and 3 layers. Then research using the comparison of the K-Nearest Neighbor (K-NN), Random Forest, and Extreme Gradient Boosting algorithms to predict customer churn in telecommunications companies was carried out by [15]. In this study, it is necessary to compare using other methods to provide more optimal results.

Research with different datasets regarding customer churn was carried out by [16] by selecting features and extraction techniques to obtain efficient features and can provide accurate prediction results. The results showed that this technique can produce higher accuracy in the Random Forest algorithm than the original prediction model. [2] conducted research related to telco customer churn prediction using temporal feature engineering which was then carried out by the ensemble process using Random Forest (RF), XGB, and GBDT + SVM algorithms. The results of the study reveal that the use of these features can improve prediction performance. Research on the prediction of customer churn in the telecommunications industry sector using different datasets was also carried out by [17] using a comparison of classification techniques and grouping techniques to identify customer churn. This study uses a feature selection technique using information gain and correlation attributes. The best result in this study was obtained by the Random Forest algorithm. While the research conducted by [18] utilizes the Logistics Regression model in predicting customer churn in the telecommunications industry. This study performs Exploratory Data Analysis using visualization and statistical tests for feature selection.

Currently, the Deep Neural Network (DNN) algorithm has been used for churn prediction, but the process of selecting hyperparameters in modeling requires more time and effort which makes the process more challenging for researchers [12]. Therefore, the purpose of this study is to find a better architecture on the Deep Neural Network (DNN) algorithm by testing hyperparameter variations in predicting customer churn. The hyperparameters used include testing for variations in the number of hidden layers, testing for variations in the optimizer used, and testing for variations in learning rates. This study also uses the K-Nearest Neighbor (K-NN), Random Forest (RF), and Decision Tree (DT) methods as other methods that are used as comparison materials to get a model with better performance.

The results showed that the DNN modeling using 3 hidden layers and the Adadelta optimizer with a learning rate of 0.1 resulted in an accuracy of 82.73%. It is superior to other comparison algorithms.

II. PROPOSED METHODE

Deep Neural Network (DNN) is one of the methods that started the emergence and success of Deep Learning [19]. DNN is a neural network-based algorithm that can be used in decision-making. The purpose of DNN is to imitate the workings of the human brain with the Multi-Layer method. This DNN consists of several hidden layers with connections between layers but no connection between units in each layer. This approach allows complex data to be more easily modeled [20].

DNN has more than 3 layers (input layer, hidden layer, output layer), in other words, Multilayer perceptron with more layers. Because the layers are relatively many, it is called deep. The learning process in DNN is known as Deep Learning [21]. To select the optimal number of hidden layers and their nodes, there is no definite rule of thumb, but there is an analytical rule, which is most often relied upon, is the optimal size of the hidden layer usually between the size of the input and output layers [22].

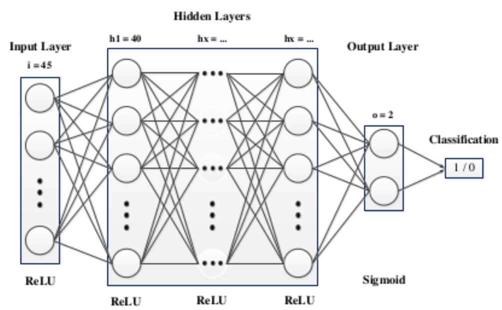

Figure 1. Deep Neural Network (DNN) Architecture

The DNN architecture in this study uses three variations of the number of hidden layers, two variations of the activation function, namely each hidden layer uses the ReLu activation function, while the Output layer uses the Sigmoid activation function. During the training process, manually add the optimizer and learning rate. And the DNN parameters are modified gradually in each training data set.

1) Layers

The three layers of the DNN consist of the input layer which is the input data layer, the hidden layer receives data from the input layer to be processed in the DNN, and in the output layer, the output nodes are binary which results in classification decisions [23]. This study uses 3 variations of hidden layers. The following is a table of the number of nodes used in each DNN layer.

TABLE 1.
NUMBER OF NODES IN EACH LAYER

No.	Number of Hidden Layer	Number of nodes in each layer
1.	3	[45, 40, 30, 40, 2]
2.	4	[45, 40, 40, 30, 30, 2]
3.	5	[45, 40, 40, 30, 30, 25, 2]

In each hidden layer variation, the number of nodes in the input layer is the same as the input data dimension, which is 45, while the number of nodes in each hidden layer must have a value smaller than the input data dimension. Therefore, the number of nodes used in the hidden layer is a variation of 40, 30, and 25. Then the number of nodes in the output layer is the number of classes contained in the dataset, namely 2 (churn and non-churn).

2) Activation Function

The activation function is a function that will transform an input into a certain output [24]. The activation functions used in this study are ReLU (Rectified Linear Unit) and Sigmoid.

3) Optimizer

Optimizer is an algorithm used for gradient optimization on neural networks such as weights and learning rates to reduce losses [25]. This study uses 5 optimizations derived from the Keras model, namely the Stochastic Gradient Descent (SGD) optimizer is a deep learning model that optimizes functions by following a gradient that has a nosy with decreasing step size [26], Adaptive moment estimation (Adam) optimization algorithm which is an extension to Stochastic gradient descent [27], Adaptive Gradient Algorithm (Adagrade) is a modified stochastic gradient descent algorithm with a learning rate per parameter [25], Adadelta is a stochastic gradient descent method based on the level of adaptive learning per dimension, and Root Mean Square Propagation (RMSProp) is a method in which the learning rate is adjusted for each parameter.

4) Learning Rate

Learning rate is a training parameter to calculate the weight correction value during the training process. The range of constant values (alpha) is in the range of zero (0) to one (1). The learning rate used in this study was 0.1; 0.01; and 0.001.

In the modeling process, the analysis process on each data variable is carried out so that the data can be used. Data analysis is carried out to reduce the complexity of unimportant data, detect or remove irrelevant elements and avoid noise from the data [28]. In this study, data preprocessing was carried out with data cleaning and data transforming.

1) Data Cleaning

Checking and deleting data related to missing data values, the aim is to avoid data anomalies at the next stage. In this dataset, there are 11 missing data values, namely the total change attribute.

2) Data Transformation

This stage is done by encoding the nominal data one-hot encoding. The transformation process on the dataset used is using the pandas' library with the get dummies method.

III. Experimental Setup

Experimental setup in this research includes dataset, modeling, and evaluation model.

A. Dataset

This study uses a collection of IBM telecommunications data downloaded via Kaggle with the URL address (https://www.kaggle.com/blastchar/telco-customer-churn). The data obtained in this study amounted to 7043 data with 21 attributes that will be processed to produce customer Churn predictions at telecommunications companies. Some of the attributes contained in the dataset are:

TABLE 1.
ATTRIBUTE NAMES AND DATA TYPES

No.	Attribute Name	Data Type
1	Customer ID	Object
2	Gender	Object
3	Senior Citizen	Int64
4	Partner	Object
5	Dependents	Object
6	Tenure	Int64
7	Phone Service	Object
8	Multiple Lines	Object
9	Internet Service	Object
10	Online Security	Object
11	Online Backup	Object
12	Device Protection	Object
13	Tech Support	Object
14	Streaming TV	Object
15	Streaming Movies	Object
16	Contract	Object
17	Paperless Biling	Object
18	Payment Method	Object
19	Monthly Changes	Float64
20	Total Charges	Object
21	Churn	Object

The dataset used in this study, there are 5174 or 73.4% of non-churn customer data, and 1869 or 26.6% churn customer data. And in this study, 80% of the data is used as training data and 20% of the data is used as testing data.

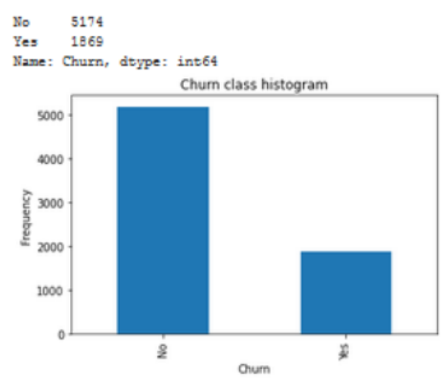

Figure 2. Churn Histogram

B. Modelling

The dataset modeling process in this study carried out four modelings, namely using the Deep Neural Network (DNN) algorithm by testing several hyperparameters and using the K-Nearest Neighbor (K-NN), Random Forest (RF), and Decision Tree (DT) algorithms. as another method that is used as a comparison material to get a model with better performance. The modeling process in this study uses the Python Library version 3 with Google Colab as the tool.

C. Evaluation Model

The research at the evaluation stage compares the accuracy of the results achieved from the four modeling algorithms used, namely the accuracy results from the Deep Neural Network (DNN) algorithm by testing several hyperparameters and the accuracy results from the K-Nearest Neighbor (K-NN) algorithm. , Random Forest (RF), and Decision Tree (DT).

IV. RESULT AND DISCUSSION

In Deep Neural Network (DNN) modeling, testing of several hyperparameters is carried out using 3 variations of the hidden layers, variations of the activation function, namely in each hidden layer the ReLU activation function is used and at the Output layer, the Sigmoid activation function is used. Then using 5 variations of the optimizer (SGD, Adam, Adagrad, Adadelta, and RMSprop), and 3 variations of the learning rate (0.1, 0.01, and 0.001). This model was trained for 30 epochs and 50 batch sizes.

The first step in this research is to test the hidden layer variations using one of the optimizers, namely SGD using a learning rate of 0.001. The following is the accuracy obtained from DNN modeling using the SGD optimizer and a learning rate of 0.01 for the hidden layer variations.

TABLE 3.
SGD OPTIMIZER TEST RESULTS USING LEARNING RATE 0.001

No.	Number of Hidden Layer	Accuracy
1	3 HL	75.20%
2	4 HL	75.20%
3	5 HL	75.20%

Based on table 3, the test results using the SGD optimizer and a learning rate of 0.001 for the hidden layer variation obtained the same accuracy value of 75.20%. So, the next step is to test the variation of the learning rate.

The following are the results of testing on hidden layer variations using the SGD optimizer by performing 3 variations of learning rate (0.1; 0.01; and 0.001).

TABLE 4.
SGD OPTIMIZER TEST RESULTS USING LEARNING RATE VARIATIONS

No.	Number of Hidden Layer	Accuracy		
		0,1	0,01	0,001
1	3 HL	81,66%	82,23%	75.20%
2	4 HL	81,66%	81,81%	75.20%
3	5 HL	81,31%	81,31%	75.20%

Based on table 4, the test results using the SGD optimizer on hidden layer variations by varying the learning rate show the highest accuracy of 82.23%, namely in 3 hidden layers using a default learning rate of 0.01. And based on table 3, the learning rate is 0.01 and the SGD optimizer shows that the deeper or more the number of hidden layers, the lower the accuracy results.

After testing the learning rate variations and getting the best configuration on the 3 hidden layers using the SGD optimizer, the next step is to research at the evaluation stage, namely classifying using the Deep Neural Network (DNN), K-Nearest Neighbor (K-NN) algorithm, Random Forest (RF), and Decision Tree (DT) to measure the accuracy of the results achieved. Based on the test results, the following is the evaluation of the DNN algorithm by testing the hidden layer variations using 3 variations of learning rates and 5 variations of the optimizer (SGD, Adam, Adagrad, Adadelta, and RMSprop).

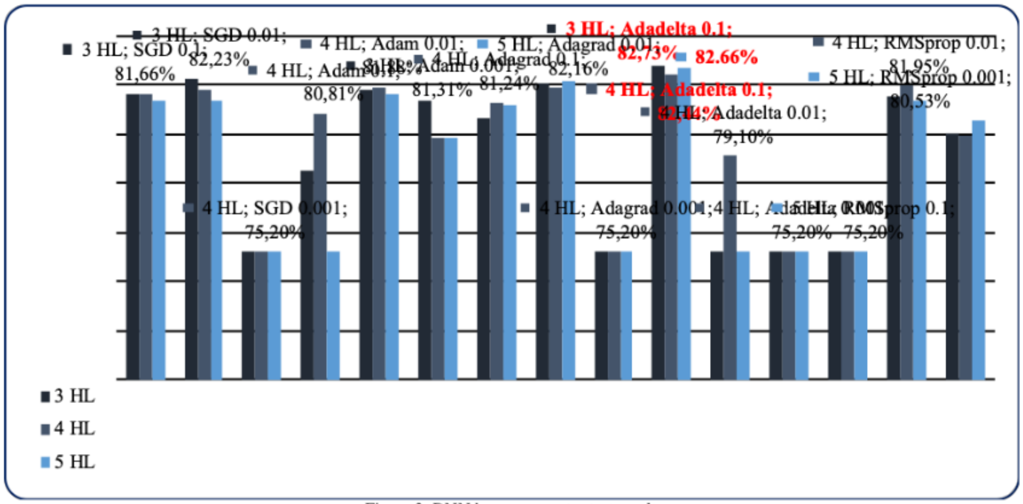

Figure 3. DNN hyperparameter test results

Based on the test results contained in Figure 3, the DNN algorithm through testing several hyperparameters, the highest accuracy gain from each hidden layer is obtained on the Adadelta optimizer with a learning rate of 0.1. The accuracy obtained from the highest value is 3 hidden layers of 82.73%, then 5 hidden layers of 82.66%, and 4 hidden layers of 82.44%. The results of accuracy in using the Adadelta optimizer by using a learning rate comparison show that the smaller the learning rate, the lower the accuracy, but it is not yet known what the optimal value for the learning rate is.

And the test results of several machine learning algorithms used in this study are as follows:

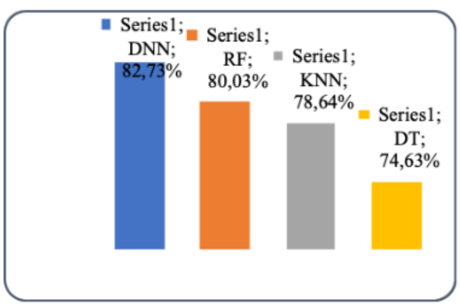

Figure 4. Comparison of Machine Learning Algorithm Accuracy Results

Based on the test results in Figure 5, the accuracy of the highest value in the machine learning algorithm is 82.73%, the Deep Neural Network (DNN) algorithm is obtained, 80.03% is the Random Forest (RF) algorithm, then the accuracy value is 78,64% obtained by the K-Nearest Neighbor (K-NN) algorithm, and the lowest accuracy was obtained with a value of 74.63% in the Decision Tree (DT) algorithm.

CONCLUSION

This study aims to create a model for predicting customer churn in the telecommunications industry. The dataset used is secondary data downloaded via Kaggle.

In this study, the modeling used is Deep Neural Network (DNN), the selection and use of appropriate hyperparameters using three hidden layers in the DNN modeling in this study resulted in better accuracy performance compared to the accuracy performance in K-Nearest Neighbor (KNN) modeling. , Random Forest (RF), and Decision Tree (DT).

The results of the research experiment resulted in DNN modeling with an accuracy value of 82.73% using 3 hidden layers and the Adadelta optimizer with a learning rate of 0.1.

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