DEVELOPING A SMART INTEGRATED MODEL BASED ON DEEP LEARNING TOOLS AND TECHNIQUES IN THE EFFICACIOUS PREDICTION OF STOCK PRICES

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ABSTRACT

Recent advances in deep learning have inspired researchers to apply neural networks to stock prediction. Much research has been done on stock price prediction, but academics have yet to find a good solution. To predict the S&P 500 index's future value, we present a convolution-based neural network model in this paper. The proposed model can predict the index's direction the following day based on the index's previous values. As demonstrated by experiments, our model outperforms several benchmarks with an accuracy rate of over 55%.

INTRODUCTION

Stock price prediction is a well-known econometrics problem. Numerous approaches attempt to predict a stock's future value. The Efficient Market Hypothesis, on the other hand, holds that the current stock price already incorporates all of the publicly available information. According to the theory, predicting a stock's future price is impossible. We can construct a deep learning model that, despite the dim outlook, can accurately predict the direction of the S&P 500 index. There is a lot of interest in using Machine Learning (ML) to improve market forecasting compared to more conventional methods due to the recent increase in computational power and the abundance of financial market data [12, 3]. Since these methods do not require any assumptions about the data and frequently achieve higher accuracy than traditional methods, artificial neural networks, support vector machines, and genetic algorithms have been combined with other methods to forecast and analyze financial markets for the past decade. In 2009, the authors of [1] surveyed more than one hundred articles and concluded that neural networks (NNs) enhance market forecasting compared to more conventional methods. Numerous other researchers empirically demonstrated that feature selection algorithms improved their model's performance by selecting the input variables using ML models like support vector regression machines (SVR) and NNs [8, 2], 10]. Due to its adeptness at nonlinear approximation and adaptive self-learning, deep learning has recently gained popularity as a stock market forecasting tool [14, 11]. Deep neural networks (DNNs) are artificial neural networks (ANNs) that use various deep learning algorithms. These networks have been utilized in numerous significant domains, including the financial markets [15].

The network that we propose has two hidden layers: completely connected and convolutional. The model uses the index's volume and previous closing values to predict the direction of the next day. The use of the convolutional layer, which makes it easier to consider individual instances in time series about their temporal neighbours, is our main insight. A method that works well with time series data is using a convolutional layer. We evaluate our model by comparing it to seven standard models. Experiments show that the proposed model performs better than the standard models in terms of precision and accuracy. Time series forecasting researchers would benefit from the proposed neural network architecture.

MODEL SPECIFICATIONS

In this section, the specifics of the proposed network architecture for predicting the S&P 500 index's direction are discussed. To predict the direction of the index the following day, we use the daily closing values and trading volume from the previous fourteen days. There are two hidden layers in the model:

Completely connected and convolutional. A weighted sum of the points close to the centre is used in the convolution operation. Consequently, each point in the sequence is viewed as its neighbour.

A. Model architecture

Figure 1 depicts the proposed architecture's specifics. The model has an input layer with 14 dimensions, a convolutional layer, a flattening layer, a fully connected layer, and an output layer with 1 dimension, as depicted in the figure. The closing values and volume of 14 trading days are represented in the input layer. There are four filters of size 3 in the convolutional layer. As a result, the data for each day in the input layer are viewed about the days before and after. We can obtain more useful features for the model thanks to this method. Finally, we use a fully connected layer to predict and examine the convolutional layer's output. In every network layer, the activation function is the rectified linear unit (ReLU).

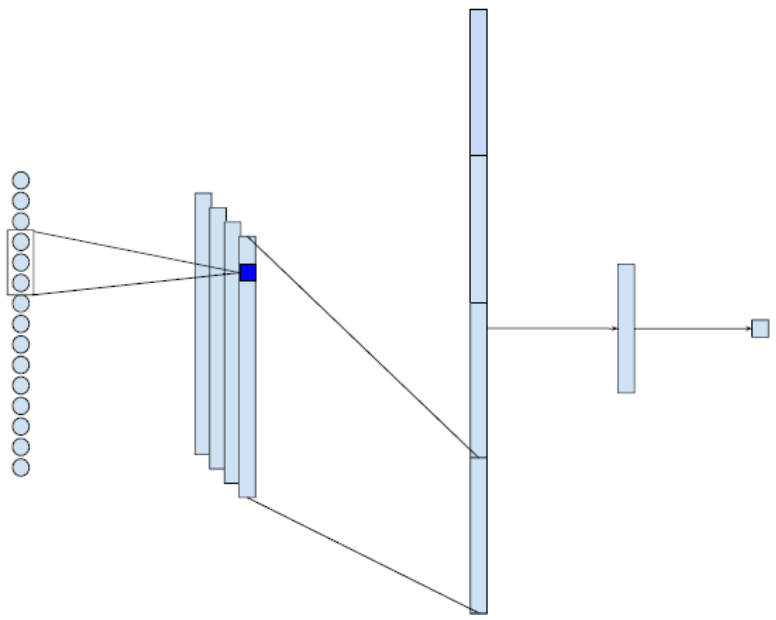


Fig. 1: The architecture of the proposed neural network model for predicting the S&P 500 index.

B. Model training

Daily index values from the previous 30 years are used to train the model. The 70/15/15 ratio divides the data into train, validation, and test sets. We use the RMSprop optimizer with a 32-batch size to train our model. The gradient descent procedure is modified by the local topology of the cost function by the RMSprop algorithm. The 32-batch batch size is chosen so that the optimization algorithm can search for the minimum across a wider range of values. To prevent model overfitting, we employ early stopping. In particular, the process is stopped when the validation error stops decreasing for more than ten epochs, and the validation error is monitored during the training. Because the model has fewer parameters, it is less likely to overfit because of the network's shallow architecture. On the Colab platform, the Keras API is used to implement the model.

NUMERICAL EXPERIMENTS

The results of the numerical experiments that were carried out to assess the usefulness of the proposed model are presented in this section. In our evaluation, seven other network architectures are compared to the proposed model. With the highest accuracy rate for predicting the index's future direction, the findings demonstrate that the proposed model performs better than the standard models.

A. Implementation

The period covered by our experiment is 1990-07-15 to 2020-07-15. The Yahoo Finance website provided the data. After being reshaped, the data size is (7545, 14, 2), where 7545 represents the number of days, 14 represents the length of each input sequence, and 2 represents the number of features. The model's inputs are the closing and volume values from 14 trading days. The model is trained in two stages. The model is initially trained on the training set using an early stopping call back. Training is stopped when the validation error stops getting smaller.

The model is retrained with the combined train and validation sets using the number of epochs obtained from early stopping.

After retraining the model, we test it on the holdout test set.

B. Benchmark models

Benchmark models to evaluate the proposed model about seven benchmark models, various architectures are represented in the model list, including convolutional, recurrent, and fully connected layers. The benchmark models follow the proposed model's general structure (Figure 2). Figure 2 shows that each model has a one-dimensional output layer and an input layer with 14 dimensions. The input layer shows the index values from the previous 14 trading days, and the output layer shows the predicted index value for the next day.

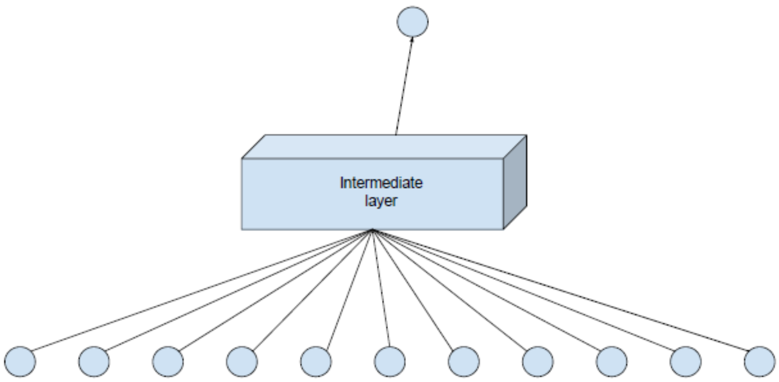


Fig. 2: The general structure of the benchmark neural networks used in the experiments.

Figure 2 uses seven distinct benchmark architectures for the intermediate layer. Table I shows the specifics of the models.

TABLE I: The descriptions of the benchmark models follow Keras nomenclature.

index	model	description
1	fc1	Dense(14)
2	fc2	Dense(14) → Dense(7)
3	rnn1	RNN(4)
4	rnn1fc	RNN(4) → Dense(4)
5	rnn2	RNN(6)
6	lstm1	LSTM(6)
7	conv1	Conv1D(4, 3)

C. Results

Figure 3 depicts the training results.

The accuracy results for predicting the direction of the S&P 500 index the following day are shown in Table II. Keep in mind that the proposed model is the most accurate i.e., 56.21 per cent. It is 6% better than the benchmark models' average accuracy rate and 1% better than the second-best accuracy rate.

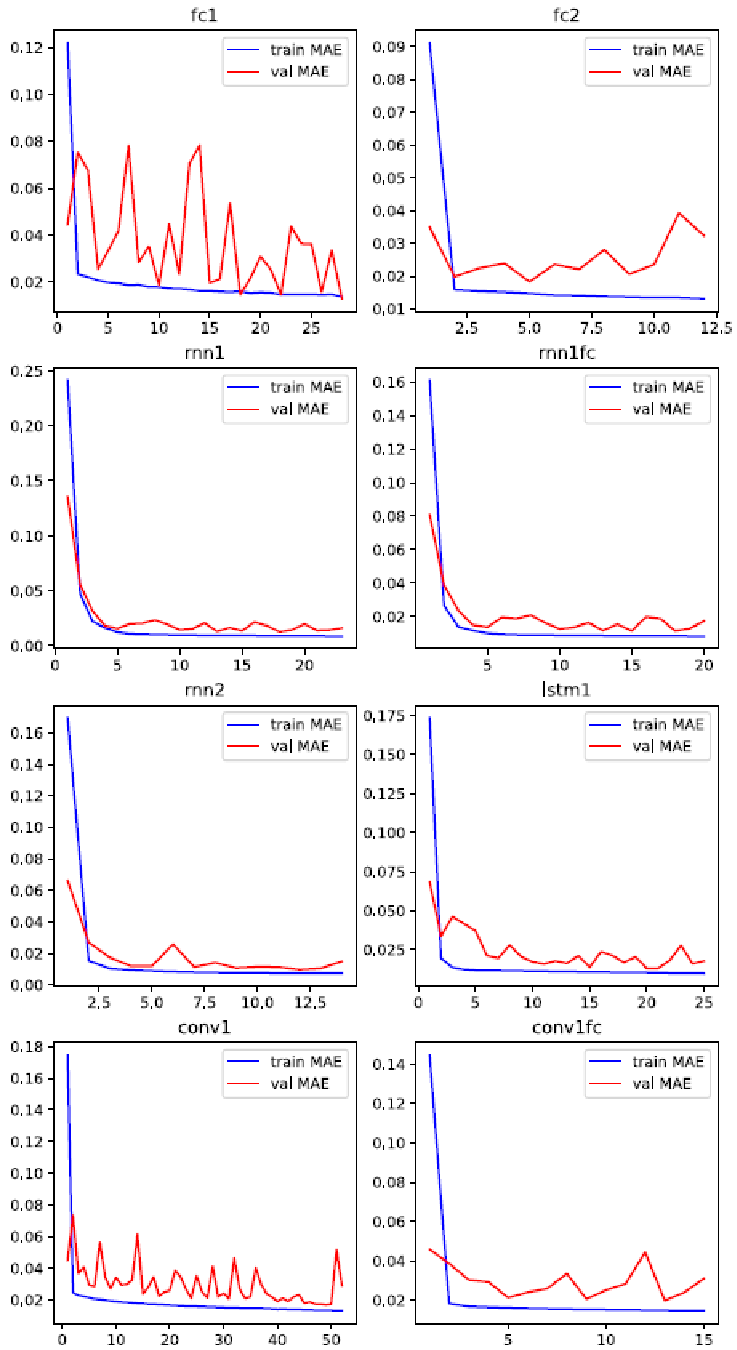
Another common benchmark for predicting the trending of the stock price is the naive strategy of randomly predicting, which has an accuracy rate of 50%. It also demonstrates the significance of our model's accuracy rate of 56.21 per cent.

TABLE II: Predicting the direction of S&P 500 index using the proposed (conv1fc) and benchmark models. Note that the proposed model achieves the top accuracy rate of 56.21%.

Model	Accuracy
`fc1`	0.5433
`fc2`	0.5004
`rnn1`	0.5523
`rnn1fc`	0.4602
`rnn2`	0.5103
`lstm1`	0.4620
`conv1`	0.4853
`conv1fc`	**0.5621**

CONCLUSION

Using a deep learning architecture for time-series forecasting, we successfully predicted the future direction of the S&P 500 index in this paper. Our model's primary insight is using a convolutional layer with four sizes of 3 filters. As a result, the data for each day in the input layer are viewed in relation to the days before and after it. The hidden layer's features become more informative as the filters are applied. Numerical results demonstrate the proposed model's efficacy compared to seven benchmark models.



Our model is the best, with a maximum accuracy rate of 56.21 per cent. Other sequential data can be studied using the proposed deep learning architecture. Time-series forecasting researchers and practitioners would find it interesting.

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