Machine Learning Performance on Predicting Banking Term Deposit

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Abstract: With the expansion of epidemic diseases and after the crises of the economy in the world, choosing financial deposits for many purposes is very helpful. To identify a customer whether deposit or not, based on the information given to analyze and predict, it is becoming increasingly difficult for banks to identify whether customer that is right for them. Many banks will be reconfigured beyond recognition to attract customers, while others are facing a shortage drawing customers to maintain the business as a corollary of advances in particular. To serve customers with the information needed to select a suitable deposit in such a rapidly evolving and competitive arena requires more than merely following one's passion. We assert such information may be derived by analyzing some descriptions using deep neural network models, a novel approach to identifying the descriptions about age, job, marital, education, default, balance, housing, loan, contact, day, month, duration, campaigns, pdays, previous, outcome, deposit (y) in choosing an appropriate deposit customer. There have been some researchers written about this prediction but they just focused on algorithms models instead of concentrating on deep machine learning. In this paper, we will muster up algorithms using the models on deep machine learning with Long-Short Term Memory (LSTM), Gated Recurrent Unit (GRU), Bidirectional Long-Short Term Memory (BiLSTM), Bidirectional Gated Recurrent Unit (BiGRU), and Simple Recurrent Neuron Network (SimpleRNN). The result will suggest suitable customers based on the information given. The results showed that Gated Recurrent Unit (GRU) reaches the best accuracy with 90.08% at epoch 50^{th}, and the following is the Bidirectional Long-Short Term Memory (BiLSTM) model with 90.05% at epoch 50^{th}. The results will be helpful for the banks to confirm whether the customers could deposit or not.

1 INTRODUCTION

The crisis of the economic and epidemic disease could lead people to bankrupt and connect to the bank for finance. Given such variety, the challenge for banks is how to choose a method corresponding to their situational finance. Basing on the phone calls, the banks want to be sure to confirm that a customer whether making a term deposit at that time or not. This is a financial campaign of the bank in maintaining the development and existing policy for customers. The banks usually call the client over one time to confirm that they have subscribed to the banking deposit or not. This prediction will help the bank to establish a new strategy for the patrons. In banking, the prediction needs to get the best accuracy to propose a new strategy in business. Confirmation in banking before proposing a package to customers is very important to the bank. They could cost much time and much money for customer investigation. After that, they will classify the customers and estimate the deposit of the customers. The suitable findings will reduce the time and money for the bank in calling and attracting customers.

In paper (Hung et al., 2019), they fully compared the Spark MLlib and ML packages and they showed that ML packages got the best accuracy in predicting term deposit. To compare Spark MLlib and ML packages they applied Random Forest and Gradient Boosting and the result for Gradient Boosting accuracy approach to 86%. They gave a good result for the banking prediction but they just got a comparison in PySpark Apache. They never tried to use deep machine learning to make a comparison in predicting customers.

In paper (Kurapati et al., 2018), they used machine learning to predict the defaulters based on the customer's information. In that paper, they used the algorithms in Scikit-Learn for prediction and compared the accuracy of algorithms before feature

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Table 1: Some example rows for data.

age	job	marital	education	default	balance	housing	y
58	management	married	tertiary	no	2143	yes	no
44	technician	single	secondary	no	29	yes	no
33	entrepreneur	married	secondary	no	2	yes	no
47	blue-collar	married	unknown	no	1506	yes	no
33	unknown	single	unknown	no	1	no	no
35	management	married	tertiary	no	231	yes	no
28	management	single	tertiary	no	447	yes	no
42	entrepreneur	divorced	tertiary	yes	2	yes	no
58	retired	married	primary	no	121	yes	no
43	technician	single	secondary	no	593	yes	no

selection and after feature selection. Getting the best algorithm is Random Forest to predict credit defaulters compared to Decision Tree, Gradient Boosting, and Extra Tree Classifier. They compared the accuracy of prediction in defaulting payment using machine learning techniques. In paper (Zhu et al., 2019), they got a study for predicting loan default base on machine learning algorithms. The result proving the performance of Random Forest showed the best answer compared to the other algorithms such as Decision Tree, SVM, and Logistic Regression. In the paper (Gupta et al., 2020), they applied machine learning for predicting bank loan systems by using Logistic Regression and Random Forest and they did not compare to the other algorithms. In the paper (Rahman and Kumar, 2020), they also used KNN, SVM, Decision Tree, and Random Forest to predict in machine learning based on customer churn prediction. However, all of the papers have not applied deep machine learning to predicting or got a comparison for the models in deep machine learning. In this paper, we got data (as shown in Fig 1) and applied deep machine learning to take an accuracy comparison using the LSTM model, GRU model, and other algorithm models. We did try many different algorithms and chose the best performance for predicting a customer depositing in a bank. After trying all the algorithms, we chose for performance five best algorithms like Long-Short Term Memory (LSTM), Gated Recurrent Unit (GRU), Bidirectional Long-Short Term Memory (BiLSTM), Bidirectional Gated Recurrent Unit (BiGRU) and Simple Recurrent Neuron Network (SimpleRNN). The main purpose is to find a new comparison to generate the customers' information especially using deep machine learning. Nowadays, banking is a useful channel for relation in finance. They have the trend to solve the financial work through the bank especially in the economic crisis. Through Coivid-19, many things have changed, the working is limited and they tend to live at home and solve the problem online where deposit banking is examined by customers. In unprecedented circumstances, the banks have to make phone calls to confirm the customers and have some instructions to invite them to make a banking term deposit. With machine learning, the banks could solve the problems faster and decide the matters rightly. This paper is aimed to confirm a customer whether they could make a deposit or not using deep machine learning. It is also convenient for the bank to solve with an enormously large of customers in a short time.

In this paper, we got input data from the following website: https://www.kaggle.com/vinicius150987/bank-full-machine-learning/data. We also used the data set with 45,211 records and a total of 16 attributes. 1 shows some examples extracted from data. The data consist of numerical columns such as age, balance, day, duration, campaign, pdays, and previous and other columns are strings such as job, marital, default, housing, loan, month, and deposit (y) which will be turned into numeric by the StringIndexer. The term deposit (y) is choosing for a label in predicting.

2 LITERATURE REVIEWS

Machine learning day by day has become a useful application in most traditional stochastic methods especially in financial market forecasting as well as support vector machines (Ryll and Seidens, 2019; Ghani et al., 2019). In this paper, we covered map all the coulumns to convert the input numeric to string. After that, we add all the attributes to the features. In the next step, we apply train_test_split to slit the data. We also try all the algorithms and choose some good algorithms which are suitable to predict such as Gradient-Boosted Trees, Random Forest, Decision Tree, Logistic Regression, and deep learning machine is LSTM

model, GRU model.
Long-Short Term Memory (LSTM) and Bidirectional Long-Short Term Memory (BiLSTM) model is a kind of recurrent neural network, is designed to memorize information through using time (Junyu, 2020; Tuan and Meesad, 2021). The structure of LSTM in every section has repeated form, usually *tanh* gate, and has been rearranged in effective layers. The target point of the LSTM network is built input data by a *sigmoid* function, called forget gate. LSTM has a function that will omit or add the information to the system state by the gate and sigmoid function (Fig 2).
Similar to LSTM, Gated Recurrent Unit (GRU) and Bidirectional Gated Recurrent Unit (BiGRU) is a supply formed data transformed from input nodes to output nodes (Verster et al., 2021; Tuan et al., 2021). GRU consists of reset gate and updates gate. The reset gate is to update the hidden state after the first investigation and control how much the previous information we want to keep in. The update gate allows control of how much the new state and information copied from the old state. GRU (Kumar et al., 2020) is a very important model for predicting the order in the artificial neural network (Fig 3). GRU has reduced the break-gradient information to LSTM.

3 RESEARCH METHODOLOGY

In this paper, we approach the way to explore the role of text preprocessing and feature representation by using the available tools in Scikit-Learn library. We use Python as a data analytics tool to implement experiments. We extract randomly a dataset into two parts in the ratio: 7:3 of total of 45,211 records. All of them consist of four stages (see Fig 1): Turn all the string attributes into numerical attributes, feature selection (adding all the numerical attributes and categorical to features), predict banking term deposit by using models, and using transformation for the testing part with model and evaluation. In the preprocessing, we clean the data with empty records and apply ML packages to evaluate with four differently detail preprocessing techniques:
+ Firstly, we divide the data into two kinds of attributes. We put the string columns: age, balance, day, duration, campaign, pdays, and previous into the numerical columns. After that we apply map for all the columns: job, material, education, default, housing, loan, contact, month, poutcome, and put all to the categorical column.
+ Secondly, we combine the numerical column and categorical column to the new column “Features” through the for the column deposit “y” to get the label column. We transform the old data to new data with selected columns.
+ Thirdly, we split data randomly into two parts: training part (70%) and testing part (30%). We train the model and execute the training in the pipeline and predict the outcome.
+ Lastly, we evaluate the algorithms and get the best algorithm with the greatest accuracy. After that, I show the term deposit prediction.
To evaluate the model, we also use the accuracy, is defined as the numbers of the ratio of numbers of samples correctly classify by algorithms to the total numbers of samples for a given data set, as shown as the equation 1:

$$Accuracy = \frac{TP_{BTP} + TN_{BTP}}{TP_{BTP} + TN_{BTP} + FP_{BTP} + FN_{BTP}} \tag{1}$$

Where TP_{BTP} is true positive samples of banking term deposit prediction, FP_{BTP} is mistake positive samples of banking term deposit prediction, TN_{BTP} is true negative samples of banking term deposit prediction, FN_{BTP} is mistake negative samples of banking term deposit prediction. With two deep learning machine models: LSTM and GRU models, we combine all the columns to features columns except the target y (deposit or not). We turn the target to 1 and 0 for prediction. In the preprocessing, we tokenize and fit the text to the features column.

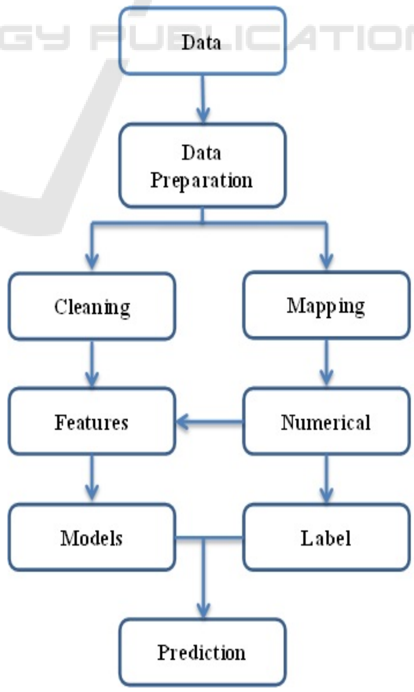

Figure 1: Steps for preprocessing dataset.

4 EXPRIMENTAL RESULTS

After processing the data, we apply machine learning models and compare them. We choose the best algorithm to apply prediction for the outcome. In Table 2, we got predictions for accuracy using the testing part. In the LSTM model, we consider the data as string and split the data into two parts with the ratio of 7:3. We built 4 layers consisting of Embedding, SpacialDropout1D, LSTM, and Dense, the shape for input and output is (64;5) with 49,669 parameters. In the GRU model, we applied the same structure to LSTM and built 4 layers consisting of Embedding, SpacialDropout1D, GRU, and Dense, the shape for input and output is (64;5) with 41,605 parameters.
In the BiLSTM model, we apply the same method and the same ratio in PySpark. We built 4 layers consisting of Embedding, SpacialDropout1D, LSTM, and Dense, the shape for input and output is (64;5) with 83,013 parameters. In the BiGRU model, we built 4 layers consisting of Embedding, SpacialDropout1D, GRU, and Dense, the shape for input and output is (64;5) with 66,885 parameters. In the BiGRU model, we built 4 layers consisting of Embedding, SpacialDropout1D, GRU, and Dense, the shape for input and output is (64;5) with 24,901 parameters. In this experiment, the GRU model showed the best performance, reaching the accuracy of 0.908 with 48s at the first 50th epoch, and could get better when repeating more times (Shown in Fig 3). The BiLSTM model comes alongside 0.905 with 52s at the 50th epoch (Fig 4). The LSTM get close to 0.903 (Fig 2) and the following is BiGRU (Fig 5) and SimpleRNN (Fig 6) respectively reaching 0.901 and 0.892.

Table 3 shows the summary of predictive number values, the first label is 1 and prediction 1 are corresponding with true prediction numbers; the second label 0 and prediction 1 are corresponding with false prediction numbers; The third label 1 and prediction 0 are corresponding with false prediction numbers; the fourth label 0 and prediction 0 are corresponding with true prediction numbers.
Compared to the algorithms' training in ScikitLearn with the same data, we tried the algorithms and choose the five best models with accuracy as shown in Table 2. We could see that with the same method, the same models and algorithms but we get the best answers in PySpark library than in Scikit-learn library (usually online in Kaggle.com).

Table 2: Five best results in deep machine learning using Scikit-Learn library.

Models	***Accuracy***
BiLSTM	0.905
BiGRU	0.901
SimpleRNN	0.892
LSTM	0.903
GRU	0.908

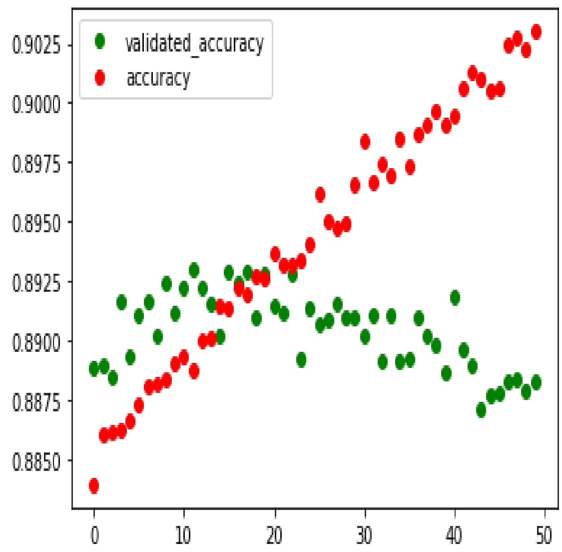

Figure 2: LSTM prediction.

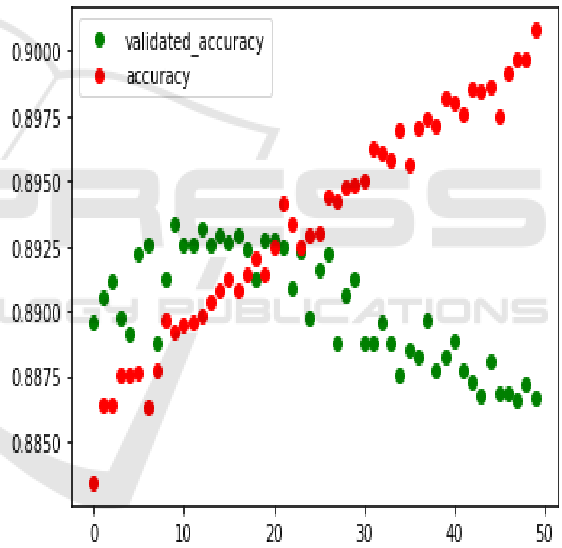

Figure 3: GRU prediction.

5 CONCLUSIONS AND FUTURE WORK

The development of technology has led to many things to solve in life especially in finance. They usually have a tendency to get benefits at home, so

Table 3: Counting prediction values summary.

label	predict	BiLSTM	BiGRU	SimpleRNN	LSTM	GRU
1	1	390	347	586	346	368
0	1	209	260	381	418	446
1	0	1156	1199	960	1179	1151
0	0	11740	11689	11568	11621	15824

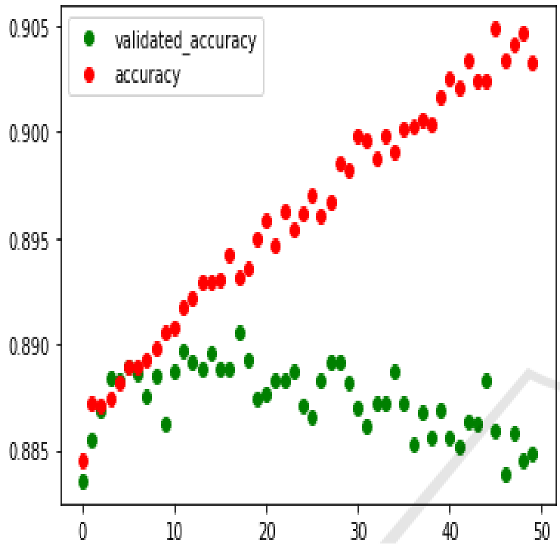

Figure 4: BiLSTM prediction.

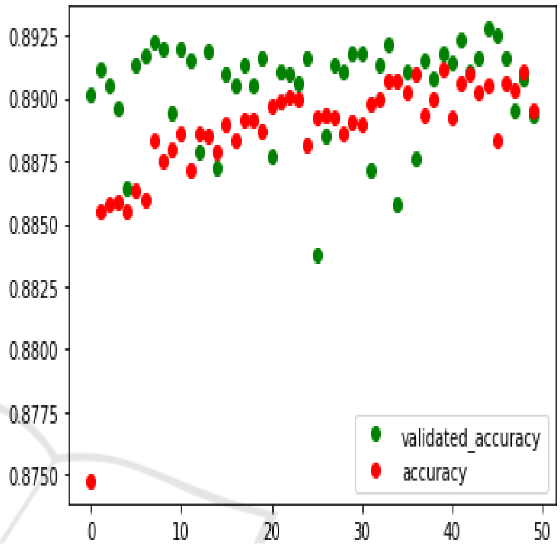

Figure 6: RNN prediction.

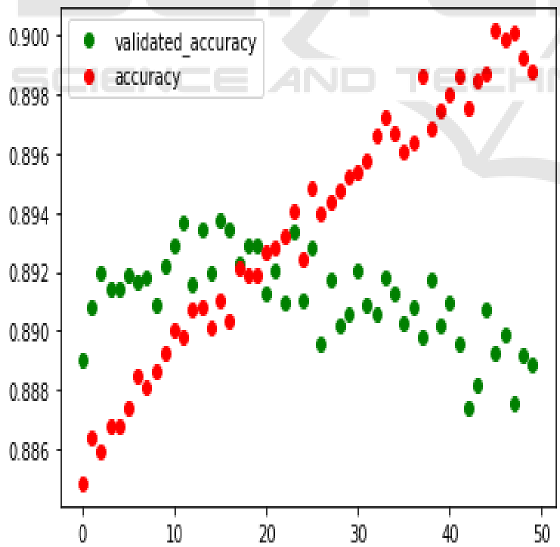

Figure 5: BiGRU prediction.

investment by making a banking term deposit is one of the channels to do this (Viswanathana et al., 2020; Prasetyo et al., 2021). So, the banks need to have a plan for calling the potential customers. To do this, they must have a method for predicting whether customers could have tended to make a profit by banking term deposit. In this paper, the comparison is a useful method to know more clearly about the nature of the problems. Machine Learning algorithms are applied to all the matters of the jobs especially in something changeable every time and every day (N.dikum, 2020; Zhong and Enke, 2019; Ren et al., 2021). In this paper, we have summarized the ease of using algorithms in machine learning in machine learning and Scikit-learn library and proposed the best models in deep machine learning such as BiLSTM model and GRU model. The results showed the best prediction in banking term deposit customers which is GRU models with an accuracy of 90.8%. The result is one of the methods for banks to confirm the target customers and for expanded research in the future.

REFERENCES

Ghani, M. U., Awais, M., and Muzammul, M. (2019). Stock market prediction using machine learning (ml) algorithms. In *Advances in Distributed Computing and Artificial Intelligence Journal*.

Gupta, A., Pant, V., Kumar, S., and Bansal, P. K. (2020). Bank loan prediction system using machine learning. In *International Conference on System Modeling and Advancement in Research Trends*.

Hung, P. D., Hanh, T. D., and Tung, T. D. (2019). Term deposit subscription prediction using spark mllib and ml packages. In *5th International Conference on E-Business and Applications*.

Junyu, H. (2020). Prediction of financial crisis based on machine learning. In *The 4th International Conference on Business and Information Management*.

Kumar, V. S., Bhardwajb, B., Guptac, V., Kumarc, R., and Mathurc, A. (2020). Gated recurrent unit (gru) based short term forecasting for wind energy estimation. In *International Conference on Power, Energy, Control and Transmission Systems*.

Kurapati, N., Kumari, P., and Bhansali (2018). Predicting the defaulters using machine learning techniques. In *Research Paper*.

N.dikum, P. (2020). Machine learning algorithms for financial asset price forcasting. In *https://doi.org/10.1093/rfs/hhaa009*.

Prasetyo, I., Utar, W., Susanto, H., Rusdiyanto, and Hidayat, W. (2021). Comparative analysis of banking financial performance: Evidence from indonesia. In *Ilkogretim Online - Elementary Education Online*.

Rahman, M. and Kumar, V. (2020). Machine learning based customer churn prediction in banking. In *Fourth International Conference on Electronics, Communication and Aerospace Technology*.

Ren, L., Dong, J., Wang, X., Meng, Z., Zhao, L., and Deen, M. J. (2021). A data-driven auto-cnn-lstm prediction model for lithium-ion battery remaining useful life. In *IEEE Transactions Industrial Informatics*.

Ryll, L. and Seidens, S. (2019). Evaluating the performance of machine learning algorithms in financial market forecasting: A comprehensive survey. In *http://arxiv.org*.

Tuan, N. M. and Meesad, P. (2021). A study of predicting the sincerity of a question asked using machine learning. In *International Conference on Natural Language Processing and Information Retrieval, https://doi.org/10.1145/3508230.3508258*.

Tuan, N. M., P., M., and H.C, N. H. (2021). English-vietnamese machine translation using deep learning. In *Recent Advances in Information and Communication Technology IC2IT*.

Verster, T., Harcharan, S., Bezuidenhout, L., and Baesens, B. (2021). Predicting take-up of home loan offers using tree based ensemble models: A south african case study. In *Research Article at https://doi.org/10.17159/sajs.2021/7607*.

Viswanathana, P. K., Srinivasan, S., and Hariharan, N. (2020). Predicting financial health of banks for investor guidance using machine learning algorithms. In *Research Article*.

Zhong, X. and Enke, D. (2019). Predicting the daily return direction of the stock market using hybrid machine learning agorithms. In *Finacial Innovation*.

Zhu, L., Qiu, D., Ergu, D., and Liu, C. Y. K. (2019). A study on predicting loan default base on random forest algorithm. In *International conference on Information Technology and Quantitative Management*.