STOCK PRICE PREDICTION

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***Abstract*— The stock market has garnered significant attention from investors, making it a popular area for both individual investors and investment companies to understand the patterns and anticipate trends. Presently, there are several methods available for stock price prediction, broadly categorized into statistical methods and artificial intelligence (AI) methods. Statistical approaches encompass models such as logistic regression and ARCH models. AI techniques include multi-layer perceptron, convolutional neural network, naive Bayes network, backpropagation network, single-layer LSTM, support vector machine, and recurrent neural network.**

I. INTRODUCTION

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By incorporating LSTM networks into the model, we aim to capture the long-term dependencies and patterns in stock price data, considering factors such as historical trends, seasonality, and volatility. The model will learn from past price movements and make predictions based on the learned patterns, enabling it to provide reliable forecasts for future stock prices.

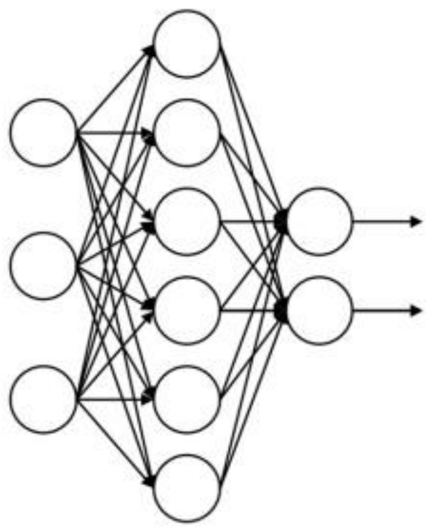
The significance of this project lies in its potential to assist investors in identifying profitable opportunities, minimizing risks, and maximizing returns. By harnessing the power of LSTM networks and their ability to process and understand sequential data, we strive to develop a robust and accurate stock price prediction model that can provide valuable insights into the complex realm of financial markets.

II. MODEL DESIGN

A. Long Short-term Memory Network

The long short-term memory network (LSTM) is a type of recurrent neural network (RNN) that is specifically designed to process sequential data. An LSTM network consists of three distinct "gate" structures, namely the input gate, forgetting gate, and output gate (as shown in Figure 1). These gates play a crucial role in determining which information is allowed to enter the LSTM network and how it is processed.

The input gate, forgetting gate, and output gate function together to selectively pass information through the LSTM network. The default activation function for the LSTM network is the sigmoid function, as depicted in Equation 1. By employing a combination of a sigmoid neural network layer and a pair multiplication operation, the LSTM network can add or remove information from individual neurons. The output of the sigmoid layer, which is a real number between 0 and 1, determines the weight assigned to the corresponding information.



Neural Network Model without dropout

Additionally, the LSTM network incorporates a layer with a hyperbolic tangent (tanh) activation function, as shown in

Equation 2. This tanh layer is responsible for updating the state of the neurons in the LSTM neural network.

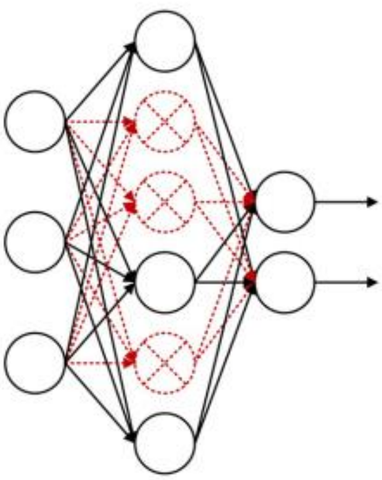
The forgetting gate of the LSTM neural network determines what information needs to be discarded, which reads ht−1 and xt , gives the neuron state Ct−1 a value of 0–1. Equation 3 shows the calculation method of forgetting probability where ht−1 represents the output of the previous neuron and xt is the input of the current neuron. is the sigmoid function.

B. Deep Recurrent Neural Network

A deep recurrent neural network (DRNN) based on long short-term memory (LSTM) is a variation of the recurrent neural network. The DRNN can enhance the model's expressive power by repeating the loop body multiple times at each moment. Diagram illustrates the structural diagram of a deep recurrent neural network, which consists of LSTM units. The operation mechanism of the deep recurrent neural network is similar to that of the LSTM.

During the construction of the task model, the dropout method was employed. Dropout involves temporarily removing neural network units from the network based on a certain probability during the training process of deep learning networks. This technique serves as a means to prevent overfitting. The principle of dropout is that, in each training iteration, neurons in each layer are randomly dropped out with a probability of P. The data in that iteration are then trained with the remaining (1-p)*N neurons, which helps mitigate the issue of overfitting. Figure represents the neural network model without dropout, while Figure shows the neural network model with dropout.

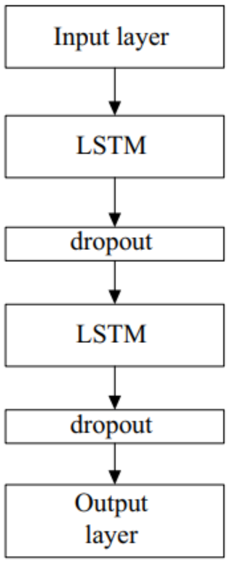
To assess the feasibility and applicability of the proposed associated neural network model, a contrast model was utilized, namely the LSTM-based deep recurrent neural network model with a dropout layer. The structure of the LSTM-based deep recurrent neural network is depicted in Figure.



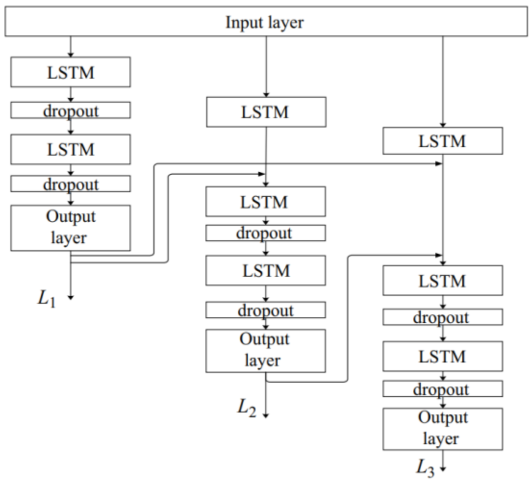
Neural Network Model with dropout

III. ASSOCIATED NEURAL NETWORK MODEL

Since the daily opening price, the lowest price and the highest price of the stock are associated to one another, and the opening price, the lowest price and the highest price are respectively predicted by different networks generally, the associations between one another are separated. Therefore, based on the deep recurrent neural network, a structural model of multi-value associated neural network (associated net) based on LSTM is designed, it is shown in Figure. The specific data processing flow of the multi-value associated neural network model is shown in Figure. Data through the input layer to all three branches simultaneously.

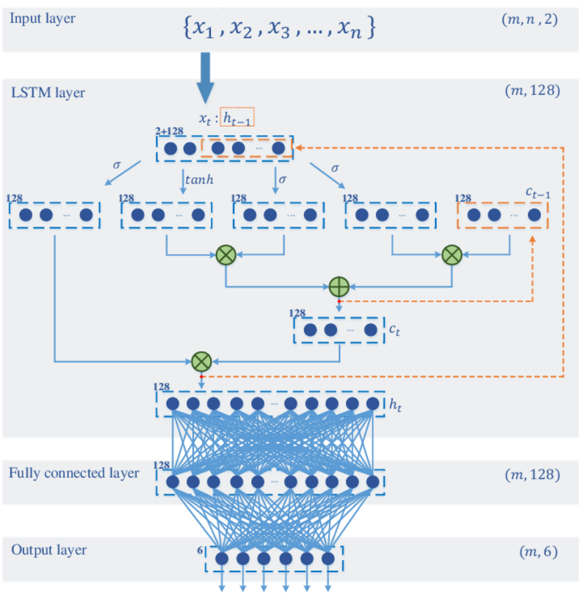


These three branches predict the opening price, the lowest price and the highest price respectively. In the Chinese stock market, the maximum fluctuation of stock price is only 10%. Therefor the model recombines the output of the left branch (opening price) and the output of the LSTM network of the second branch as the input parameter data of the predicted lowest price, and the highest price is subject to the opening price of the day, the impact of the lowest price, so the output of the left branch (opening price) and the output of the intermediate branch (lowest price) and the output of the LSTM network of the third branch form the highest of the new data forecast price.



IV. ALGORITHM

The stock price prediction research paper follows a systematic algorithmic approach. Firstly, historical stock data is retrieved from a reliable source by specifying the stock symbol and desired date range. The retrieved data is then pre-processed, involving the extraction of relevant features such as closing prices, data cleaning, and scaling using techniques like MinMaxScaler for normalization.



The pre-processed data is split into training and testing sets, with a typical allocation of around 80% for training. Next, an LSTM model is constructed, defining its architecture with parameters like the number of LSTM layers, units, and activation functions. Additional layers such as dropout or dense layers may also be added. The model is then compiled with an appropriate optimizer and loss function. Training the model involves feeding the training data into the LSTM model, specifying the number of epochs and batch size for training. The training progress is monitored, and the loss function is evaluated.

After model training, the performance is assessed by making predictions on the testing data and comparing them with the actual stock prices. Evaluation metrics like RMSE are calculated to measure the accuracy of the model. Further analysis is conducted to interpret the results and identify any limitations or challenges encountered during the prediction process. Potential enhancements, such as incorporating additional features or implementing ensemble methods, are explored. The impact of market volatility and external factors on the model's performance is also considered.

V. EXPERIMENTAL RESULTS

The experimental analysis conducted in this research paper involved training and evaluating the LSTM model for stock price prediction. The historical stock data was retrieved from a reliable source, and preprocessing techniques such as feature extraction and data scaling were applied. The dataset was then split into training and testing sets, with the majority allocated for training purposes.

The LSTM model was constructed with a specific architecture, including the number of LSTM layers, units, and activation functions. The model was compiled with an appropriate optimizer and loss function, and the training process began. The number of epochs and batch size were determined, and the model's performance was monitored through the evaluation of the loss function.

After training, the model was tested on the separate testing dataset. Predictions were made using the trained model, and the actual stock prices were compared with the predicted prices. Evaluation metrics, such as root mean squared error (RMSE), were calculated to quantify the accuracy of the model's predictions. The RMSE value provided insight into the extent of deviation between the predicted and actual stock prices.

The results of the experimental analysis were carefully analyzed and interpreted. The accuracy of the LSTM model in predicting stock prices was assessed based on the evaluation metrics. The limitations and challenges encountered during the prediction process, such as market volatility and external factors, were considered.

VI. CONCLUSION

In conclusion, this research paper explored the application of the LSTM model for stock price prediction. The LSTM model demonstrated promising results in capturing temporal dependencies and predicting stock prices based on historical data. By preprocessing the data, training the LSTM model, and evaluating its performance, we gained insights into its effectiveness and limitations.

The experimental analysis revealed that the LSTM model produced predictions that were relatively close to the actual stock prices. The evaluation metrics, such as the root mean squared error (RMSE), provided a quantitative measure of the model's accuracy. Although the model showed promising results, it is important to note the challenges posed by market volatility and external factors that can influence stock prices.

This research paper highlighted the importance of continuous evaluation and refinement of the LSTM model. Future work could involve incorporating additional features such as volume and technical indicators to enhance prediction accuracy. Exploring ensemble methods and hybrid models that combine LSTM with other techniques could also be beneficial.

VII. REFERENCES

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