Multiple-Branch Convolutional Neural Network for SSEC Daily Return Prediction

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Abstract: This study proposes a Multiple-branch Convolutional Neural Network (MBCNN) model to predict the daily return direction of the Shanghai Securities Composite Index (SSEC). Due to the complexity and volatility of financial markets, traditional machine learning methods such as Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), and Decision Tree (DT) often face limitations in capturing intricate patterns. To address this, the model leverages multiple feature branches, incorporating historical price data, global market indicators, and other financial metrics. The effectiveness of MBCNN is evaluated against classical machine learning approaches, with results demonstrating superior performance in both accuracy and F-measure metrics. Additionally, the study explores the impact of Principal Component Analysis (PCA) on model performance, revealing that PCA does not enhance prediction accuracy. Experimental results confirm that MBCNN outperforms traditional models, offering improved classification capabilities and robustness. These findings provide valuable insights and a foundation for future research on stock market trend prediction.

1 INTRODUCTION

The capacity to predict trends in stock market indices is crucial for shaping economic policies and guiding investment choices (Ayyildiz & Iskenderoglu, 2024). By predicting the SMI trends, firms can optimize their planning processes, while investors can enhance the efficiency of their stock trading activities (Akyildirim et al., 2022). However, it is quite difficult to forecast the stock market's price movement because of its great volatility, dynamic nature, and complexity.

Many scholars have studied this issue. In the "Efficient Markets Hypothesis", Nevasalmi's stated that all the information of the stock has been reflected in the current stock price, so the stock price has nothing to do with historical information, and it is impossible to predict its price trend. However, the validity of the Efficient Markets Hypothesis has been debated in many studies (Nevasalmi, 2020). According to the Adaptive Market Hypothesis, markets are flexible and change throughout time, alternating between efficiency and inefficiency at various points in time (Lo, 2004). Therefore, incorporating historical data can increase the accuracy of stock trend forecast.

Several researchers have used machine learning to the subject of stock prediction as these algorithms have produced good results in a variety of study domains. Such as Support Vector Machine (SVM) (Xiao et al., 2020), Artificial Neural Network (ANN) (Chen et al., 2017) and random forest (RF) (Weng et al., 2018), Because of their superior generalization capabilities, these machine learning algorithms were successfully utilized to predict financial markets.

Currently, deep learning algorithms, such as long short-term memory (LSTM), time convolutional network (TCN) and convolutional neural network (CNN), are also used in this fields. Ruize Gao et al. employ CNN to deal with the implications of evaluating several markets on the goal of market stock prediction and successfully enhance accuracy when compared to typical machine learning methods (Gao et al., 2022).

However, the outcomes of these algorithms are significantly influenced by the input variables (Gao et al., 2022). Therefore, many scholars have made a lot of attempts at feature engineering. Xiao Zhong et al. add more than 60 relevant features and use Principal Component Analysis (PCA) to process data and it significantly improves the model effect (Zhong &

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Enke, 2019). Ayyildiz et al. combine a variety of machine learning models with the k-nearest neighbors (KNN) to forecast changes in stock prices (Ayyildiz & Iskenderoglu, 2024).

The aim of this study is to predict the daily return direction of the Shanghai Securities Composite Index (SSEC) by employing deep learning algorithm. In this study, a multiple-branch Convolutional neural network is approached and compared with four classical machine learning methods including SVM, RF, Logistic Regression (LR) and Decision tree (DT). Also, PCA is attempted to be combined with machine learning algorithms in the hope of improving model accuracy.

This study consists of five parts. In the second part, the dataset used in the study is explained. In the third part, the deep learning algorithm used in this study is introduced. In the fourth part, the experimental results of the algorithm are discussed. Eventually, in the fifth part, the conclusion of the study is explained.

2 DATA DESCRIPTION

2.1 Introduction of SSEC

This research concentrates on the Shanghai Securities Composite Index (SSEC), which monitors the aggregated performance of both A-share and B-share securities traded on the Shanghai exchange, offering vital insights into the operational dynamics of China's capital markets. This research selects a time range from June 1, 2018 to January 1, 2023 to eliminate bias produced by a brief amount of time. The dataset originates from finance.yahoo.com. In Table 1, part of dataset for the SSEC is presented.

Table 1: Part of dataset for the SSEC.

Date	Close	High	Low	Open	Volume	Stock
2018-06-01	3075.136963	3102.087891	3059.785889	3084.753906	129900	000001.SS
2018-06-04	3091.190918	3098.4021	3076.993896	3083.427002	114600	000001.SS
2018-06-05	3114.206055	3114.769043	3080.045898	3088.008057	118700	000001.SS
2018-06-06	3115.179932	3117.524902	3103.532959	3109.175049	120200	000001.SS
2018-06-07	3109.499023	3128.715088	3105.577881	3121.184082	127800	000001.SS

2.2 Target

This study's prediction target is the daily return direction. Equations (1), (2), and (3) are used to compute the three sorts of returns: $R_{c-c,t}$, $R_{c-0,t}$, and $R_{0-c,t}$.

$$R_{c-c,t} = \frac{Close_t - Close_{t-1}}{Close_{t-1}} \quad (1)$$

$$R_{c-o,t} = \frac{Open_t - Close_{t-1}}{Close_{t-1}} \quad (2)$$

$$R_{o-c,t} = \frac{Close_t - Open_{t-1}}{Open_{t-1}} \quad (3)$$

The close and open prices of the SSEC on trading day t are shown by the variables $Close_t$ and $Open_t$, respectively. Most of the current studies focus on the prediction of $R_{c-c,t+1}$, and few predictions of $R_{c-o,t+1}$. However, it is also very important for investors to determine the trend of the stock's opening price on the next day, so the prediction target of this study is the direction of $R_{c-o,t+1}$. Figures 1 and 2 show the line graphs of $R_{c-c,t}$ and $R_{c-o,t}$ over time, respectively, from which can find that the fluctuation of $R_{c-0,t}$ is smaller compared to that of $R_{c-c,t}$.

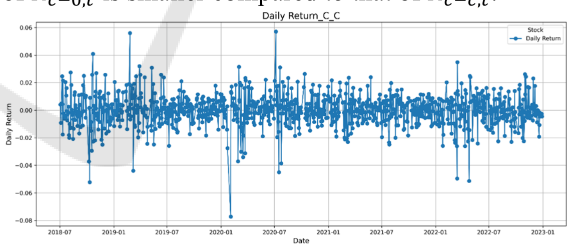


Figure 1: Plot of $R_{c-c,t}$ versus time. (Picture credit: Original)

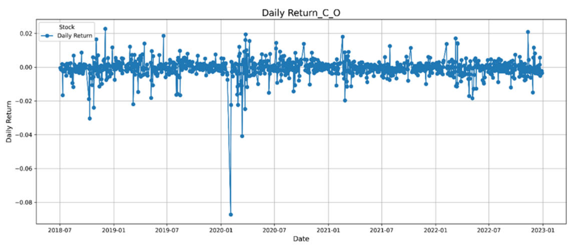
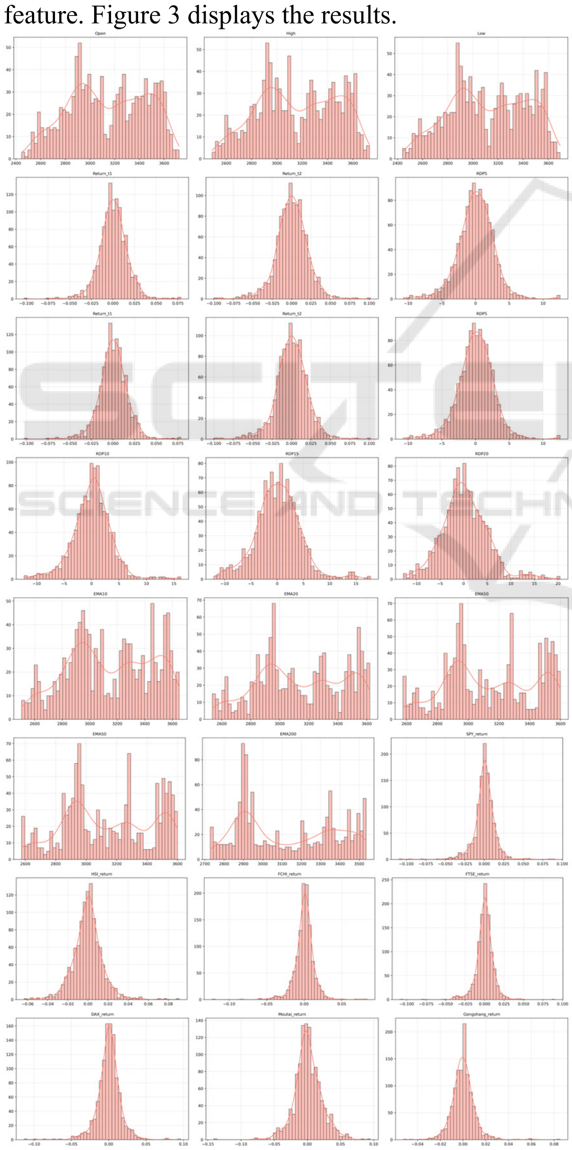


Figure 2: Plot of $R_{c-o,t}$ versus time. (Picture credit: Original)

2.3 Features

According to the imperfect efficient market theory, the more thorough the historical information added, the more accurate will be. Therefore, this study not only considers the historical price information of SSEC, including basic information, the daily return, the relative difference in percentage and the exponential moving average, but also takes global market information, including other 5 major markets, top 9 companies' information in SSEC, and other relevant information like gold and oil price, rate between countries into account. Total 35 features.

Then, this paper analyses the distribution of each feature. Figure 3 displays the results.



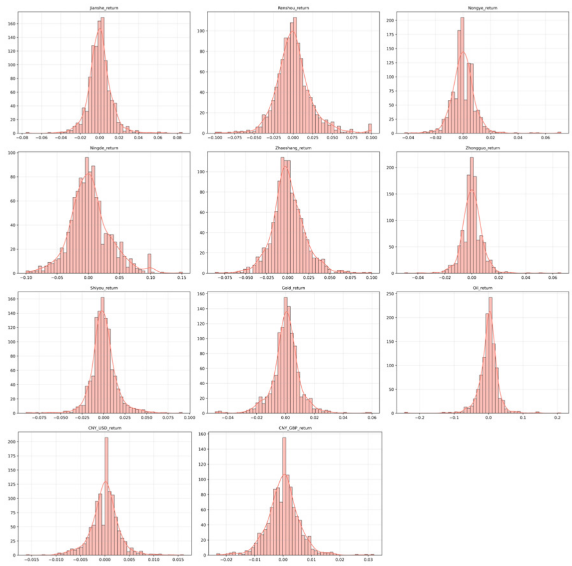


Figure 3: Distribution of feature. (Picture credit: Original)

From the Figure 3, it can be found that the distribution of most features is close to normal distribution, indicating that the data is relatively good.

Then, this paper explored the correlation between features, and the specific results are shown in Figure 4. The Figure 4 reveals that the correlation coefficient between features in the same group is lower. This analysis also provides a basis for subsequent feature branch selection.

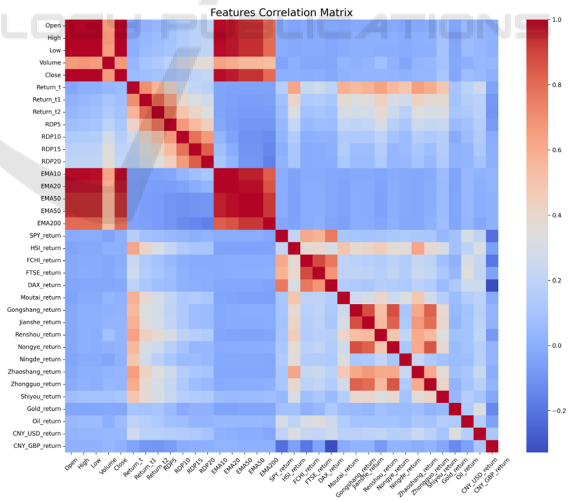


Figure 4: Correlation between features of thermal map. (Picture credit: Original)

2.4 Principal Component Analysis

Principal Component Analysis (PCA) is a dimensionality reduction technique that is widely utilized in machine learning. The fundamental principle involves projecting high-dimensional datasets via linear dimensionality reduction, while optimally preserving essential feature characteristics and reducing the impact of data redundancy and noise through variance-maximizing coordinate transformations.

In this study, PCA is used to reduce the dimensionality of the original features, and then the new features are input into the four machine learning models for prediction including SVM, RF, LR and DT. The performance of these four improved models will also be compared with the model presented in this paper.

3 MULTIPLE-BRANCH CONVOLUTIONAL NEURAL NETWORK

3.1 Convolutional Neural Network

Convolutional Neural Network (CNN) is a deep learning model designed for processing structured data (e.g., images and time series). The core feature of CNN is the use of convolutional operations to extract the local features of the data, and then progressively distill them from the low-level features to high-level features through a multilayer network. The network consists of a convolutional layer, an activation function, a pooling layer and a fully connected layer. The convolutional layer uses convolutional kernels to extract features from local regions of the input data, capturing local spatial correlations while reducing the number of parameters.

3.2 Framework of MBCNN

In this study, considering that the original features contain several different dimensional features, Multiple-branch Convolutional neural network (MBCNN) is used to perform prediction. The original features will be divided into 5 groups, each group of features will be processed by different convolutional units and standardized. The convolutional architecture employs weight-sharing branches to establish global feature correlations and a convolutional unit is used to extract multiple features. Then data will enter the Concatenation layer and go through a dense layer, finally an output layer. The detailed network structure is shown in Figure 5.

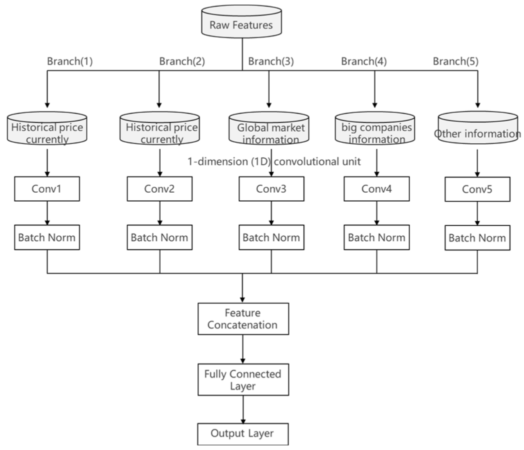


Figure 5: The framework of MBCNN. (Picture credit: Original)

3.3 Feature Extraction Block of MBCNN

The features in Branch (1) include important historical price information ('Open', 'High', 'Low', 'Volume','Close','Return_t','Return_t1','Return_t2'). The features in Branch (2) include the rest historical price information ('RDP5','RDP10','RDP15','RDP20','EMA10', 'EMA20', 'EMA50', 'EMA50', 'EMA200'). The reason for dividing the historical information into two different branches for extraction is that the information in branch (1) is that the recent performance of the stock index contains more key information. The features in Branch (3) include other major markets information ('SPY_return','HSI_return','FCHI_return','FTSE_return','DAX_return'). The features in Branch (4) include information of top 9 companies in SSEC. The features in Branch (5) include other important information ('Gold_return','Oil_return','CNY_USD_return','CNY_GBP_return'). Then, to better extract features, this paper chooses 1-dimension (1D) convolutional unit, since it has a significantly lower computing cost than 2-dimensional (2D) CNN and is more suitable for processing time-series data, (Gao et al., 2022). After that, each block's outputs are normalized by a normalization layer. The entire features extraction process is completed.

4 EXPERIMENT

4.1 Experimental Setting

In this study, four traditional machine learning models, including DT, SVM, RF, LG, will be compared and experimented with the MBCNN proposed in this paper, and their prediction performances will be evaluated comprehensively by different metrics. The ratio of the test set for all experiments was 0.2 and specific experimental settings can be found in Tables 2 and Table 3.

Table 2: Experimental settings of comparing models.

Comparing models	Parameter
DT	Max depth: 5.
RF	Max depth: 5; the number of trees: 100.
SVM	Kernel function: rbf; C: 1; degree: 3.
LR	Max iter: 1000; solver: lbfgs; C: 1; Penalty: l2.

Table 3: Experimental settings of MBCNN.

Parameter	Value
Optimizer	Adam
Loss Function	Binary crossentropy
Metrics	Accuracy
learning rate	0.001
Epochs	100
Batch Size	32
Validation weight	0.2
Test weight	0.2
Class Weights	balanced

4.2 Evaluation Metric

This study uses accuracy to assess the performance of the various models. However, the data set contains unbalanced data, so the F-measure is chosen as the second assessment metric (Gunduz et al., 2017; Hoseinzade & Haratizadeh, 2019).

The source of accuracy and F-measure is the confusion matrix, which compiles the numbers of cases that were categorized properly and improperly. True positive (TP) refers to situations when both the actual and projected outcomes are “up”, and true negative (TN) refers to situations where both predictions and actual results are “down”. False positive (FP) happens when the real result is “down” but the forecast is “up”, and false negative (FN) happens when the actual result is “up” and the prognosis is “down”. They are calculated by the Equation (4), Equation (5), Equation (6), Equation (7).

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5}$$

$$\text{F} - \text{Measure} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{6}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

4.3 Experimental Result

Table 4 shows the results of the experiment. In Accuracy metric, MBCNN improves 6.90%, 1.31%, 6.16% and 1.31% over DT, RF, SVM and LR, respectively. On the F-Measure metric, MBCNN improves 10.83%, 2.87%, 7.99% and 3.47% over DT, RF, SVM and LR, respectively. These results show that MBCNN has better overall performance than traditional machine learning models in classification tasks. The data processed by PCA did not have the expected effect on the prediction performance of the machine learning models, and this paper argues that it is related to the structure of the data used, and that PCA lost the key information of the data or introduced noise in the process of dimensionality reduction, which led to a decrease in the prediction effect of the model.

Table 4: The experimental results.

Model	Accuracy	Precision	Recall	F-Measure
DT	0.725	0.662	0.642	0.646
PCA+DT	0.637	0.533	0.728	0.615
RF	0.765	0.726	0.691	0.696
PCA+RF	0.686	0.586	0.716	0.644
SVM	0.730	0.659	0.667	0.663
PCA+SVM	0.642	0.541	0.654	0.592
LR	0.765	0.720	0.667	0.692
PCA+LR	0.662	0.570	0.605	0.587
MBCNN	0.775	0.804	0.852	0.716

To further evaluate the predictive performance of MBCNN, Receiver Operating Characteristic (ROC) curves are plotted for each model. The ROC curve is an important tool used to evaluate the performance of a binary classification model. It calculates the True Positive Rate (TPR) and False Positive Rate (FPR) with different thresholds and plots the relationship between them to measure the overall performance of the classifier. From Figure 6, it can be seen that the curve of MBCNN lies above three other traditional machine learning models, suggesting that it has a higher TRP at different thresholds and a lower FPR. And then LR has higher AUC values than MBCNN, indicating that for the LR model, positive samples are overall more likely to be assigned higher predictive probabilities than negative samples.

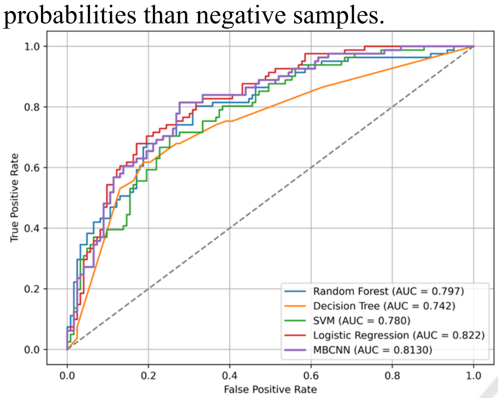


Figure 6: ROC curves of each model. (Picture credit: Original)

5 CONCLUSION

In this paper, a deep learning model is proposed to predict the return direction of SSEC by integrating different groupings of feature divisions. The first contribution of this paper is to predict the $R_{c-o,t}$ direction of SSEC using deep learning techniques, which helps investors to make modifications to their investment decisions for the next day to cope with changes in the stock market. Second, in this study, the effect of applying PCA for data processing on model performance was investigated, which is not able to improve models' performance. Third, this paper proposes the MBCNN model to predict the return direction of SSEC by extracting 35 features through multiple branches. And this model is compared with four traditional machine learning models and the experimental results show that the model proposed in this study outperforms the traditional models in terms of prediction accuracy and F-measure. In terms of ROC curve performance, the MBCNN model is also excellent, with AUC=0.812>0.8, which is slightly lower than that of the LR model (AUC=0.822) but much better than the other three models.

However, from the results of the ROC curves, it can be concluded that the shortcoming of this study is that the performance of the MBCNN model is not as stable as that of the LR model. Although MBCNN outperforms LR at a threshold of 0.5, the overall positive and negative prediction discrimination rate is not as good as LR. Therefore, Future research can further improve the branch network structure to make it better adapt to the input data structure and improve the prediction performance. Meanwhile, in this research, PCA did not improve model performance, most likely because PCA was not applicable to the data structure of this study. In the future, the people can further explore the effect of adding dimensionality reduction algorithms, such as PCA and KNN, on the performance of the model in the case of multi-feature.

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