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Stock Market Prediction using Time Series-based Metaheuristic CNN Approach

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***Abstract*—In contrast to conventional procedures and models, machine learning is an organized and all-encompassing use of computer procedures and algebraic models that have been extensively adopted in various industries. In the realm of economics, machine learning is chiefly used for the research of future investment market price trends. In this study, we employed classical and machine learning models to forecast linear and nonlinear issues to reduce the risk associated with predicting stock time-series data. The proposed time series-based metaheuristic CNN (MCNN) model is utilized to create a prediction with risk assessment, while the LSTM (long short-term memory) neuronal network prototypical is used to skill and forecast stock value and stock value sub-correlation. Lastly, we test the planned model based on numerous metrics, and the experiment consequences demonstrate that: (1) The MCNN model correctly predicts the price of stocks and their correlation; (2) compared to the present model for assessing performance. Consequently, our suggested approach offers provision and technique reference with minimal risk for stockholders in the stock market exchange.**

***Index Terms*— Stock market, CNN, MCNN, LSTM, Performance.**

I. INTRODUCTION

The stock marketplace is an umbrella word for a collection of marketplaces where the issuance and trading of shares, bonds, and other types of securities occur through different physical and electronic exchanges and over-the-counter markets. The stock market is one of the most crucial elements of a market economy because it gives firms access to cash by enabling investors to purchase company shares. The arena of the stock market is constantly evolving as a result of refining. In order to generate a return, investors must prepare meticulously in light of the daily fluctuations. Forecasting stock market data presupposes that information now accessible to the public has predictive correlations with future stock returns. Due to the complexity of the stock marketplace, anticipating stock market trends is one of the most challenging jobs in the financial industry. Investors in the stock market are always searching for a method that may ensure quick profits by predicting stock movements and minimizing investment risk. This stimulates domain-specific academics to create new forecasting models. Since it is vital to create a model to evaluate stock price trends with sufficient data for decision making, it is recommended that changing the time series using CNN is a superior algorithmic method to predicting directly, as it yields more accurate results. Before using non-stationary data, the MCNN Model turns it into static data. It is one of the maximum used representations for forecasting linear time sequence data. Python is a statistics

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processing and graphics programming language and environment. Data analysts often use the Python programming language for statistical programming and data analysis.

A. Motivation and Background

The company's stock or shares will be exchanged on the stock exchange. It is a partnership with a controlling body, and those who trade stocks must be registered with the Security and Exchange Board of India (SEBI). The purpose of the SEBI is to facilitate the growth of stock exchanges in India. As the basis of the legal framework, market regulation, and the activities of financial intermediaries, it protects the interests of retail speculators and aids in times when the stock market is difficult to predict. Predicting future stock prices is often a stance that is very volatile for businesses. Anticipating stock prices is a method that forecasts future stock prices using historical data. Frequently, the stock market reveals stock prices based on the production and consumption of goods. When there is more awareness of the stock prices of the group, the stock costs will increase; however, there will be a decrease in the stock costs when there is less interest owing to risk. Profits must be increased for financial professionals who may have invested in certain companies. This should be done if their offer is exchanged at the appropriate moment.

Future stock market forecasting is one of the record challenging endeavors in the marketplace sector. This is beneficial because it enables us to plan for the future by providing a firm understanding of segregating assets and forecasting future costs. Additionally, financiers attempt to identify risks optimally so that investment returns may be substantially enhanced. The economic outlook will ensure that exchange safeguards are included in the transactions between manufacturers and consumers.

New investors will be better able to comprehend the market and make a prudent choice about their stock market investments due to this study's emphasis on accurately projecting stock prices with less risk for diverse industries.

The primary aids of this study are as tracks:

(1) By comparing the relationship and time sequence of stock value data with risk analysis, a novel deep learning approach (MCNN) is suggested for risk-based stock value prediction. In this technique, CNN is utilized to withdraw the temporal component of information and to predict data, and it may use the time arrangement of stock value data to generate more accurate and risk-averse forecasts.

II. RELATED WORK

In current years, neuronal networks have been a popular study path in stock prediction due to their ability to extract data characteristics from vast quantities of high-frequency raw data without requiring previous information. In 1988, White attempted to forecast IBM stock using a neural network, but the results were disappointing. The experimental findings demonstrate that neural networks have clear benefits in nonlinear information prediction; however, the precision must still be enhanced. 2005 saw the introduction of a neural network-based technique for predicting time series by Sun et al. This technique syndicates the optimum panel algorithm (OPA) with the radial basis function neuronal network (RBF). In 2018, the investigational findings of Hu et al. demonstrated that a convolutional neuronal network could forecast time sequence and that deep learning is better suited to tackling the time series issue. CNN is often employed to tackle problems involving image identification and feature extraction; hence its predictive accuracy is relatively poor when used alone.

Kamalov utilized approach to predict the stock prices of four big US community firms in 2020. The findings of an experiment demonstrated that these three strategies outperformed comparable research in predicting the way of price alteration.

This study (Zhang et al., 2019) creates a prototype to forecast gas concentration based on LSTM multidimensional time-series information. The author has used the LSTM prototype, which operates on the time sequence information of the gas concentration set, to improve the accuracy of gas concentration prediction. The batch extent and the number of layers are utilized in the gas prediction prototypical. After training the LSTM prototypical, this improved prototypical is utilized to estimate the gas concentration of upcoming time intervals. Here, the training information set is modified from 0 to 1. The Minmax scaler method from the sklearn preprocessing package is used to make this adjustment.

To forecast the concentration of contaminants in the air, (Chaudhary et al., 2018) have suggested an LSTM prototypical based on the deep learning approach. The author used the LSTM prototype, which operates on the time sequence information of the pollutant's concentration set, to improve the precision of the forecast of the concentration of contaminants in the air. The batch extent and the number of layers are the parameters used by the air pollutants prediction model. After training the LSTM model, this improved model is utilized to estimate the concentration of air contaminants throughout upcoming periods. During the data training phase of data preparation, the MinMax scaler of the sklearn package was used to modify the data to fit within the range of 0 to 1. The MinMax scaler method from the sklearn preprocessing package is used for this modification.

A. DL Approach used in Stock Price Prediction

However, the writer notes that the LSTM prototypical is seldom used for financial time series data, despite being better suited to such data. The author has deployed the LSTM model for predicting the stock market data between 1992 and 2015, using the period from 1992 to 2015. Unlike memory-free cataloging models such as Random Forest, Deep Neuronal Networks, and Logistic Regression, LSTM representations have shown superior performance.

In this study work, (Guo; 2020) has suggested a method for predicting volatility based on Environmental, authority, and communal news flow, as it is essential to assess the supportable development of an investment's location and the associated risks. This information is organized and relates to the situation, authority, and society; ESG information may be included and imported into the model. This model's output is helpful for the development of ESG investment recommendations. Textual financial ESG data, according to the author, are the inputs to the model. To anticipate ESG-related news, they have used a model based on Natural Language Processing, a deep learning technology. The data has been converted from text to numbers using a transformers-based language model.

In this study article, (Mehtab and Sen; 2019) have used the NIFTY 50 dataset from the National Stock Exchange of India. They took advantage of the Nifty 50's closing price data. 2015 to 2017 data are included in the dataset. They have projected the statistics from the year 2018 to the year 2019. They have used a variety of categorization approaches in order to forecast the movement of the stock value. They have used various regression representations to forecast the closing stock value. They have used various machine learning procedures such as multivariate regression, bagging, improving, arbitrary forest, decision tree, and support vector machines to forecast the closing price of the stock value, while LSTM, a deep learning network, has been used to forecast the closing price of the stock value.

Here, in this study article, (Moghar and Hamiche; 2020) have used to anticipate the stock value on upcoming dates. The writer wishes to determine the accuracy with which the LSTM predicts future stock prices. In addition, they want to know the number of epochs used to get the best stock price prediction outcomes. They used a dataset from Network Stock Exchange for their investigation (NYSE). They evaluated 80% of the information for training purposes and 20% for testing. In order to maximize the presentation of the prototypical, they used the mean squared error during training. In order to evaluate the presentation of the prototypical, increasing epochs were analyzed. The author observed that less training data and more epochs provide more accurate predicting results.

In this study article, (Saud and Shakya, 2020) have used deep learning approaches since they are more accurate at predicting stock values. To examine the parameter of lookback time, the author has used RNN models. Vanilla RNN, GRU, and LSTM are the deep learning models used by the author for the study. The selected data set for the study provides stock price information for the banks listed on the Nepal Stock Exchange (NEPSE). The author has preprocessed the information and used the closure value of the next day for analytical purposes. In order to scale the data, Z score normalization has been used. The data is divided into training and testing data in a 9:1 ratio. After fitting the three models, comparisons are made based on the acquired findings. The findings indicate that the GRU prototypical achieves the best outcomes linked to other deep learning representations.

Here, in this study report, the crucial information from the most current contract has been extracted by analyzing the data (Wen et al.; 2019). This data is utilized to predict the ups and downs of the upcoming or the next instant. Using machine learning models, it is possible to identify the nonlinear relationships in the stock price reliably. The S & P 500 data set has been selected for the investigation. The stock price data over time will be very erratic and non-stationary. Thus, it will be challenging to forecast future stock market statistics. To avoid these familiar patterns, the author has devised a system that reconstructs the sequences influenced by these sequenced patterns. Later, they used the convolutional neural network to forecast the future stock price based on time series data.

III. METHODOLOGY

A. MCNN Model

CNN has the trait of paying devotion to the record evident elements in the line of sight; hence it is extensively employed in feature engineering. CNN has the feature of growing according to the order of time and is extensively employed in time sequence. A CNN-based stock forecasting model is developed following CNN's features. The model building illustration is shown in the figure, and the primary construction is a CNN consisting of an input layer, a one-dimensional convolution layer, a pooling layer, an LSTM secreted layer, and a complete joining layer.

B. CNN

Time series forecasting is a viable use of the method. CNN's local perception and weight sharing may drastically minimize the number of limitations, hence enhancing the effectiveness of model learning [24]. CNN is built mainly of two layers: convolution and pooling.
Each convolution layer consists of several kernels; its computation formula is shown in formula (1).

$$l_t = \tanh\left(x_t * k_t + b_t\right) \quad (1)$$

After the convolution layer's process, the data's features are extracted, but the extracted feature dimensions are enormous. To resolve this issue and decrease the price of training the system, a pooling layer is supplementary after the convolution layer to decrease the feature dimension:
where l_t signifies the production price after convolution, tanh is the activation function, x_t is the input vector, k_t is the weight of the convolution kernel, and b_t is the bias of the convolution kernel.

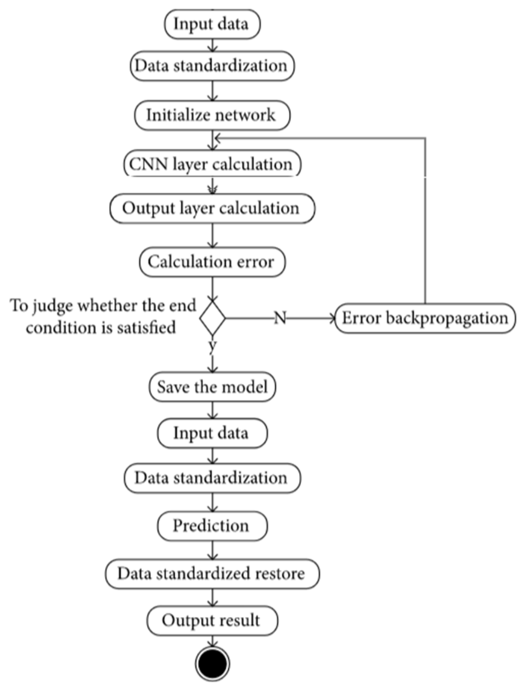

Figure 01: Work Flow for Predicting the Stock market predication with risk analysis

IV. EXPERIMENTS

To demonstrate the efficacy of MCNN, we compared it to different approaches utilizing a similar training set and test set information inside a similar operating situation. All studies use Windows 10 and the operating system's default settings. According to the influencing elements, such as the starting price, maximum price, lowest price, closing price, volume, turnover, ups and downs, and change, a risk analysis is conducted to make predictions.

A. Data

Wind's database provides the daily trade information. Each piece of data comprises several components, with the starting value, highest value, lowest value, closing value, volume, turnover, ups and downs, and change, for risk analysis and accurate stock forecasting. Take the data from a subset of trading days as the training set and a subset of trading day data as the test set. After transcribing and testing the examined dataset following a company's prediction, the risk analysis shown in the following figure was conducted.

Figure 02: Closing price analysis of stock market using live dataset with MCNN approach

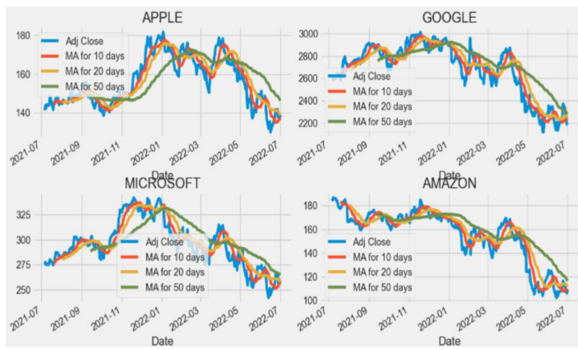

Figure 03: Comparison of the predicted value and the real value with closing price of some company Using MCNN

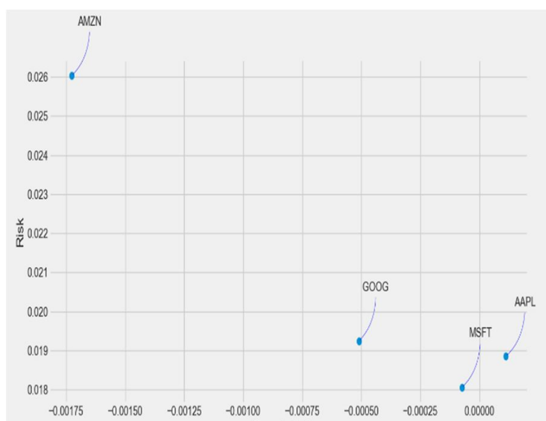

Figure 04: Comparison of risk analysis with expected return in particular time duration

The trained prototype is then utilized to forecast the test set information to skill and the trained prototype is then utilized to forecast the test set information, and the actual value is linked with the projected value, as seen in the figures below.

V. Conclusion and Future Work

In this study, machine learning and deep learning models were used to evaluate the accuracy of stock price forecasting. To forecast the stock prices of various firms, we have used the Proposed approach to decide the company names. The firms' dimension and stock price data have been stored in the Postgres database; consequently, extraction, transformation, and loading of the stock price data have been completed successfully. Successfully and with minimal risk, exploratory data analysis has been performed to ascertain the inner characteristics of the stock price forecast. A comparative time series analysis has been undertaken between these

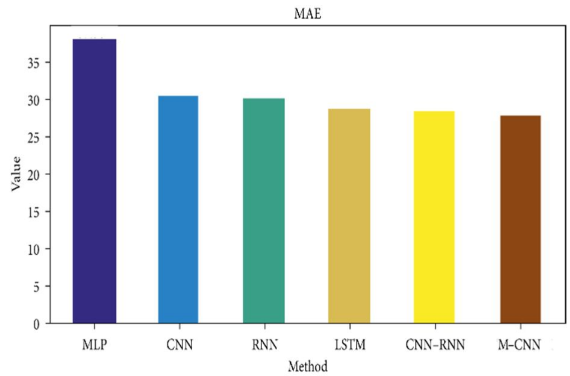

Figure 05: The result of mean absolute error (MAE) comparison among different methods

models with risk analysis. The computed Prediction value for the Proposed model is lower than that of current techniques. Therefore, we have effectively implemented, analyzed, and compared the findings of the Proposed method to those of current models. If the data set comprises other firms and their associated stock values in the future, this research may be conducted on a broad scale with additional performance metrics.

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