ICIC Express Letters
Volume **16**, Number **6**, June **2022**

ICIC International ©2022 ISSN 1881-803X
pp. 679–686

TELEKOM-NET: THE EMBEDDED BI-LSTM AND EXPERT KNOWLEDGE MODEL FOR STOCK FORECASTING AND SUGGESTION

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Received June 2021; accepted September 2021

Abstract. *Stock price forecasting has become a concern of academia and industries in recent years. There have been several studies that apply various methods such as fundamental analysis, machine learning and deep learning to predicting stock price; although machine learning/deep learning made rapid progress in the stock forecasting task, we argue that raw machine learning/deep learning, which only works in black-box way, is not relevant enough to predict stock. Therefore, we proposed the TELEKOM-NET model that combines fundamental stock analysis with a decision scoring tree to enhance the state-of-the-art Recurrent Neural Network (RNN) model to predict stock price. This research has conducted two evaluation tests, namely based on the training-testing score and the proposed real-world evaluation method. In comparison, the real-world evaluation conducted trading activities for three months on a weekly trading frequency. Our proposed model resulted in 6.2205e-04 Mean Squared Error (MSE) with an average difference price of 17.6 rupiah in predicting BMRI stock and produced suggestion 66.67% accuracy of the real-world evaluation method.*

Keywords: Stock forecasting, Long short-term memory, Real world evaluation, Indonesian stock exchange

1. **Introduction.** IDX or Indonesian stock exchange combines all stock in Indonesia from nine sectors, i.e., Trade, Infrastructure, MISC-IND, Consumer, Agriculture, Property, Finance, BASIC-IND, and Mining, which company registered on Bursa Efek Indonesia [1]. The stock price in Indonesia is affected by uncertainties variables related to the influencer, economy and politics at the macro level, and even price can also be affected by Bandarmology. Bandarmology is a group or person with a large amount of money to manipulate the small to the average market capital price of the stock in a certain period of time. Due to this Bandarmology problem and many uncertain variables of fluctuating stock price, the authors design a model based on fundamental analysis [2] that translates to a decision scoring tree and close price variable based on long short-term memory recurrent neural network [3]. This design model is made to support the decision of the retail investor.

The idea of choosing a combination of decision score trees and LSTM is based on the author's intuition to combine pattern forecasting price and fundamental analysis. The decision tree was chosen as the foundation due to simplicity in making decisions based on expert knowledge and flexibility in determining important fundamental financial report parameters. At the same time, the long short-term memory recurrent neural network was

DOI: 10.24507/icicel.16.06.679

chosen because of its accuracy in recognizing patterns in sequential data [4], and combination of several machine learning and deep learning models has been able to improve the accuracy of the stock case in previous studies [5-7].

Empirically in IDX cases, especially in the banking sector, the primary component that determines stock valuation is fundamental analysis from company financial reports [8]. The statistics chart on RTI Business shows that trading in the finance sector LQ45 IDX increase and decrease value was not too significant, ranging from 1%-5%, making this sector an appropriate and secure stock research scene. Following previous research, the banking sector has stability pace [9]. In this research, our model evaluates the model on the test dataset. Instead, we evaluate the model with a new method for assessing stock model performance. We experimented with the model in 3 months of trading activities with a frequency of selling and purchasing BMRI stock per week. Then we want to prove that the combined decision scoring tree produces better results in stock forecasting instead of black-box work by deep learning and machine learning architectural models. This study contributes to developing a stock price forecasting model that flexibility for embedding expert knowledge and combining them with a current state-of-the-art deep learning model.

This work contains five sections as follows: Section 1 is the introduction of the study, Section 2 contains related and previous research conducted, Section 3 contains how we compose the TELEKOM-NET model, Section 4 talks about how we evaluate and test the model, and Section 5 shows conclusion of the study.

2. **Related Research.** Forecasting stock prices has been carried out by several studies using Machine Learning (ML) and Deep Learning (DL) algorithms [10]. In order to predict the risk and volatility of the stock, investors can be considered to increase potential future profits [11,12]. The implementation of forecasting using machine learning models was done in 2017 by Bhuriya et al.'s study, predicting the close price by considering open price, high price, low price, and number of trend [11]. Bhuriya et al. used three machine learning techniques, i.e., linear regression, polynomial, and Radial Basis Function (RBF) regression, on the TCS Stock Database dataset from 25 August 2004 to 23 September 2016 [11]. The result is that the technique using linear regression has the best confidence value than the others [11]. Although it has good accuracy and conducted training on datasets with a bank sector, this study does not provide precise results on specific cases in the bank sector [11].

In the same year, Ghazanfar et al. experimented by comparing several machine learning classifiers such as multilayer perceptron, Adaboost, and BayesNet in predicting stock prices in several sectors [13]. Ghazanfar et al. used company data indexed on the Karachi Stock Exchange (KSE) for six months with features consisting of open price, high price, low price, current price, and change. Best experimental results in Root Mean Squared Error (RMSE) predict close prices in the banking sector using the multilayer perceptron classifier (RMSE = 0.1913) [13]. However, we discern that adding more additional features from the company financial report will improve the model to predict stock movement more accurately than using a plain DL/ML model that predicts in a black-box way. Several studies use additional information in order to increase predictability based on fundamental data [14-16].

In the Indonesia stock forecasting case, Tanulia and Girsang conducted experiments using Support Vector Machine (SVM) models such as linear regression, polynomial, and Radial Basis Function (RBF) by adding additional features such as comments sentiment from Twitter [17]. The dataset used from LQ45 companies in Indonesia was collected from 1 August 2018 to 1 April 2019 with close price as a feature [17]. Tanulia and Girsang append the sentiment in the form of comments and percentage of topics taken from interactions between users and the official Twitter company account as additional features. The experimental result reveals that the SVM model that used RBF is better than polynomial and linear [17]. However, applying additional features such as sentiment analysis from user's interactions on Twitter, the correlation might not significantly affect stock movements due to uncorrelated interactions to stock movement price in Twitter and extensive audience variety background unrelated to stock price [17].

Additionally, previous research also applies the deep learning method in analyzing sentiment from trusted news that has been selected to predict stocks [14]. Kiefer et al. revealed the research results using the deep learning method when applied to time series-based like forecasting cases outperform machine learning method [18]. In addition, Artha et al. also revealed that deep learning methods such as artificial neural networks could be used for forecasting stocks [19]. Chen et al. used the China Stock Index dataset, which was taken throughout 513 trading days with the features of open price, high price, low price, close price, and volume [14]. Additional features consist of news on 85 trusted Sina Weibo accounts that have been selected [14]. Chen et al. used these two data on two different RNN models, namely RNN (Single-RNN) and RNN with classifier Adaboost (RNN-Boost) [14]. The experimental results of the RNN-Boost model (RMSE = 2.05) resulted in higher accuracy than the Single-RNN (RMSE = 2.17) [14].

In the case of using the deep learning method in predicting banking sector companies in Indonesia previously conducted by Artha et al. [19]. Artha et al. proposed a combination of Wavelet transform and Neuro-Fuzzy System (WNFS), which allows adding it to a neural network, as known as part of a Wavelet Neural Network (WNN) [19]. Artha et al. used a dataset of banking companies in Indonesia (BMRI) from 14 September 2015 to 12 September 2017. Artha et al. used three inputs (features) from estimated data that had been determined based on the lag value through ARIMA law [19]. The experimental results on this model resulted in an MSE value of 5.8454×10^{15} [19]. Unfortunately, [19] is not equipped with additional external variables seen in the absence of additional features. Otherwise, the research we propose will help investors, especially beginners to carry out stock trading activities in banking companies by adding additional features.

3. **Research Method.** We compare four categories from previous studies to see how our proposed model fits (see Table 1). The first category looks at whether the research reports on the model are used explicitly for testing banking companies (Using Specific Bank

Table 1. Comparison of previous research

	Using Specific Bank Sector Dataset	**Using Additional Feature**	**Using Deep Learning Method**	**Using Indonesia Cases**
Bhuriya et al. [11]				
Ghazanfar et al. [13]	Yes		Multilayer Perceptron	
Tanulia and Girsang [17]		Sentiment from Social Media		Yes
Chen et al. [14]		Sentiment from News	RNN-Boost	
Artha et al. [19]	Yes		WNN	Yes
Our	Yes	Expert Knowledge	LSTM	Yes

Sector Dataset). Then, the next category is whether previous research adds external variables outside of the dataset used in predicting stocks, such as sentiment from social media or news sentiment (Using Additional Feature). The third category describes whether the model has implemented the deep learning method (Using Deep Learning Method) due to the fact that recent research reveals that the use of the deep learning method outperforms the machine learning method in several cases, especially pattern data recognition [18,20,21]. The final category looks at whether the model is using Indonesia case, and the model trained with Indonesian Company datasets.

We propose a deep learning model that meets all categories named The LSTM and Expert Knowledge Model (TELEKOM-NET) from the four categories previously mentioned. Our model uses the architecture of the RNN, which includes LSTM in predicting stocks. Previous studies proved that RNN models such as LSTM are suitable for time series cases such as stock forecasting and the result is outperformed by machine learning [18,22-24]. The output of the RNN model will be embedded into the decision scoring tree model along with an additional feature which included the expert knowledge variable features. Our model is trained specifically for forecasting close prices on shares of a banking company in Indonesia, namely PT. Bank Mandiri Tbk (BMRI). The combination of this model is expected to support trading activities, especially in the banking sector. Figure 1 illustrates The TELEKOM-NET model's overall approach.

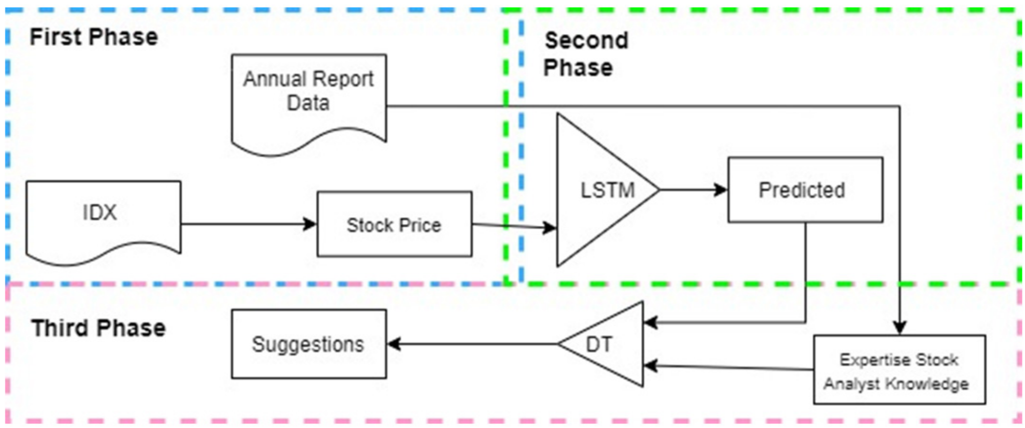

Figure 1. The overall approach of TELEKOM-NET

3.1. **Dataset acquisition.** Dataset is collected using hand-made scripts to gather data from a trusted third-party trading application and authorized website from the Indonesian Stock Exchange[1]. From these sources, we retrieve the attribute of open price, high price, low price, frequency, buy/sell volume, and close price records of 3 years with 488 rows and key stats of company financial reports. Attribute details can be seen in Table 2.

Table 2. Financial report attribute retrieved

Financial report attributes			
net income reports	current valuation	balance reports	per share reports
price performance	cash flow reports	market size reports	solvency reports
company growth reports	dividend reports	management effectiveness reports	profitability reports
analysts price consensus reports			

[1]www.idx.co.id

3.2. **Models.** In Figure 1 Phase 2, in order to search best close price prediction model, we experiment with several RNN models with Adam optimizer, default learning rate 0.01, and running several RNN models with 50 epochs to find the best model by evaluating the model loss Mean Squared Error (MSE). After finding the best RNN model for predicting close stock price, then we embed the close price prediction variable and translate stock expertise knowledge, and add it into a decision tree to support trading activities. The parameters of decision tree shown in Table 2 are chosen as relevant as possible by expertise knowledge. Our decision tree model based on expert knowledge [8,16,25] will tend to decide to buy if the price-earnings ratio is getting smaller and the output from BI-LSTM score (ls) is not negative and projects a high price gap (pg). Then, the decision tree also considers tending not to buy if the market cap (mc), net income growth (ni), and dividend yield (dy) are getting smaller. For these combination models of BI-LSTM and Decision Tree (DT), the variable can be modified as needed to adjust expertise knowledge or to add from sentiment analysis score.

Our contribution is the proposed model of TELEKOM-NET. The model is a hybrid model and able to use additional data to forecast the stock price. The model shows flexibility and competitive results in training-testing mean squared error score and accuracy of real-world evaluation. Another additional contribution is that the authors proposed real-world evaluation. Real-world evaluation is an evaluation method based on conducting real trading activities and then summarizing the trading activities records.

4. **Result.** Performance evaluation is carried out in the training and testing process using two types of loss functions, namely Mean Square Error (MSE). The MSE value describes how consistent the model is by looking at the difference between the original and predicted data (difference in error) [22,26,27]. The performance evaluation was carried out to investigate which LSTM model to embed with the decision tree model based on expert knowledge. Then, we conducted the real-world evaluation measurement of how this model is applied to real cases at the BMRI company for three months (2nd November 2020-25th January 2021).

4.1. **Model experiment & evaluation.** We experiment with several RNN models to find the best close price prediction model. The models are Vanilla LSTM with Dense Layer, BI-LSTM with dense layer, Vanilla LSTM and Stacked LSTM. We find that BI-LSTM outperforms the MSE loss score compared to other models in Table 3. The result can be reproduced and obtained in the Github link[2]. The result from Table 3 can be concluded that Bi-Directional LSTM had the highest accuracy level on testing and meaningful price difference.

Table 3. The comparison among Vanilla LSTM + Dense Layer, Bi-Directional LSTM, Vanilla LSTM and Stacked LSTM

	Training	Testing		
	MSE	Mean price prediction	Mean price diffrence	MSE
Vanilla LSTM + Dense Layer	8.9655e-04	6466.016	23.57	1.3751e-05
Bi-Directional LSTM	**6.2205e-04**	**6424.8633**	**17.57**	**1.0944e-03**
Vanilla LSTM	5.6327e-04	6457.638	15.19	1.1119e-03
Stacked LSTM	5.7020e-04	6414.3584	28.07	1.0950e-03

[2]https://github.com/Anderies/TELEKOM-NET

4.2. **Real-world trading evaluation.** This stage presents a table from November 2020 to January 2021 based on five items shown in Table 4. Stock prediction is the stock price predicted by the Bi-Directional LSTM model. The stock price is the actual stock price in the real world. Suggestions result from a recommendation to "buy" or "don't buy" based on expert knowledge. Stock prediction condition is an item to see whether the stock price predicted increases or decreases from the previous week. Also, the stock condition item recognizes whether the stock price in the real world is increasing or decreasing. Correction variable represents whether the suggestions provided accurate suggestions. It is a conclusion that combines prediction result and stock price in actual condition. It indicates that the accuracy of suggestions is correct. Furthermore, when the stock price prediction and stock price in the real world decrease from the previous week while the suggestion delivers 'don't buy' advice, the accuracy is also correct. Then, if there is a differentiation of stock prediction condition and stock condition in the real world, it will provide an incorrect suggestion result, which means the corrections variable is 'incorrect'.

Table 4. Real-world trading evaluations

	Stock prediction	Stock price	Suggestion	Stock prediction condition	Stock condition	Corrections
9/11/2020	6035	6150	buy	price increase	price increase	correct
16/11/2020	6141	6200	buy	price increase	price increase	correct
23/11/2020	**6212**	**6400**	**don't buy**	**price decrease**	**price increase**	**incorrect**
30/11/2020	**6216**	**6325**	**buy**	**price increase**	**price decrease**	**incorrect**
7/12/2020	6234	6700	buy	price increase	price increase	correct
14/12/2020	6744	6725	buy	price increase	price increase	correct
21/12/2020	**6799**	**6700**	**buy**	**price increase**	**price decrease**	**incorrect**
28/12/2020	6729	6350	don't buy	price decrease	price decrease	correct
4/1/2021	**6363**	**6500**	**don't buy**	**price decrease**	**price increase**	**incorrect**
11/1/2021	6513	6850	buy	price increase	price increase	correct
18/1/2021	6876	6925	buy	price increase	price increase	correct
25/1/2021	6998	7300	buy	price increase	price increase	correct

The results from Table 4 indicate that our model proves incorrect suggestions in 4 weeks out of 12 weeks. The error occurred on 23rd November 2020. The model offered incorrect suggestions "don't buy" since the model wrongly predicted the stock price would decrease while the real-world close price increased from the previous week. Then on 30th November 2020, the model predicted an increase in stock price from the previous week, but the stock price went down, and the model provides an incorrect "buy" suggestion. Also, on 21st December 2020, the model predicted an increase in stock price from the previous week while the stock price in real world went down and affected an incorrect suggestion. Afterward, on 4th January 2021, the model incorrectly predicted the stock price would decrease while the real-world stock price increased from the previous week. Therefore, our model performs correct suggestions 8 out of 12 times, which means our percentage correct accuracy is more than 66.67% in providing suggestions to buy stocks for especially toward banking sector on BMRI cases.

5. **Conclusion.** The authors highlight that the proposed TELEKOM-NET model offers more logical results than raw ML/DL models. Since the decision scoring tree combination can help the RNN model determine the increase and decrease in stock prices preferable compared to raw ML/DL, which only works in a black-box way in predicting stock fluctuations. Our model also has been tested in this study with two different evaluations, namely the comparison of the LSTM model and a real-world evaluation based on trading

activities in three months. In the future, the authors' working on this model can be applied to be an application with all finance sectors in Indonesia Stock Exchange (IDX) to sort best score list stock to buy or sell with new significant variables chosen by expertise and embedded with event-driven or new sentiment analyst.

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