HYBRID CNN-LSTM MODEL FOR MINUTE-WISE STOCK MARKET PRICE PREDICTION

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DECLARATION

I declare that this is my own work and this thesis does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

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Name of the supervisor: Dr. Sapumal Ahangama

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Abstract

Stock market prediction is considered as a challenging problem because of the non-linear and dynamic price changes in stock markets. And need to deal with high volume and high frequency data. Despite the fact that a variety of machine learning and deep learning approaches can be applied to construct prediction algorithms, stock value prediction is difficult due to the high frequency data. Economic factors such as change in corporate policy, economic shifts, expectations of investors, other stock markets' movements and government change influence the stock market movements. When developing a prediction model, these influenced factors need to be considered to get highly accurate results. The successful stock market prediction results in better decisions and high profits.

Minute-wise stock market prices provide better understanding about stock price behavior within a particular day. Since it is very important to thoroughly analyze stock price behavior to make trading decisions, analyzing and predicting trading trends within a day is very crucial. Rather than predicting daily close price, open price and highest price, if we can predict the next upcoming couple of minutes or hours stock price with highest accuracy, then it is a great improvement in stock market prediction. Stakeholders including buyers and sellers can get good predictions and they can make proficient decisions on time.

This paper considers implementing a hybrid CNN-LSTM model to predict minute wise stock market prices by using minute-wise stock market data which provides a best performance. Stock market data of different companies including Apple, Google and Amazon were collected from Yahoo Finance API. As for the evaluation, several benchmark models were created and compared their performance with the proposed model. Furthermore, proposed model was evaluated using various datasets and timeframes. The next 5 minutes forecasted stock prices were compared with the actual prices and measured the performance of model. In this research, as for the evaluation metrics, Mean Absolute Percentage Error and Root Mean Square Error were used and the best model was selected considering the validation results. Models were fine-tuned using different time windows, model parameters and selected the best parameters for the forecasting model. Finally, the proposed model outperformed the state-of-art models for predicting short-term stock market values.

Keywords - Deep learning; LSTM; CNN; Hybrid CNN-LSTM; Machine Learning; Stock price prediction;

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LIST OF ABBREVIATIONS

Abbreviation	Description
ANN	Artificial Neural Network
RF	Random Forest
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
NN	Neural Network
MAPE	Mean Absolute Percentage Error
LSTM	Long Short-Term Memory
SVM	Support Vector Machine
RMSE	Root Mean Square Error
HMM	Hidden Markov Model
DL	Deep Learning
SVR	Support Vector Regression

CHAPTER 1 – INTRODUCTION

1.1 Introduction

This chapter provides an overview of the research. It describes the background of stock market prediction systems, the research problem, the research objectives, and the motivation for the study. Finally, the structure of the final report is discussed.

1.2 Background

Financial stock markets are regarded as the center of the global economy [1], with billions of dollars moved every day. As a result, stock markets play a vital part in economic growth, and accurately forecasting the stock market's future behavior is extremely valuable in many sectors. As a result, understanding current trends and forecasting their future prices can be quite beneficial in accomplishing financial objectives [2].

Predicting the value of shares is a challenge due to the non-linear and dynamic nature of the financial stock markets [3]. And also need to process large amounts of high-frequency data. The dated market concept makes it impossible to estimate stock markets, and stock prices are supposed to behave arbitrarily, however advanced technological analysis demonstrates that the majority of share prices are reflected in past records. As a result, movement trends are important for accurately forecasting values.

Stock market forecasting is a difficult task because it is dependent on many internal and external factors, such as management decisions, financial information from other companies, international situations, share market movement patterns in other countries, political conditions, the global economy, financial statements, and company performance [4]. There are many technical criteria that can be used to derive statistical information from the stock prices. In general, stock indices are frequently constructed from the stock values with substantial stock market investments and are frequently used to gauge each country's economic position. For example, the findings suggest that market capitalization has a favorable impact on each country's economic growth [5]. The ambiguity of share price fluctuations makes trading riskier for investors. Furthermore, determining the state of the market is typically challenging for governments.

Predicting stock prices and trends using past data is very useful for maximizing the profits and minimizing the losses in trading. Indeed, stock prices are usually non-parametric, dynamic, and nonlinear; hence, they frequently result in poor model performance and an inability to forecast accurate values and trends. Although accurate stock market forecast results help investors make better decisions.

1.2.1 Usage of Machine Learning and Deep learning for Stock market Prediction

Machine learning (ML) has been the most powerful technology, with numerous algorithms for optimally utilizing behavior in various applications [6]. Machine learning is typically accepted as a method for identifying valid information and detecting patterns in data sets. Ensemble models, as opposed to typical machine learning approaches, are a machine learning-driven approach that uses numerous common algorithms to solve specific problems and outperforms each method in time series prediction. This has been demonstrated. Bagging and boosting are popular and successful ensemble approaches for machine learning prediction tasks.

Recent advancements in tree-based models include the introduction of XGBoost and gradient boosting algorithms, that have been mostly used by computer scientists to construct high-performance Machine Learning models. Indeed, deep learning (DL), a recent ML trend, can identify deep nonlinear patterns in its own system and has an outstanding capability to extract substantial information from financial time series. In contrast to a simple artificial neural network, other neural network approaches such as concurrent neural networks, recurrent neural networks, and Long Short-Term Memory (LSTM) have found significant success in the financial sector due to their superior performance.

Deep Learning is an engineering discipline that deals with artificial neural networks, and also a subfield of machine learning which is inspired by the function and structure of the brain [7]. Recently most researchers used Deep learning technologies to implement stock forecasting models with high success rates. Stock market prediction is challenging due to the number of variables that are affected for stock prices. For previous works related to stock market prediction models, classical algorithms like linear regression and also using some linear models like Autoregressive Integrated Moving Average (ARIMA), Autoregressive Moving Average (ARMA) were used. Recent Machine learning models have shown improvements in stock market predictions. Techniques such as Random Forest (RF), Support Vector Machine (SVM), Naive Bayes, and other techniques which based on neural networks such as Artificial Neural Network (ANN), Recurrent Neural Network (RNN), Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) are mostly used algorithms for stock market prediction [8]. And also, they have shown promising results.

Through the self-learning method, ANN can detect hidden features. These are excellent approximations that can find the input and output relation of a massively complex dataset. As a result, ANN is an excellent option for stock price prediction. It is evident that the stock price forecasting is dependent on the prior data significantly. And also, it is related to the recent data as well. Thus, training would be insufficient if only the most recent data is taken. Recurrent Neural Networks use the network to keep track of current events and create relationships between network units, making it suitable for forecasting. LSTM is an improved advanced subset of the RNN algorithm [9]. Most recent stock market prediction solutions have applied the LSTM approach for implementing forecasting models with better accuracy than other techniques.

1.3 Research problem

Several research projects have been done in the past decades for forecasting stock market trends and prices using statistical methods (ex: moving average, ARIMA), machine learning methods, and deep learning techniques (ex: LSTM, CNN, RNN).

The main drawback in these research studies are they have considered the long-term basis information such as daily, weekly or average stock prices.

But in the real world, stock prices change each second. Buyers and sellers keep watching the stock market dashboard without blinking their eyes. That much frequently it changes.

It is very crucial if researchers could develop short term basis stock price prediction models with high accuracy. But the main limitation is there are not available datasets with that much frequency. Currently there are datasets with minute wise frequency. That is the minimum possible frequency that can be accessed freely.

In literature there are a limited number of research studies that have been conducted by considering short term basis and they have used CNN, ARIMA, LSTM, RNN, Dynamic mode decomposition like statistical, neural network and deep learning techniques.

Although minute-by-minute daily stock price changes in the next couple of minutes are extremely important when trading in stock markets, most research studies generally were concentrated on predicting closing price, opening price, average price, or daily trend on a daily basis or weekly basis. If there is a solution to determine the stock price trend over the next few minutes with great accuracy, buyers and sellers can choose the best time to trade their stocks in short time periods.

Furthermore, if there is a way to find the stock price trend of the next couple of minutes with acceptable performance, then buyers and sellers can decide the most suitable moment to trade their stocks and their decisions also will be more accurate.

So, as the solution for the above problem, to provide short term basis stock market predictions, a new approach for predicting short term basis stock prices is being implemented through this research study.

1.4 Objectives

To tackle these above problems a better solution is to implement a deep learning prediction model using a different approach. Deep learning models such as LSTM can be used to predict stock market values with high performance as mentioned in the literature. To achieve solutions for the research problems the following objectives are expected from this research.

- Implementing a high-performance forecasting model to predict stock values for the next couple of minutes (5 minutes) considering minute-wise stock prices of different companies.
- Implement a short-term basis prediction model with highest acceptable performance.
- Fine tune the model considering different model parameters such as number of hidden layers, epoch values, batch size and so on.

1.5 Motivation

Although there are several Machine learning and Deep learning techniques that can be applied to implement prediction algorithms, financial stock value prediction is quite challenging due to the high frequency of stock data. Share market movements are influenced by economic factors such as change in corporate policy, the psychology of investors, economic shifts, movements of other stock markets, investors' expectations and government change. When developing a prediction model, these influenced factors need to be considered correctly to achieve highest results.

Recently researchers are moving to deep-learning-based methods to implement stock market prediction systems and are highly considered about achieving highest accuracy. Deep learning models can be used to find hidden features through a self-learning process. So, they are good for predicting stock market prices on a long-term basis as proved in many previous research studies.

Stock market data is considered high frequency data and when it comes to the minute-wise stock prices they are having higher frequency than daily, weekly or other time basis data. Hence it is a challenge to predict values for minute-wise stock prices.

In this research, a hybrid deep learning model is implemented using CNN and LSTM technologies to predict values minute-wise for different companies with acceptable high-performance results.

1.6 Summary

The thesis is organized as follows: the first chapter provides an overview of the project, including aims, background, problem, and motivation. In the second chapter, a critical evaluation of the literature on stock market forecasting using machine learning and neural networks will be undertaken. The third chapter discusses the technology stack that was used to create the proposed solution. The fourth chapter will cover the approach for implementing a minute-wise stock market prediction system, as well as a detailed discussion of the design, data preprocessing, and model creation. The fifth chapter compares and analyzes the models in order to evaluate the methodology. Finally, chapter six concludes the solution with a summary on the research's conclusion and future study.

CHAPTER 2 - LITERATURE REVIEW

2.1 Introduction

This chapter examines existing stock market prediction techniques and solutions from a variety of perspectives. The introduction to share market prediction systems is discussed first, followed by an explanation of the stock market forecasting system's process. Then, using examples, the approaches that other researchers have used to build forecasting systems were described. The drawbacks of previous research studies also clearly mentioned in this section.

2.2 Stock market prediction

The stock market is an important factor in developing and prosperous countries, and all investments in the market aim to maximize profit and minimize the risks associated with it. As a result, much research has been done on stock market forecasts by using different technologies, algorithms and methods.

Isaac, Adebayo and Benjamin [10] have done a research study regarding already developed stock market predictions models and they have mentioned those predictions models can be categorized into three categories. Those categories are as follows.

- Technical analysis
- Fundamental analysis
- Technology (Machine Learning) methods

Fundamental Analysis

Stock price predictions for a company are done by using the company's economic factor related information such as sales, profits, revenue in fundamental analysis [11]. In this approach data is collected from unstructured sources such as social media, balance sheets, yearly reports. This analysis is good for long term basis predictions. Figure 2.1 shows the process of fundamental approach.

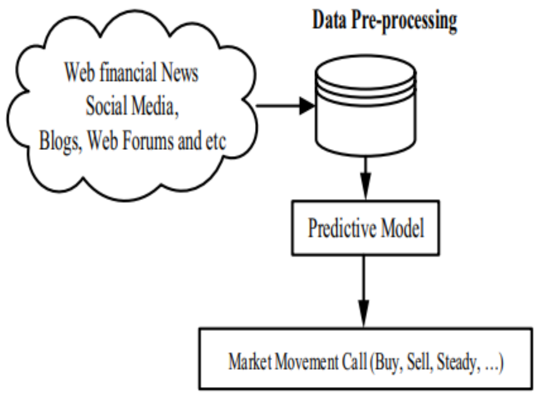

Fig. 2.1: Fundamental Analysis approach

Technical analysis

Past and present stock prices are used as trained data and do price predictions in this analysis type. And this is more suitable for short term basis predictions. As Rajashree et al. [12] have mentioned MA (Moving Average), exponential moving average (EMA), Simple-moving average (SMA), ARIMA (Autoregressive Integrated Moving Average), ARMA (Autoregressive Moving Average) like statistical techniques are widely used in this approach.

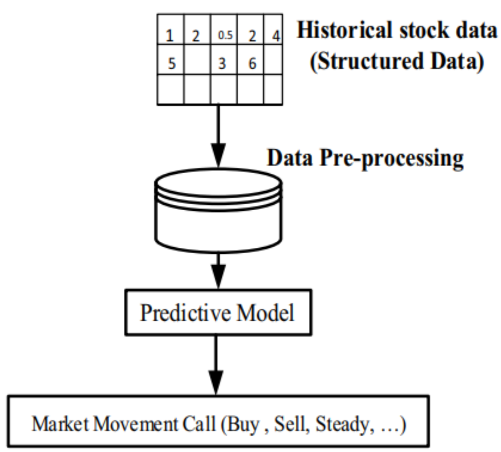

Fig. 2.2: Technical Analysis Approach

Technology (Machine Learning) methods

Machine Learning and Neural networks-based techniques (as example LSTM, RNN, CNN, Hidden Markov Model) are used in this approach to create prediction models [10].

In recent research studies deep learning based models are mostly implemented and they have been provided best performance as well.

Data Mining tools and techniques can be used for extracting hidden trends in stock market data and used to implement stock market prediction solutions. Regression techniques, Knowledge Discovery databases, Fuzzy logic like mechanisms are used to analyze the market trend as well as increase the accuracy. When developing a data mining model there are several steps needs to be followed as mentioned in below.

2.3 Process of developing stock market developing system

According to D.P. Gandhmal and K. Kumar [13], stock market prediction system has been displayed in a block diagram as follows.

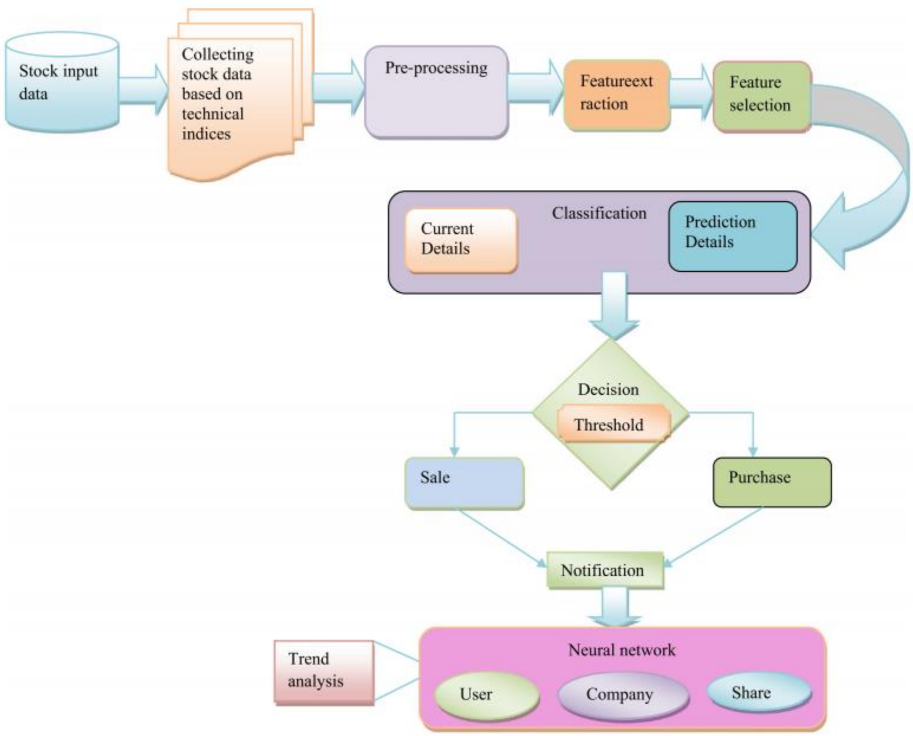

Fig. 2.3: the process of Stock market prediction model

The initial step of model development is data collection. When it comes to stock prices, datasets can be gathered from different sources such as National Stock Exchange, Taiwan Stock Exchange Weighted Index (TAIEX), Bombay Stock Exchange (BSE). Then after data pre-processing step is done to remove noise and handle missing data. To begin, attribute relevance analysis must be conducted to the data in order to remove the unwanted attributes. After that, the pre-processed data is used to choose relevant features that can be used to predict stock patterns. The chosen characteristic is next evaluated in order to extract knowledge from a vast amount of data. Then after models are implemented and decisions are made considering results of models.

Current, forecasted, and threshold values are used to make decisions, and further processing is done using the threshold value to declare profit or loss. If the investor is profitable, the shares can be used to increase sales; if the investor is losing money, the shares are given more attention to develop. According to authors, Neural Networks can be used to make better decisions in stock market prediction.[13]

Furthermore, stock market price forecasting techniques can be divided into two categories as follows.

Prediction based techniques

- ANN
- Recurrent Neural Network (RNN)
- Hidden Markov Model (HMM)
- Convolutional Neural Network (CNN)
- Naive Bayes (NB)
- Neural Networks (NN)
- SVM
- Support Vector Regression (SVR)

Clustering based techniques

- Filtering
- Fuzzy methods
- K-means
- Optimization approaches

2.4 Machine Learning based related works

Hidden Markov model technique dependent on augmenting Markov chain. HMM model forecasts the probability of a set of random states or variables, each of which can take on a variety of values [14]. Many researchers have used HMM techniques for stock price prediction related studies [15]. Poonam Somani, Shreyas Talele and Suraj Sawant [16] have developed a model for identifying stock market fluctuations using HMM technique. According to them, HMM approach performed better in identifying variations in stock prices where traditional techniques are not possible. Gupta and Dhingra used posteriori HMM technique to forecast ethics in stocks. Md. Rafiul Hassan [17] implemented a stock market prediction model combining fuzzy model and HMM model. And predicted the next upcoming day stock price. They have used HMM techniques to identify similar patterns on historical data. Their combined model provided better performance than ANN, ARIMA, and HMM models.

The Naïve Bayes algorithm is a classification approach that uses the Bayes theorem to create Bayesian Networks [18]. It is assumed that the presented dataset comprises a single class feature that is unconnected to other features. The Naïve Bayes technique is a simple algorithm to implement and able to handle enormous datasets, outperforming more advanced classification techniques. A.M. More [19] used a Neuro-linguistic programming (NLP) approach to gather financial data and create stock charts that aid users in making appropriate and lucrative trades. It makes use of the Hadoop platform to retrieve massive volumes of stock data in parallel, makes choices using Naive Bayes methods to deal with probability interference, and predicts future trends using previous knowledge.

Support Vector Machine is a supervised machine learning algorithm based on hyperplanes (concept of decision boundaries) [20]. It is an effective predictive tool for stock predictions and many researchers have used this technique. Ni, L.P. et al. [21] developed a stock price index prediction model using fractal selection method and SVM. The fractal selection method can be used to solve nonlinear problems and select features. Saahil Madge [22] has used SVM technique to create a stock market prediction model. Whether stock price will increase or decrease on a particular day was predicted by using the SVM model. But according to final outputs, this is most suitable for long term trend predictions.

K-Means clustering, Fuzzy logic like techniques also have been used by many researchers to implement stock market related prediction systems. Nanda, S.R. et al. [23] developed a model to classify stock data into clusters considering specific investment criteria. And those classification results were used to create a portfolio for reducing the risk in selecting stocks when investing.

M.Y. Chen and B.T. Chen [24] created a novel fuzzy logic-based time series model for forecasting stock market values. A granular computing technique was used to develop the model, which included entropy-based discretization and binning-based division mechanisms. To forecast market indexes, the model used fuzzy time series models. The technique neglected other crucial factors such as financial data, technical indicators, and trade volume.

2.5 Deep Learning based related works

M. Nabipour, P. Nayyeri and H. Jabani [25] have implemented a deep learning model on future stock market prediction for stock market groups. For experimental evaluations, four groups were selected from the Tehran stock exchange. They collected 10 years of historical data based on four groups; petroleum, diversified financials, basic metals and non-metallic minerals. Various tree-based machine learning models such as Decision tree, XGBoost, Random Forest, Bagging, Gradient Boosting, Adaboost and neural networks-based algorithms were implemented for stock market value prediction. Prediction has been done as 1, 2, 5, 10, 15, 20, and 30 days in advance. MAPE (Mean Absolute Percentage Error), MAE (Mean absolute error), Root Mean Square Error (RMSE), and Mean Squared Error (MSE) have been used as model evaluation metrics. In their study LSTM has provided the best results with the lowest error but had high runtime. As future works they have mentioned analyzing the other hyperparameter effect on final result and improving algorithms for other stock market value prediction.

Ishita Parmar et al [26] focused on the LSTM and Regression based Machine Learning model to predict stock values in their work. When a significant length of time has passed, it approximates real trends. The MSE and RMSE metrics were used to evaluate the model, providing a train score of 0.00106 MSE and a test score of 0.00875 MSE. Respective RMSE values were 0.03 and 0.09. Jinqi Tang and Xiong Chen [27], have implemented a hybrid model that combines RNN and LSTM techniques. LSTM technique is applied for time series data and CNN technique was used for abstract high-dimensional data. Both historical pricing and news are used as input data. For prediction these two models are combined. In evaluation, hybrid model has achieved 54.45% for Mean Accuracy 54.45% (LSTM is 52.64%, FFNN is 50.33% and CNN is 51.38%)

When implementing a stock market prediction, feature extraction is a very important task. So, Ehsan Hoseinzade, Saman Haratizadeh [28] has implemented a CNN model for stock market prediction considering different stock markets. They gathered a diverse set of data, comprising past information from the target market, currency exchange rates, commodities, and data from possibly related financial markets. Their focus is to create a model that can forecast the trend of stock market price or index fluctuations. This developed model has been applied to predict the movement of indices of NASDAQ, S&P 500, NYSE, RUSSELL and Dow Jones Industrial Average. They have used 82 features to represent each index of each day, for the prediction model. And in terms of F-measure in the evaluation phrase, 3% to 11% values achieved by five indices over the baseline algorithms.

According to Naveen’s [29] prediction model, using several features of the stock market, NUMERAI stock value has been predicted. 21 features were taken to train the prediction model. Neural network model was implemented with 200 hidden layers, 8 epochs and 128 batch size. And the model was evaluated by using accuracy rate and loss rate. The Neural Network model was optimized to predict share prices market with 0.1 loss for the Five-fold cross validations and 83% accuracy.

Stock market contains high frequency data. So, collecting data in real time is very important. Xiongwen Pang, Yanqiang Zhou [30] and colleagues have done a study for developing an innovative neural network to predict stock market values by collecting data in real time and off-line analysis. Since the initial weight of the random selection problem can be easily prone to incorrect predictions, they have used the concept of stock vector. They used a deep LSTM neural network with an embedded layer and an LSTM with an automated encoder to predict the stock market. Experiments showed that the deep LSTM with embedded layers produced the best outcomes, according to their findings.
Although stock market prediction has been done by many researchers in different scenarios using various machine learning techniques, data was not processed in real time. Abin Shakya, Anuj Pokhrel [31] have done research for developing a stock price prediction model to predict minute wise values. As input factors they collected traded volume, number of transactions and last traded price. They gathered six months of data from the Merolagani website by crawling. They have implemented a feed-forward neural network and to get good performance, they have tuned the model considering the number of neurons in the hidden layer. Their model was used to predict stock prices within a two-minute interval, and they predicted several companies' stock prices which were listed in Nepal Stock Exchange Limited. As for the validation method, K-fold cross-validation was used by them. They experimented with different models for different companies by adjusting the number of hidden layers, and the best result was discovered for ADBL, which was modeled by a 3-20-10 network and had an accuracy of 86.12 percent. System performance can be improved by increasing the depth of the neural network as the paper mentioned.

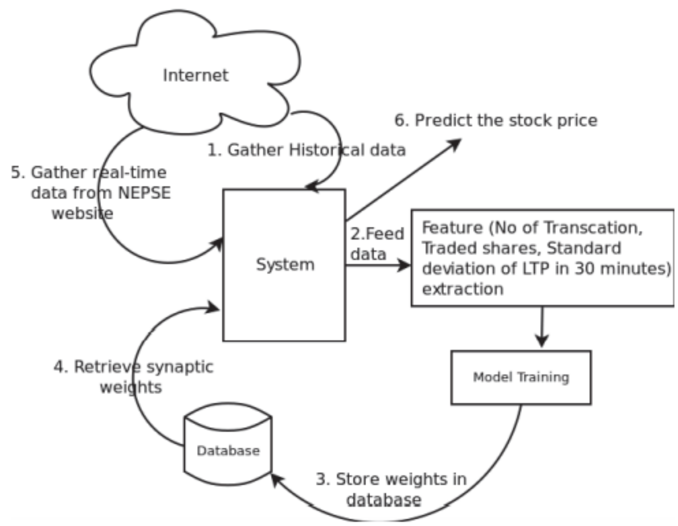

Fig. 2.4: Real time stock market prediction model

For analyzing time-series data, a RNN model was developed by Xie and Wang [32]. They have gathered a large volume of intraday records data from China Shanghai Shenzhen 300 Index. To classify the daily characteristics of intraday data, the RNN model was applied by them. In this study, performance was evaluated using the model's average profit and precision.

Ghosh et al. [33] have implemented a LSTM model and their objective was to find out the best timespan for forecasting stock prices. They have used closing prices of five companies and developed LSTM models to predict future prices in various timespans. So here considered time spans were 3 months, 6 months, 1 year and 3 years. Considering these predictions their goal was to predict future growth of each company. The day wise stock prices data was collected from the Bombay Stock Exchange for different companies. And considering the percentage of error they have evaluated their models and when predicting for a 3-month time period their models were provided best results. According to their study, a company’s future growth can be predicted using a stock price prediction model which is implemented by LSTM technique.

Unnithan et al. [34] developed a dynamic mode decomposition (DMD) model for stock market prediction which is considered as a spatio-temporal, data-driven, equation-free algorithm. DMD is a technique for discovering a dynamical system from high-dimensional data. Since it is used to predict stock prices which is considered dynamic and high dimensional. They have collected ten years' stock prices from 75 companies which are listed in the NSE and trained the model. The daily closing price is taken to implement the model. As the evaluation metric MEAPE is used. The final conclusion from this research is that this DMD technique can be used for predicting future values with less computation as well as this might be used for short term basis predictions. And also, limitation of this method is it cannot identify sudden changes in stock prices because of that it provides high error value in those scenarios.

Wenjie Lu, Jiazheng Li [35] and others have implemented a CNN-LSTM model for forecasting the stock market prices. In this research they have used CNN for extracting the time feature and for predicting future prices LSTM was used. The model architecture of their research as follows.

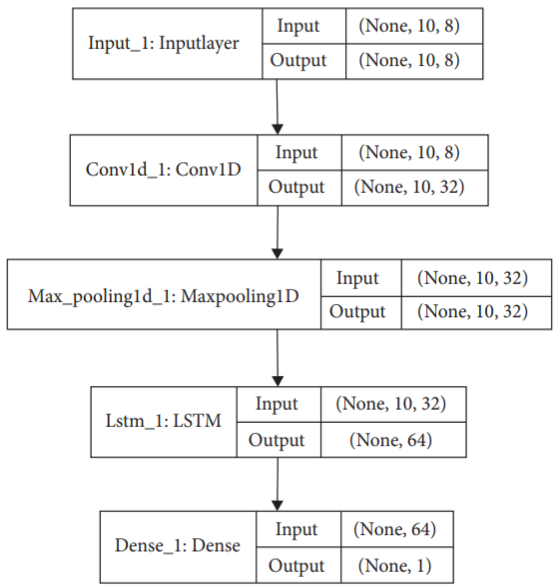

Fig. 2.5: CNN-LSTM model structure

As historical data they collected stock price data from 30 years and opening, lowest, highest, and closing prices, and turnover, volume, change and ups/downs values, were considered as features for developing the models. Finally, the next day's closing price was forecasted from the implemented models. They have developed MLP, RNN, CNN, LSTM, CNN-RNN and CNN-LSTM models and according to the experimental results which was provided by RMSE, R^2 and MAE metrics, CNN-LSTM model was well performed.

Jaydip Sen, Sidra Mehtab and Gourab Nath [36] have conducted research regarding stock price prediction and implemented a deep learning model. They have collected historical data from the NIFTY 50 index records which are available in Indian National Stock Exchange (NSE). They developed CNN and LSTM models for forecasting open values for next upcoming week using two previous weeks records. According to their results (RMSE results), the univariate encoder-decoder convolutional LSTM model outperformed other models.

Zhao et al. [37] have developed a prediction model using RNN/LSTM/GRU technology. They introduced attention mechanism and it focus on key information. They developed a forecasting model applying attention mechanism (T-RNN/AT-LSTM/AT-GRU). Using accuracy and f1-score measures, these models were evaluated. According to their results, GRU-M model performed well, and they have come up with a conclusion that attention mechanism layer improves the accuracy of models.

Qingfu Liu et al. [48] have implemented a stock price prediction model using Deep Learning techniques by considering price charts and stock fundamentals. They have done image modelling for price charts using deep learning and predicted future price movements using close stock prices of previous days. Elminaam et al. [49] implemented a prediction model for predicting next day's closing price using different machine learning techniques such as linear regression, KNN, Random Forest and Gradient Boosting. RMSE and MAE evaluation metrics were used to evaluate these models and came up with conclusions regarding best accurate model.

Several external and internal factors effect for stock price changes and if we need to consider those effects, then we need to collect data from different sources. Since data come from different data sources integrating is difficult. Isaac and team [50] implemented a novel multi-source information-fusion predictive framework named IKN-ConvLSTM using CNN and LSTM deep learning technology. They have selected six heterogeneous data-sources and fed integrated data to the model. Those data sources were tweets, Web news, Google trends, forum discussion, historical macroeconomic variables, and past stock data. The figure 2.6 shows the process flow of proposed IKN-ConvLSTM model.

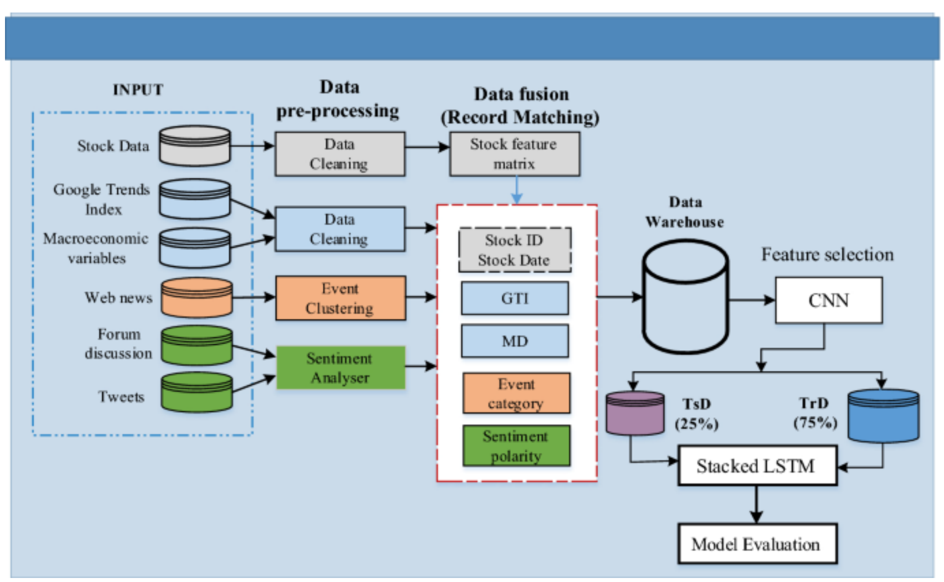

Fig. 2.6: Process flow diagram of Proposed IKN-ConvLSTM model

The proposed model compared with other models which were implemented by using Multi-Layer Perceptron (MLP), classical SVM and Decision Trees (DT) techniques. The model provided 98.31% accuracy, 0.9672 F1 score, 0.8939% sensitivity as performance results. Finally, they have come with a conclusion that the stock market prediction models provide good prediction accuracy when data is selected from multi data sources rather than single data source.

Financial stock news which spread through Facebook, tweeter like social media effect the stock market movements. Pooja Mehta et al. [51] implemented a stock market prediction model by parting public sentiment from other parameters. Public sentiment, opinions, news and historical stock prices were taken as input to the prediction model. Datasets were collected from different companies of Indian Stock Market within four-year time period. As for model implementation, sentimental classification and LSTM techniques were used. The proposed model was compared with Naïve Bayes, Support Vector Machine, MNB classifier, linear regression models and according to the accuracy results LSTM model outperformed the other models by resulting 92.45 accuracy. They have proved that when taking sentiment with stock price, more accurate predictions can be done, and buyers and sellers can buy and sell stocks with more profit.

Due to the non-linearity and high volatility, stock market data were difficult to predict. But using LSTM and CNN deep learning techniques, stock market predictions can be done accurately. Moreover, using empirical mode decomposition and complete ensemble empirical mode decomposition statistical techniques time series data can be analyzed effectively. H. Rezaei et al. [52] have done a research study by implementing novel CEEMD-CNN-LSTM and EMD-CNN-LSTM models to improve the analytical capability of stock market prediction. They have proved that prediction accuracy is improved when using deep learning with these statistical techniques, rather than using CNN or LSTM alone. And also, CEEMD-CNN-LSTM model performed better results than EMD CNN-LSTM model according to their results.

M. Ghahramani and H. E. Najafabadi [53] implemented a deep learning neural network model to predict stock prices and novel idea to prepare data for preprocessing the data. XGBoost for feature engineering and technical indicators for feature generation. Prediction model consisted convolutional layer, LSTM layer and fully connected layer. As the dataset, twenty years data of daily data of S&P500 index and cryptocurrency two coins datasets were used. And f1 score, accuracy, precision and recall metrics were used as evaluation metrics. According to the results they have proved a considerable amount of profit can be achieved through this prediction model.

According to Kelum Gajamannage, Yonggi Park [54], the accuracy of real time stock prediction system is highly subjective to the ANN architecture and how the model is training. They have developed two LSTM models, one model for finding the best number of epochs and other model was used to make predictions using best number of epochs. As the state of art methods extended Kalman filter (EKF), ARIMA and autoregression were used and, several datasets were used in different markets: stocks, cryptocurrencies, and commodities. They have chosen Apple, Google, and Microsoft companies for stocks; Bitcoin, Cardano, Ethereum for cryptocurrencies; and Gold, Oil, and Natural Gas for commodities. According to the MAE evaluation results LSTM model outperformed the other models and it was selected as the best model for predicting stock prices in this study.

According to Z. Shi et al. [55] traditional statistical methods such as ARIMA, is not capable of describe non-linearity of stock market. Furthermore, they are not providing good accuracy in stock market predicting. Since deep learning has ability of nonlinear generalizability, authors proposed an attention-based CNN-LSTM and XGBoost hybrid model for stock market prediction. This model integrated with the ARIMA, CNN model with Attention mechanism, LSTM and XGBoost regressor. ARIMA was used for preprocess data and CNN-LSTM with attention mechanism was used to pre-train model. For fine-tuning, XGBoost was included. They have collected 15 years daily records from Chinese stock market. According to the RMSE and MAE evaluation results proposed model was more effective and can avoid investors risk as well.

The following table (Table 2.1) includes the summary of literature which discussed above.

TABLE 2.1: SUMMARY OF DEEP LEARNING BASED STOCK PRICE PREDICTION MODELS

Author	Title	Model	Summary
M. Nabipour, P. Nayyeri and H. Jabani (2020)	Deep Learning for Stock Market Prediction	LSTM	Implemented a short-run prediction models using four groups. Tree based ML models, RNN, ANN and LSTM models were developed and evaluated using RMSE, MAE, MSE. 1, 2, 5, 10, 15, 20, and 30 days ahead values were predicted and LSTM model outperformed other models. As limitation, they have mentioned that if consider other hyperparameters then

			it may affect the final results.
Jinqi Tang and Xiong Chen (2018)	Stock Market Prediction Based on Historic Prices and News Titles	Hybrid model using RNN-LSTM and CNN	The news and historical prices were taken as input and developed a hybrid model for predicting future prices. Rather than taking news and historical data alone, model performed better when data was combined. Mean accuracy was used for evaluation models.
E. Hoseinzade and S. Haratizadeh (2019)	CNNpred: CNN-based stock market prediction using a diverse set of variables	CNN model	Implemented a model for stock market prediction considering different stock markets by gathering diverse set of data. Forecasted the trend of stock market price or index fluctuations. Model used to predict the movement of indices of NASDAQ, S&P 500, NYSE, RUSSELL. F-measure was used as an evaluation metric.
P.Naveen , B Diwan (2020)	Stock Market Predictions using Neural Network Model	a single layer sequential neural network	Daily stock prices of NUMERAI tournament dataset with 21 features were used to implement the prediction model. Model was evaluated using the accuracy rate and loss rate. As limitation, they have mentioned randomized search may have provide better results than grid search that they have used.
Xiongwen Pang, Yanqiang Zhou (2018)	Stock market prediction based on deep long short-term memory neural network	LSTM with embedded layer	Developed LSTM neural network models with embedded layer and auto encoder to predict stock market values by collecting data in real time and off-line analysis. ELSTM model

			provided the best results when predicting the Shanghai, A-share composite index. As evaluation metrics, MSE and Data accuracy were used.
Abin Shakya, Anuj Pokhrel (2018)	Real-Time Stock Prediction using Neural Network	feed-forward neural network	developing a stock price prediction model to predict two-minute wise values using Merolagani website crawling data. The aim was to create a real time prediction model using real time market information. They proved that using market supply and demand information, a short-term prediction model can be implemented with acceptable accuracy. Model was evaluated using Prediction accuracy and Sum of Squared Error. They have mentioned that the performance would be increased if it is improved by increasing the depth of hidden layers.
A. Ghosh, S. Bose, G. Maji, N. Debnath, and S. Sen (2019)	Stock Price Prediction Using LSTM on Indian Share Market	LSTM model	objective was to find out the best timespan for forecasting stock prices. Used closing prices of five companies and developed LSTM models to predict future prices in various timespans. According to the percentage of error, when predicting for a 3-month time period models were provided best results. According to their study, a company's future growth can be predicted with good accuracy.

N. Unnithan, E. A. Gopalakrishnan, V. Menon, and S. Kp (2019)	A Data-Driven Model Approach for Day Wise Stock Prediction	Dynamic mode decomposition model	The daily closing price is taken to implement the model. As the evaluation metric MEAPE is used. The final conclusion from this research is that this DMD technique can be used for predicting future values with less computation as well as this might be used for short term basis predictions. They found that when sudden change happens this model may not provide good accuracy.
Wenjie Lu, Jiazheng Li (2020)	A CNN-LSTM-Based Model to Forecast Stock Prices	CNN-LSTM model	The next day's closing price was forecasted using different prediction models and the best model was selected using MAE and RMSE and R^2. As limitation, they mentioned that this model fails to consider the impact of emotional facts such as news for the future price predictions.
Jaydip Sen, Sidra Mehtab and Gourab Nath (2020)	Short-term stock market price trend prediction using a comprehensive deep learning system	univariate encoder-decoder convolutional LSTM model	Developed CNN and LSTM models for forecasting open values for next upcoming week using two previous weeks records. According to their results (RMSE results), the univariate encoder-decoder convolutional LSTM model outperformed other models. As future works they suggested to implement generative adversarial networks (GANs)-based predictive models to increase the accuracy.
J. Zhao, D. Zeng, S. Liang,	Prediction model for stock price trend	RNN/LSTM/GRU	Developed a prediction model using attention method with

H. Kang, and Q. Liu (2021)	based on recurrent neural network		RNN/LSTM/GRU. They found that when using attention mechanism accuracy can be improved and deeper NN models do not provide better results.
I. K. Nti, A. F. Adekoya, and B. A. Weyori (2021)	A novel multi-source information-fusion predictive framework based on deep neural networks	IKN-ConvLSTM	implemented a novel multi-source information-fusion predictive framework using CNN and LSTM. Aim was to integrate different heterogeneous data sources and train the model using integrated data. Conclusion: The stock market prediction models provide good prediction accuracy when data is selected from multi data sources rather than single data source.
H. Rezaei, H. Faaljou, and G. Mansourfar (2021)	Stock price prediction using deep learning and frequency decomposition	CEEMD-CNN-LSTM (Complete Ensemble Empirical Mode Decomposition CNN-LSTM)	Implemented novel CEEMD-CNN-LSTM and EMD-CNN-LSTM models to improve the analytical capability of stock market prediction. They have proved that prediction accuracy is improved when using deep learning with these statistical techniques, rather than using CNN or LSTM alone.
M. Ghahramani and H. E. Najafabadi (2022)	Compatible deep neural network framework with financial time series data, including data preprocessor, neural network model and trading strategy	Deep Learning model using CNN, LSTM	Implemented a deep learning neural network model to predict stock prices and a novel idea to prepare data for preprocessing the data. Used XGBoost for feature engineering and technical indicators for feature generation. Proposed model proved that considerable amount of accuracy can be achieved by using this

			model with novel data pre-processing technique.
Kelum Gajamannage and Y. Park (2022)	Real-time Forecasting of Time Series in Financial Markets Using Sequentially Trained Many-to-one LSTMs	LSTM models	Developed two LSTM models, one model for finding the best number of epochs and other model was used to make predictions using best number of epochs. According to the MAE evaluation results LSTM model outperformed the other models which were implemented using extended Kalman filter (EKF), ARIMA and autoregression.
Z. Shi, Y. Hu, G. Mo, and J. Wu (2022)	Attention-based CNN-LSTM and XGBoost hybrid model for stock prediction	Attention-based CNN-LSTM and XGBoost hybrid model	Since deep learning has ability of nonlinear generalizability, authors proposed an attention-based CNN-LSTM and XGBoost hybrid model for stock market prediction. This model integrated with the ARIMA, CNN model with Attention mechanism, LSTM and XGBoost regressor. According to the RMSE and MAE evaluation results proposed model was more effective and can avoid investors risk.

2.6 Minute-wise stock price prediction research studies

A short-term basis stock price prediction model was developed by Selvin et al. using a sliding window approach [38]. They have collected minute wise stock prices from NSE listed companies (IT sector and Pharma sector namely Infosys, TCS and Cipla) for one year. Then 100 minutes window size was used for the sliding window approach and 10 minutes future of values were predicted. The best window length was identified by developing various models considering different window sizes and their error value. As for model development they have used CNN, RNN and LSTM algorithms and according to the RMSE evaluation results CNN performed well and was selected as the best model. Furthermore, their other observation is that LSTM and RNN models are not capable of identifying the beginning and end prices of time window with good accuracy. But CNN provided better results because it has done predictions only using current window rather than previous information. They have compared these models with ARIMA model as well. But ARIMA model’s error percentages were higher than these neural network models.

A minute wise stock price prediction system was implemented by Kuttichira et al. using Dynamic Mode Decomposition technique [39]. They collected data from the companies listed in the National Stock Exchange and minute wise records were used to predict the next couple of minutes stock prices. As an evaluation metric MAPE was considered and came up with conclusions. When samples are collected from all of the sectors, the prediction was found to be more accurate than when samples were gathered from just one. When the sample window was fixed, it was possible to provide predictions for a longer period for particular types of sampling. According to their evaluation result, the DMD method performed best compared to ARIMA.

K.Yadav and team [47] has implemented a short term stock market prediction model to predict stock prices real time using fast RNN, Bi-Directional Long Short-Term Memory (Bi LSTM) and CNN techniques. They have used one day minute wise stock prices with 1 minute time interval to train the model. They compared this model with ARIMA, FBProphet like other models using RMSE evaluation values and computation time. According to their results, the fastRNN model which implemented as a hybrid model outperformed other model providing 0.02 RMSE value.

The following table (Table 2.2) includes the summary of research studies which implemented minute wise stock price prediction models.

TABLE 2.2: SUMMARY OF MINUTE WISE STOCK PRICE PREDICTION MODELS

Author	Title	Model	Summary
S. Selvin, V. Ravi, E. A. Gopalakrishnan, V. Menon, and S. Kp (2017)	Stock price prediction using LSTM, RNN and CNN-sliding window model	CNN sliding window model	A short-term basis stock price prediction model was developed using a sliding window approach and datasets from different domains were used to train the model. According to the RMSE evaluation results CNN performed well than RNN and LSTM. CNN

			provided better results because it has done predictions only using current window rather than previous information. Hence, it is capable with identifying beginning and end prices of time window with good accuracy. To analyze the trends with sudden changes, CNN technique is preferred, because it use current information for the analysis.
D. P. Kuttichira, E. A. Gopalakrishnan, V. K. Menon, and K. P. Soman (2017)	Stock price prediction using dynamic mode decomposition	Dynamic mode decomposition	Several companies' data were used to predict the next couple of minutes stock prices. As an evaluation metric MAPE was considered and DMD method performed best compared to ARIMA. They proved that when samples are collected from all of the sectors, the prediction was found to be more accurate than when samples were gathered from just one.
K. Yadav, M. Yadav, and S. Saini (2021)	Stock Market Predictions Using FastRNN, CNN, and Bi-LSTM-Based Hybrid Model	Fast RNN, CNN and Bi-LSTM	A short-term prediction model was implemented using one day minute wise stock prices with 1 minute time interval. RMSE was used to evaluate the model and according to the results, hybrid fast RNN model provided the best results than other models.

2.7 Summary

This chapter provided a thorough examination of the application of machine learning and deep learning techniques to stock market forecasting. In this review, ML and DL stock market prediction models were discussed by taking several models which was implemented by other researchers. Already available minute-wise stock market prediction models were evaluated, and their limitations were recognized. Furthermore, the possible technologies for addressing the research problem were discovered as a result of this review.

CHAPTER 3 - METHODOLOGY

3.1 Introduction

The methodology or design of the research project is described in Chapter 4. This chapter is divided into four sections. The details of the training dataset are described first. The second section focuses on data preprocessing. The discussion of developing deep learning algorithms takes up the third section. Finally, the chapter's summary is discussed.

3.2 Data Collection

When developing a machine Learning model, as the first step, we need to collect enough data to train the ML model. From the data that is provided to the machine, it will learn things. It's necessary to gather reliable trustworthy data because then machine learning models could detect accurate trends from data. The accuracy of the Machine Learning model is determined by the quality of the data that is provided to the machine. If input data is faulty or outdated, the model will provide inaccurate results or predictions that aren't useful.

In order to forecast the future stock prices minute-wisely, minute-wise datasets are required in different companies. For that purpose, minute-wise stock price datasets were collected using Yahoo Finance API. It provides weekly data in one time API call and is limited to access one month data.

Yahoo Finance API is the API service which is available from Yahoo Finance. The API provides real-time and historical cryptocurrency and stock market data. It provides rich financial data for public corporations, mutual funds, etfs, bonds, crypto currencies, and national currencies. It provides a free tier, and the Yahoo Finance API's free tier allows 100 calls per day. The main benefits of using Yahoo Finance API are simpleness and ability to access huge amount of data freely. It provides free third-party APIs for access data. And also, they charge for higher usage plans. For this research, core standard data was gathered from its open-source stock market APIs and other than that, market news, analysis, also can be accessed.

Initially around 13000 records per each company dataset were collected and they are included records of stock prices where duration is seven weeks. Since we are developing a forecasting model, 95% of the dataset was taken as training data.

The attributes of these datasets are;

Datetime - Date with time for each record
Close - Closing stock price when end of 1 minute time period
High - Highest stock price that has been recorded within 1 minute time period
Open - Open stock price when starting the 1-minute time period
Low - Lowest stock price that has been recorded within 1 minute time period
Adj close
Volume - The number of stocks that have been traded within that time period

3.3 Analyzing data

Descriptive analysis is used to analyze past data using data visualization techniques as well as statistical methods. They provide insights of current data and are helpful to understand patterns, and other information in the dataset. Using analysis results, we can come up with better mechanisms to deal with future data.

In this stock price dataset several features were included such as volume of stocks, close price and adj close price. Those features were analyzed using data visualization techniques to get insight about those features and check whether there is any noise, seasonal patterns are included.

3.4 Data Pre-processing

The process of transforming raw data that have been collected, into a format that can be comprehended is known as data preparation. Data from the real world is normally insufficient, inconsistent, and/or deficient in specific behaviors or trends, as well as including various errors. Data Preprocessing is an important step in tackling these issues.

In order to get a well-accepted result, the data used in research should have the following qualities: accuracy, consistency, completeness, interpretability, and accessibility. Before moving on to the next stage, implementing the model, data preparation is a critical step that must be performed.

Removing any unnecessary information from the collected data, such as missing values, duplicate values, converting data types, Rearranging the dataset by changing the columns and rows, as well as the index of rows and columns, converting categorical to numerical, converting the data using log transformation if there are outliers found in the data, scaling the features to provide equal importance to all features, are some of data preprocessing steps that used when developing a ML model.

This stage involves converting noisy and undesired data into a format that can be understood. In order to make the dataset full and consistent, a few data preparation techniques which have been mentioned in the following were used in this research.

The following mentioned steps were carried out in this research under the data pre-processing step.

- Convert date-time field's format

The dataset which was collected from Yahoo Finance API contains the datetime field as a text value rather than in a date format. And also, it has unnecessary values which are not required to our models as well. Example: last five characters. 2021-12-31 13:30:00-05:00
So, I have removed unnecessary characters as well as converted datetime into DateTime format.

- Close price - normalization

Since close price is used for predicting upcoming values and it is a float point value, this field has been normalized. Finally scaled data contains (0,1) values and those were used to create forecasting models.

3.5 Attribute Selection

As a preprocessing technique, attribute selection is used to reduce the amount of data. It is obvious that data reduction lowers data and keeps only the relevant data that is relevant to the problem domain. Hence it helps to improve the effectiveness of the machine learning model development process. Attribute selection is important because it reduces the number of attributes in a model to those that are thought to be most significant to predicting the target value.

The goal of attribute selection is to determine the most relevant minimum set of features to save time and money while enhancing model performance. The dataset already contained seven attributes and only selected attributes were used to model implementation.

In this research, the main objective is creating a forecasting model to predict stock prices minute-wisely. In that case close stock prices and datetime attributes have been selected for further proceedings. Since the other attributes have not been used for forecasting, they have been removed from the dataset.

3.6 Model development

In this step, deep learning model is developed and trained using pre-processed dataset. After training a machine learning algorithm on the obtained data, a machine learning model provides the output. It is critical to select a model that’s appropriate for the requirement. The most crucial phase in machine learning is training. To detect patterns and make predictions, have to provide the prepared data to the machine learning model during the training. As a result, the model learns from the data and is able to accomplish the task assigned. The model improves in predicting over time as it is trained.

In this study, several deep learning algorithms were developed to forecast the minute wise stock prices using CNN and LSTM techniques. Then the performances of proposed and benchmark models were compared considering the evaluation measurements.

CNN

CNN is a type of artificial neural network used in Deep Learning for classification and image/object detection. A conventional neural network has an input layer, hidden layers, and an output layer. CNN was inspired by the brain's architecture. In CNNs, artificial neurons or nodes gather inputs, analyze them, and deliver the result as an output, much like a neuron in the brain. CNNs are another neural network where information flows one direction from inputs to outputs. That’s because it is a feedforward network. CNNs, like artificial neural networks, are biologically inspired. The visual cortex in the brain, which is composed of alternating layers of simple and advanced cells, inspired this CNN architecture. There are many different CNN architectures, but they all have convolutional and pooling layers arranged into modules. A conventional feedforward neural network has one or more fully connected layers [43]. For time series prediction also, CNN can be used.

Convolutional layer consists of multiple convolution kernels, and it extract the features of data, but the dimension would be high. Because of that, pooling layer is added after the convolutional layer to reduce the training cost by reducing feature dimension. In this research, CNN technique was used to effectively extract the features from data.

LSTM

LSTM is a Deep Learning technique as well as a type of RNN [41]. So, it can understand long-term dependencies and can be used to solve problems like sequence prediction. LSTM can process the sequence of data other than images. It is very useful in speech recognition, time series, machine translation and other applications. Figure 3.1 shows the structure of LSTM. LSTM makes it possible for information to persist. It is capable of dealing with RNN's vanishing gradient problem. LSTM is widely applied in time series because it has the feature of expanding according to the sequence of time. A sequence of repeating neural network modules makes up all recurrent neural networks. Ordinary RNNs have a relatively simple structure, such as a single tanh layer, for this repeating module. LSTMs, on the other hand, have a chain-like structure, but the repeating module is distinct. Instead of one, there are four neural network layers, each of which interacts differently. LSTM model is widely used for stock market prediction problems and in this research LSTM technique was used to predict the stock price.

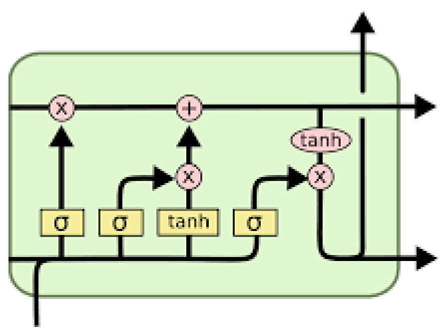

Fig. 3.1: LSTM logic

CNN-LSTM

In the CNN-LSTM architecture, CNN and LSTM both techniques are used. CNN layers used for extracting features on input data and they are linked with LSTMs to improve sequence prediction [44]. As shown in figure 3.2, after the input layer, CNN layers are included when developing this model. Then after LSTM layers and Dense layers are added respectively. This architecture is a combination of two neural network models. In here, feature extraction is done by CNN model and feature interpretation is done by LSTM.

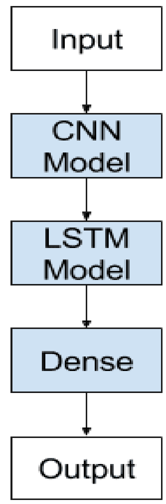

Fig. 3.2: The architecture of CNN-LSTM

The proposed Model

The following hybrid CNN-LSTM model architecture diagram (Figure 3.3) represents the main structure of the CNN-LSTM model including one-dimensional convolutional layer, one Max pooling, three LSTM hidden layers, one Flatten layer and two dense layers.

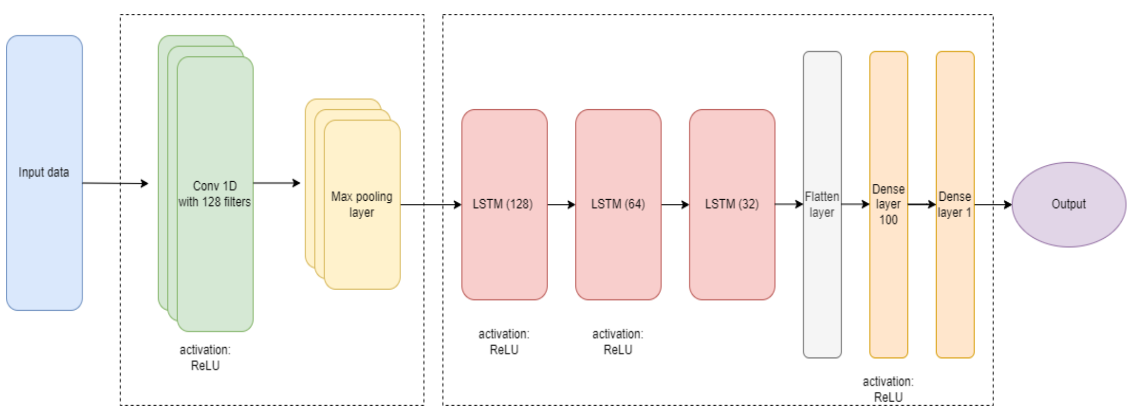

Fig. 3.3: CNN-LSTM architecture

Sequential model is developed using following layers.

Convolutional 1D layer: In this layer, the features are extracted from the input sequential data (stock market data) and 128 feature map is provided as an output. ReLU activation function was used as an activation function and purpose of activation function is to control how well model learns from training dataset.

Max pooling layer: Used to summarize important features by reducing the dimension and simplify the feature map.

LSTM layers: Three LSTM layers with 128, 64 and 32 hidden neurons which make model deeper. When using multiple layers, model provides the sequential output rather than one output. In here also ReLU activation function was used.

Flatten layer: A single long vector is created by flatten the feature map and it would be utilized as input to the dense layer.

Dense layers: They are deeply connected neural network layers with other layers. The number of neurons that specified in the layer affects to the output shape of this layer. In this model, two dense layers are included with 100 and 1 units.

Output: Next couple of minutes stock prices are provided as an output.

When implementing this high-performance hybrid deep learning model, parameters such as number of filters, number of hidden layers were selected by fine tuning these models and considering the evaluation performance. The model parameters are shown in table 3.1. Using holdout method, the pre-processed data set has been separated into two parts: training and testing.

TABLE 3.1: PARAMETER DETAILS OF PROPOSED MODEL

Parameters	Value
Convolutional layer filters	64
Convolutional layer activation function	relu
Convolutional layer kernel size	2
Convolutional layer padding	Same
Max Pooling layer pool size	2
Max Pooling layer padding	same
No of hidden units in LSTM layer 1	128
Activation function of LSTM layer 1	relu
No of hidden units in LSTM layer 2	64
Activation function of LSTM layer 2	relu
No of hidden units in LSTM layer 3	32
No of units in Dense layer	100
Dense layer activation function	relu
No of units in Second Dense layer	1
optimizer	adam
Loss function	mse
Batch size	16
No of epochs	20

Benchmark models

Four benchmark models were implemented to predict stock prices minute wise and used their results to compare them with the proposed model.

Benchmark 1: CNN sliding window model by S. Selvin et al. [38] (for short term prediction)

In this approach, CNN model was developed with convolutional 1D layer, max pooling layer, flatten layer and dense layers. The original model was developed to predict minute wise stock values for three companies which were in pharma and IT domains. Day stamp, time stamp, transaction id, stock price and sold volume were included in their original dataset which used in original research. 90 minutes were taken as sliding window and 10 minutes values were predicted. But in this benchmark, model was modified according to the selected datasets and proposed model. The model parameters also were selected according to the proposed model as following.

TABLE 3.2: PARAMETER DETAILS OF BENCHMARK MODEL 1

Parameters	Value
Convolutional layer filters	64
Convolutional layer activation function	relu
Convolutional layer kernel size	2
Convolutional layer padding	Same
Max Pooling layer pool size	2
Max Pooling layer padding	same
No of units in Dense layer	100
Dense layer activation function	relu
No of units in Second Dense layer	1
optimizer	adam
Loss function	mse
Batch size	16
No of epochs	20

Benchmark 2: Univariate encoder-decoder Convolutional LSTM model by J. Shen et al. [36]

The original model was implemented to predict open stock prices of one week time period using Yahoo Finance data. This sequential model includes ConvLSTM2d layer, flatten layer, repeat vector layer, one LSTM layer and two dense layers. The difference in this model is that it has configured with ConvLSTM2d class in Keras for CNN encoder sub model. The parameter settings which used to implement benchmark model are included in following table 3.3.

TABLE 3.3: PARAMETER DETAILS OF BENCHMARK MODEL 2

Parameters	Value
Convolutional layer filters	64
Convolutional layer activation function	relu
Convolutional layer kernel size	1,4
Convolutional layer padding	Same
Repeat vector output size	1
No of hidden units in LSTM layer	200
Activation function of LSTM layer	relu
No of units in Dense layer	100
Dense layer activation function	relu
No of units in Second Dense layer	1
optimizer	adam
Loss function	mse
Batch size	16
No of epochs	20

Benchmark 3: CNN-LSTM model by W. Lu et al. [35]

The original research was done for predicting the next day's closing price using the past data including the highest, opening, lowest, closing prices and, volume, turnover, ups and downs, and change values as features. MAE, RMSE and R^2 as the evaluation metrics in the original research. But when using this approach as a benchmark model, input dataset and no of features that have been used were different than original model.

The parameters that have been used in benchmark model were as same as the original model and details regarding parameter settings are included in table 3.4.

TABLE 3.4: PARAMETER DETAILS OF BENCHMARK MODEL 3

Parameters	Value
Convolutional layer filters	32
Convolutional layer activation function	tanh
Convolutional layer kernel size	1
Convolutional layer padding	Same
Max Pooling layer pool size	2
Max Pooling layer padding	same
No of hidden units in LSTM layer	64
Activation function of LSTM layer	tanh
No of units in Dense layer	1
Dense layer activation function	relu
Learning rate	0.001
optimizer	adam
Loss function	mse
Batch size	16
No of epochs	20

Benchmark 4: Hybrid fast-RNN model by K. Yadav et al. [47] (for short term prediction)

The original research was done for predicting minute wise stock prices and the main objective was achieving performance (accuracy) and accuracy both together. Hence researchers have designed the model combining fast-RNN, Bi-directional LSTM, CNN techniques. The model parameters which were used in developing benchmark model is shown in table 3.5.

TABLE 3.5: PARAMETER DETAILS OF BENCHMARK MODEL 4

Parameters	Value
Simple RNN layer - No of unites	50
Simple RNN layer activation function	tanh
Convolutional layer filters	300
Convolutional layer activation function	relu
Convolutional layer kernel size	3
Convolutional layer padding	Same
Max Pooling layer pool size	1
Max Pooling layer padding	same
No of hidden units in Bi-directional LSTM layer	50
No of units in Second Dense layer	1
optimizer	adam
Loss function	mse
Batch size	64
No of epochs	20

For the model development Keras libraries were used and Python was used as a programming language. Python is a popular programming language that allows data analysts and other professionals to execute complex statistical computations, machine learning models, data visualizations (such as histograms, pie charts, line graphs, bar charts, and three-dimensional plots), data analysis and management, and other data-related tasks. Keras and TensorFlow are popular Python frameworks that make it easier and faster for programmers to build data analysis and machine learning systems. Keras is an open-source library for Artificial Neural Networks, and it provides a Python interface for implementing ANNs. It includes various implementations of mostly used neural network components such as optimizers, layers, activation functions. Jupyter Notebooks were used to write codes and execute models.

3.7 Summary

This chapter discussed the approach that has been used in developing different deep learning models for minute-wise stock market forecasting. Data collection, data preprocessing, model development like steps have been used when developing deep learning models and they were presented in this chapter.

CHAPTER 4 - EVALUATION

4.1 Introduction

This chapter discusses the details of the results obtained from the evaluations done for forecasting minute-wise stock prices using deep learning techniques as mentioned in the methodology. This chapter justifies and evaluates the overall solution considering the different time windows and different companies that have been used in this research.

4.2 Descriptive Data Analysis Results

Following line charts (Figure 4.1, 4.2 and 4.3) show how stock prices (close price) have changed over time considering Apple, Amazon and Google datasets.

According to these charts, we can see that there are no seasonal patterns occurred in this time period (weekly pattern or daily pattern). But there are some sudden changes in trends can be seen. In google and Amazon datasets it can be clearly identified. Furthermore, when considering the trend of stock prices, the up and down are somewhat similar in all three diagrams. The prices have been decreased around 0-6000 range and prices were increased after 7000 data point in all three diagrams. Although there are fluctuations are available, when considering the trend, it is clearly shown that these companies' prices are affected in same manner.

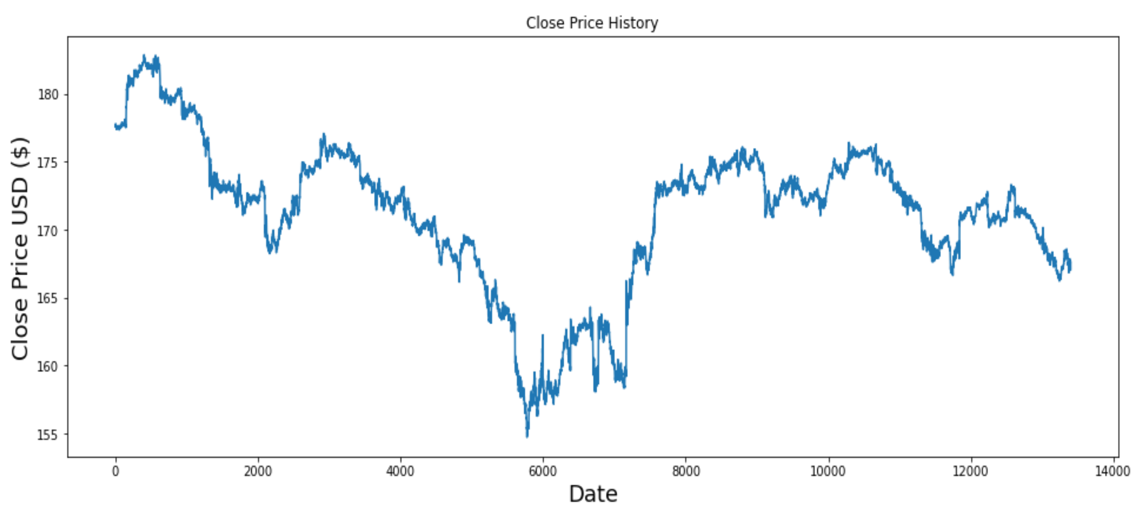

Fig. 4.1: Apple closing price visualization

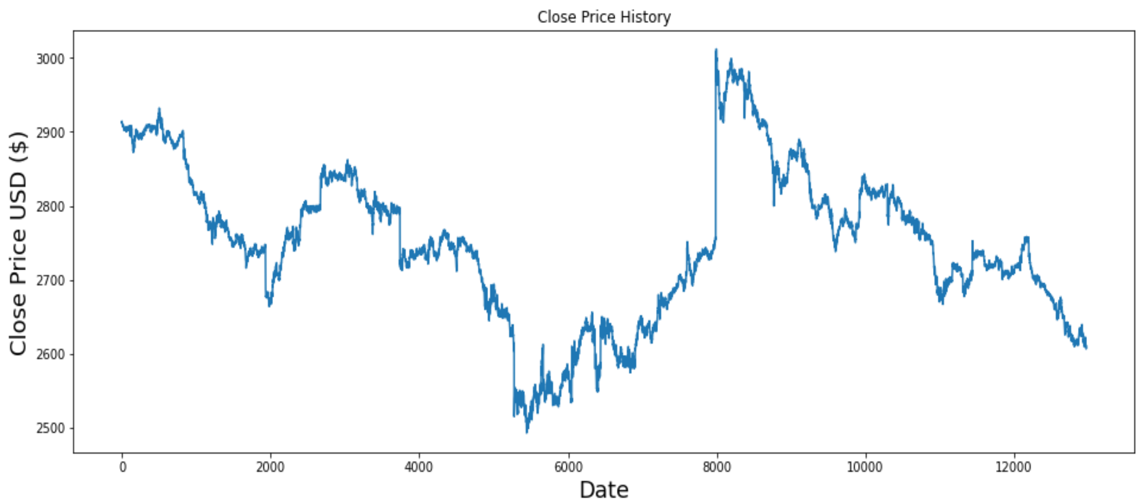

Fig. 4.2: Google closing price visualization

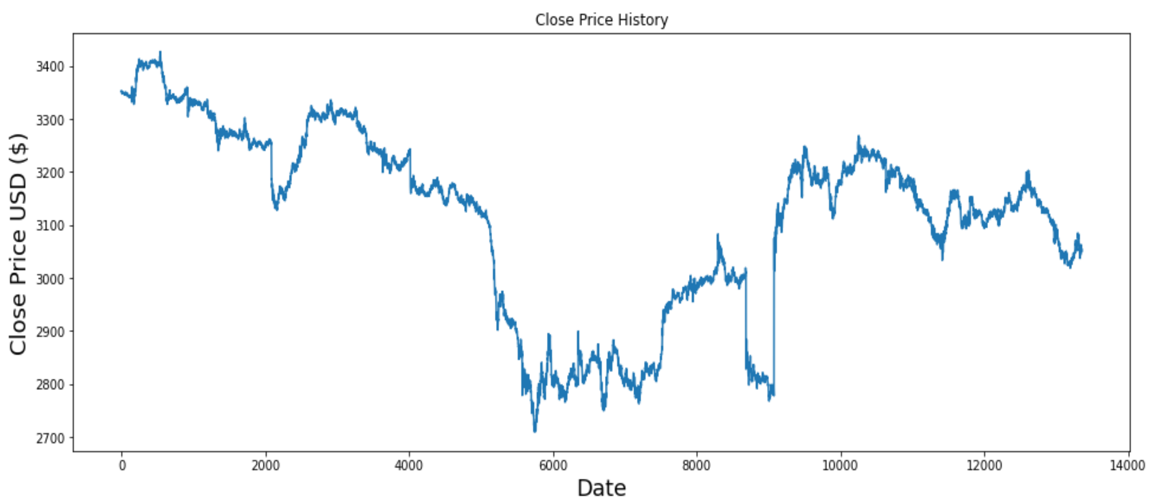

Fig. 4.3: Amazon closing price visualization

The following Figure 4.4, 4.5 and 4.6 presents how moving averages of prices are changed over time. In here different times periods were considered to calculate moving average. (10 minutes, 20 minutes, 50 minutes)

When considering the moving averages also, the pattern of the trend is somewhat similar in all three companies. But in amazon and Google, there is sudden price changes are included.

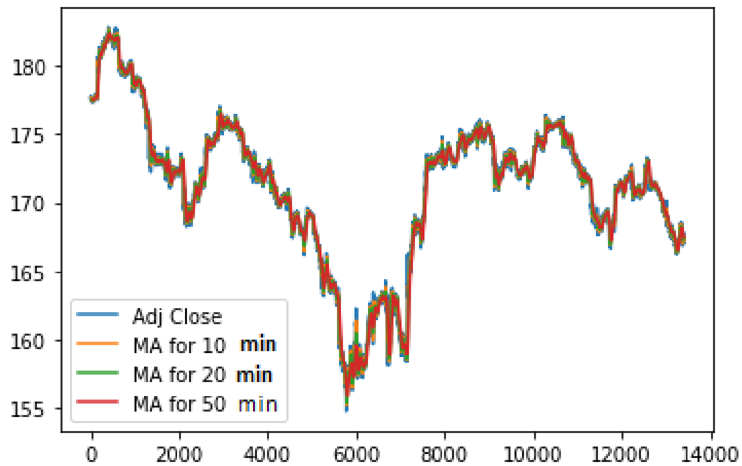

Fig. 4.4: Apple moving average visualization

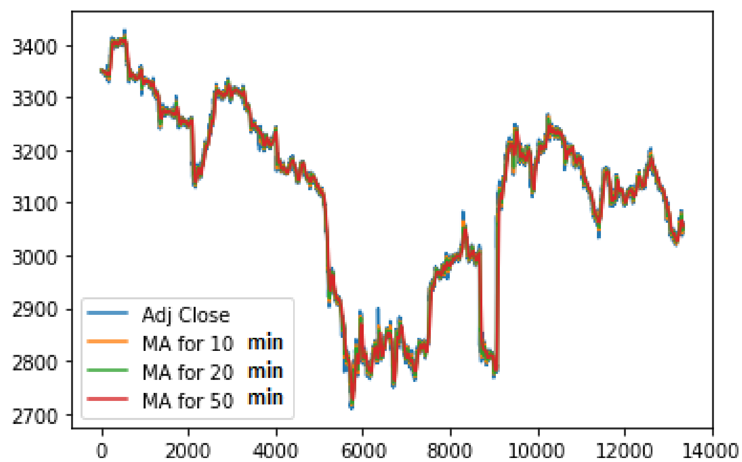

Fig. 4.5: Amazon moving average visualization

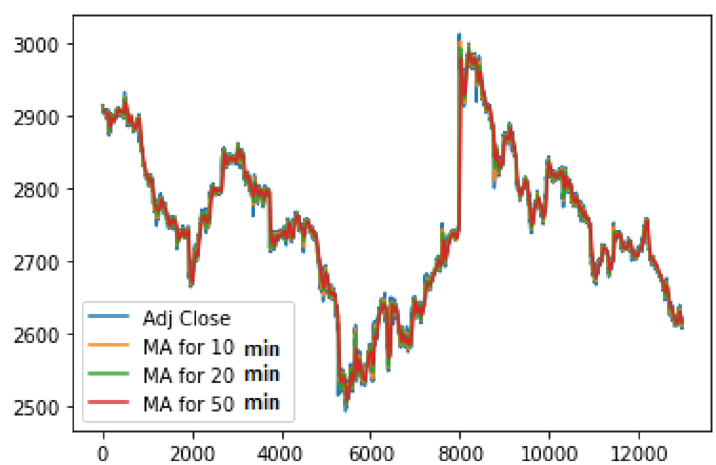

Fig. 4.6: Google moving average visualization

Following charts (Figure 4.7, 4.8, 4.9) show how the volume of stocks (close price) changes over time in different companies. According to these charts several spikes have occurred in different time periods.

Change volume with time

These charts represent how the stock volumes are changed with the time. In there also we can see, there are sudden high-volume changes included in Google and Amazon datasets. That could be affect for the module accuracy of prediction model when implementing with Google and Amazon datasets.

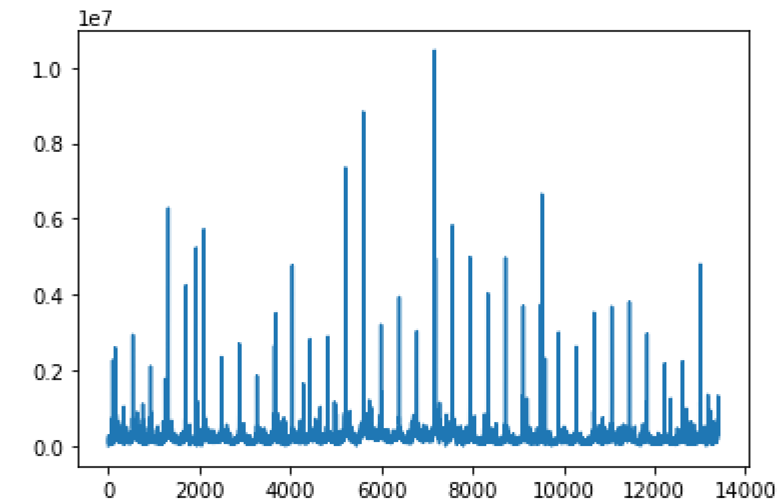

Fig. 4.7: Apple Volume change visualization

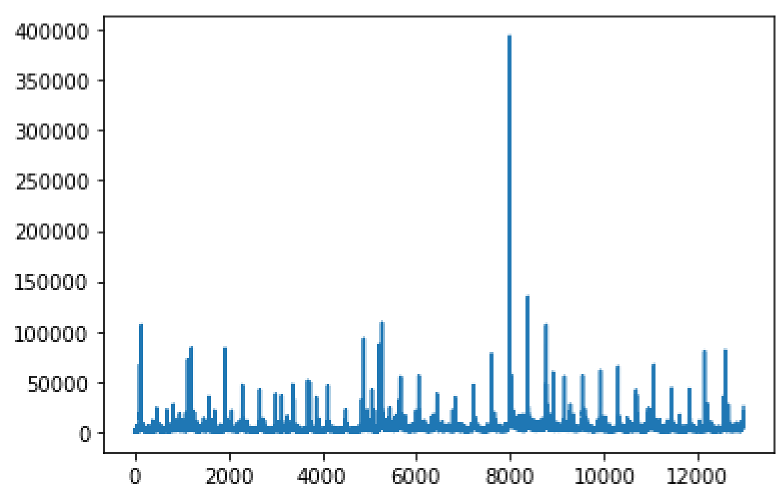

Fig. 4.8: Google Volume change visualization

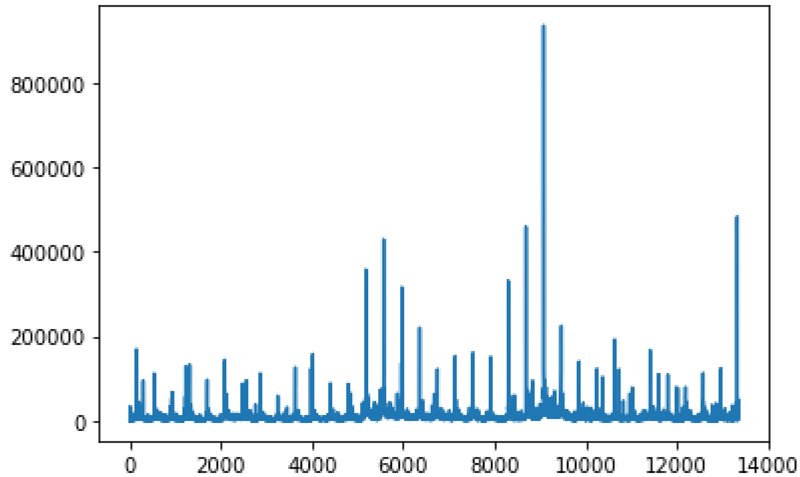

Fig. 4.9: Amazon Volume change visualization

4.3 Evaluation for forecasting model

In time series forecasting, a numerical value is predicted using past data. But it is actually different from the actual value. Hence the performance of the forecasting model is dependent on the ability of forecasting future values without much deviation with real value. Considering how well a ML model reacts for new data, the performance of the forecasting model can be calculated.

Different forecasting evaluation metrics are available for measuring the performance of forecasting models. Some of them are; R-Squared, Mean Absolute Error (MAE), Mean absolute percentage error (MAPE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Normalized Root Mean Squared Error (NRMSE) and so on.

In these evaluation metrics, accuracy measurements are based on the forecasting error values. Error provides information about how well the model performs on the testing dataset. Hence these above-mentioned evaluation metrics use forecasting error to calculate measurements. And also, if a model provides less errors, then that model is considered well performed. And if error is high then that model is not good. The following explained the evaluation metrics that have been used in this research study to evaluate models.

4.4 Evaluation metrics

In this research, RMSE and MAPE evaluation metrics were used to measure performance of models.

RMSE

The general equation for RMSE is as follows.

RMSE = $\sqrt{\overline{(f - o)^2}}$

f= forecast values
o = real values

The same RMSE formula can be written below as well. This formula is used in this research to evaluate models.

RMSE = $\sqrt{\frac{\sum_{i=1}^{N} \|y(i) - \hat{y}(i)\|^2}{N}}$

N - size of dataset
y(i) - real value
$\hat{y}$(i) - predicted value

RMSE can be used to measure the error in machine learning models when it comes to forecasting numeric values such as time series values. It is the standard deviation of measure which is called residuals. They provide information about how far these predicted data points are from actual values. This metric is mostly used when it is required to measure performance in regression models, forecasting models as well as climatology [45].

MAPE

MAPE is another loss function which is mostly used for forecasting evaluations and regression model evaluations [46]. It measures the performance as a percentage. The formula for MAPE metric is given in below.

$$\text{MAPE} = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|$$

A_t - the actual (real correct) value

F_t - the forecast value

n - the number of data points.

4.5 Evaluation results

In this research I have divided the dataset into trained and testing datasets using the hold-out method. 80% of data was used as trained data. Train dataset was used to train the model and Test dataset was used to evaluate the performance.

For each model I have measured the RMSE and MAPE values. And also, I measured those evaluation metrics by changing time-windows such as 60 min, 30 min and 15 min.

I measured these evaluation measurements considering the validation results and forecasting results. I forecasted upcoming 5 minutes data and then I calculated the RMSE and MAPE considering actual values of that record. Furthermore, following tables contains comparison results for the proposed model, based on different criteria.

Comparison of proposed model with benchmark models

As benchmark models, I have selected four research studies which have been implemented to predict stock prices. Those research studies that have been used as benchmarks are listed in following.

Benchmark 1: CNN sliding window model by S. Selvin et al. [38] (for short term prediction)
Benchmark 2: Univariate encoder-decoder Convolutional LSTM model by J. Shen et al. [36]
Benchmark 3: CNN-LSTM model by W. Lu et al. [35]
Benchmark 4: Hybrid fast-RNN model by K. Yadav et al. [47] (for short term prediction)

Table 4.1, 4.2 and 4.3 contains the evaluation results of benchmark models and proposed model using Apple, Amazon and Google datasets. Benchmark 2 and 3 models were implemented for daily price predictions rather than short-term (minute wise) prediction. (These benchmark models were implemented under same conditions such as time-windows, number of input features) as described in previous section. All models were evaluated using RMSE and MAPE metrics.

TABLE 4.1: COMPARISON RESULTS WITH BENCHMARKS FOR APPLE DATASET

	Validation		Prediction (5 minutes records)	
Model	RMSE	MAPE%	RMSE	MAPE%
Benchmark 1	0.3447	0.1797	0.4364	0.2352
Benchmark 2	0.2029	0.0872	0.4287	0.2176
Benchmark 3	0.3424	0.1614	0.2762	0.1507
Benchmark 4	0.2215	0.1125	1.8064	1.0516
Proposed CNN-LSTM	**0.1956**	**0.0865**	**0.1775**	**0.0914**

TABLE 4.2: COMPARISON RESULTS WITH BENCHMARKS FOR AMAZON DATASET

	Validation		Prediction (5 minutes records)	
Model	RMSE	MAPE%	RMSE	MAPE%
Benchmark 1	5.8306	0.2713	6.5629	0.1848
Benchmark 2	5.2265	0.1265	4.6854	0.1235
Benchmark 3	7.3613	0.1857	5.8850	0.1712
Benchmark 4	5.1875	0.1414	6.8852	0.1835
Proposed CNN-LSTM	**5.0587**	**0.1237**	**3.7901**	**0.1048**

TABLE 4.3: COMPARISON RESULTS WITH BENCHMARKS FOR GOOGLE DATASET

	Validation		Prediction (5 minutes records)	
Model	RMSE	MAPE%	RMSE	MAPE%
Benchmark 1	4.7064	0.1510	6.4652	0.2127
Benchmark 2	5.3517	0.1748	6.2152	0.1867
Benchmark 3	4.4694	0.1277	3.5277	0.1855
Benchmark 4	4.0303	0.1318	8.5249	0.2710
Proposed CNN-LSTM	**3.7942**	**0.1154**	**4.4137**	**0.1492**

Table 4.1 contains the evaluation results of benchmark models and proposed model using the Apple company dataset. According to the above table, RMSE metric of benchmark 1 reports validation as 0.3447 and its MAPE is 0.1797. Benchmark 2 reports the 0.2029 RMSE and 0.0872 MAPE validation. Furthermore, benchmark 3 and 4 reports RMSE values 0.3424 and 4.2215 respectively. When considering the proposed model, it reports

0.1956 RMSE value and 0.0865 MAPE value. So, benchmark 1 reports the highest error value for Apple dataset, while the proposed CNN-LSTM model reports the lowest error, while providing lowest RMSE value. Proposed model recorded the best performance for Apple dataset.

When considering the forecasting process, 5% of collected data were used for forecasting purpose, while 95% were used for validation purpose. After training the model by using 60 minutes time window, next 5 minutes records were predicted and calculated the evaluation measurements. As shown in table 4.1, the proposed model recorded 0.1775 RMSE and 0.0914 MAPE values as the lowest error values. Other benchmark models provided the high error values when comparing with the proposed model for the apple dataset.

Table 4.2 contains the evaluation results of benchmark models and proposed model using the Amazon company dataset. According to the above table, RMSE metric of benchmark 1 reports validation as 5.8306 and its MAPE is 0.2713. Benchmark 2 reports the 5.2265 RMSE and 0.1265 MAPE validation. Furthermore, benchmark 3 and 4 reports RMSE values 7.3613 and 5.1875 respectively. When considering the proposed model, it reports 5.0587 RMSE value and 0.1237 MAPE value. So, benchmark 3 reports the highest error value for Amazon dataset, while the proposed CNN-LSTM model reports the lowest error, while providing lowest RMSE value. Proposed model recorded the best performance for Amazon dataset. According to forecasting results, as shown in table 4.2, the proposed model recorded 3.7901 RMSE and 0.1048 MAPE values as the lowest error values. Other benchmark models provided the high error values when comparing with the proposed model for the amazon dataset.

Table 4.3 contains the evaluation results of benchmark models and proposed model using the Google company dataset. According to the above table, RMSE metric of benchmark 1 reports validation as 4.7064 and its MAPE is 0.1510. Benchmark 2 reports the 5.3517 RMSE and 0.1748 MAPE validation. Furthermore, benchmark 3 and 4 reports RMSE values 4.4694 and 4.0303 respectively. When considering the proposed model, it reports 3.7942 RMSE value and 0.1154 MAPE value. So, benchmark 2 reports the highest error value for Google dataset, while the proposed CNN-LSTM model reports the lowest error, while providing lowest RMSE value. Proposed model recorded the best performance for Google dataset. According to forecasting results, as shown in table 4.3, the proposed model recorded 4.4137 RMSE and 0.1492 MAPE values as the lowest error values. Other benchmark models provided the high error values when comparing with the proposed model for the google dataset.

According to these results, the proposed model performs well than the other benchmark models for three datasets. Hybrid Fast-RNN model was performed better in most times than other three benchmark models and provided the output quickly. And also, CNN model (benchmark 1) was performed worst for Apple dataset. Benchmark 3 and 2 performed worst for Amazon and Google datasets respectively.

Comparison based on different company datasets

Table 4.4 shows the validation results of hybrid CNN-LSTM model using different company datasets (Apple, Amazon and Google).

TABLE 4.4: VALIDATION RESULTS OF PROPOSED MODEL

	Apple	Amazon	Google
RMSE	0.1846	4.5768	3.2500
MAPE%	0.0776	0.1075	0.0911

According to these results, this proposed model provides better results for Apple company dataset than other two companies. For the Apple dataset, model achieves 0.1846 RMSE and 0.0776% MAPE. The Amazon and Google datasets provided the 4.5768 and 3.25 RMSE values respectively. The sudden fluctuations included in the Amazon and the Google datasets may result these low results comparing with the Apple dataset.

Comparisons based on different datasets of various industry domains

The proposed model and four benchmark models were tested using different datasets from different domains such as beverage, banking, auto mobile and energy. I selected McDonald Corporation (MCD) which is a multi-national American food chain from beverage domain. From banking domain, JPMorgan Chase & Co. (JPM) was selected. And the General Motors Company (GM) which is a multi-national American automotive company was selected from automotive domain. Then Duke Energy company (DUK) was selected from energy domain, which is considered as a famous company in regulating electric and natural gas.

From 2022-05-25 to 2022-06-22, four weeks data were collected from each company and data were pre-processed using same pre-processing steps that I have been used to pre-process other Apple, Amazon and Google datasets. And epoch value was set as 100 for these models.

TABLE 4.5: VALIDATION RESULTS ON DIFFERENT DATASETS FROM DIFFERENT DOMAINS

		MCD	JPM	GM	DUK
Proposed	RMSE	0.1581	0.3373	0.1351	0.1148
	MAPE %	0.0449	0.1319	0.0959	0.0910
Benchmark 1	RMSE	0.2733	0.3241	0.1386	0.1763
	MAPE %	0.0817	0.1353	0.3098	0.1558
Benchmark 2	RMSE	0.1692	0.2024	0.1732	0.1223
	MAPE %	0.0510	0.0681	0.1995	0.1130
Benchmark 3	RMSE	0.1915	0.2340	0.1836	0.1251
	MAPE %	0.0576	0.0803	0.1953	0.1114
Benchmark 4	RMSE	0.1725	0.2217	0.1728	0.1339
	MAPE %	0.0509	0.0773	0.1984	0.1196

According to the evaluation results that is shown in table 4.5, proposed model provided the best results for MCD, DUKE and GM companies while benchmark 2 model provided the highest accurate for JPM company. Moreover Benchmark 1 provided the worst accuracy for MCD and DUKE companies when considering these error values.

When models were trained using McDonald dataset, 0.1581 RMSE and 0.0449 MAPE% value was achieved by the proposed model. For the benchmark 1, 2,3 and 4 models, it provided 0.2733, 0.1692, 0.1915 and 0.1725 RMSE values respectively. Second highest accuracy was provided by benchmark 2 model for McDonald company (RMSE 0.1692 and MAPE% 0.0510).

For the DUKE company, benchmark models provided 0.1763, 0.1223, 0.1251 and 0.1339 RMSE values for 1st, 2nd, 3rd and 4th benchmark models respectively. And the proposed model achieved 0.1148 RMSE and 0.0910 MAPE% while achieving the best performance for that dataset. For the JPM company, benchmark 2 model provided highest accuracy while providing 0.2024 RMSE and 0.0681 MAPE%. The proposed model provided 0.3373 RMSE and 0.1319 MAPE% which is somewhat less performance when considering with other models.

For the General Motors dataset also proposed hybrid CNN-LSTM model performed highest performance while providing 0.1351 RMSE and 0.0959 MAPE% values. But benchmark models recorded 0.1386, 0.1732, 0.1836 and 0.1728 RMSE values which were higher than the proposed model (high error values). And 0.3098%, 0.1995%, 0.1953% and 0.1984% MAPE values were recorded by benchmark 1, 2,3 and 4 models for this company.

As sum up, the proposed model provided the best performance rather than selected benchmark models when considering the evaluation metrics for McDonald, General Motors and Duke Energy companies. But for the JPM company, one of the benchmark models provided the better results. The reason for that might be the parameters that have been used for proposed model is not fine-tuned by considering these datasets. For getting better results, the parameters of machine learning models should be fine-tuned according to the dataset. But for other three companies, the proposed model performed better than benchmark models although without fine-tuning. When considering the overall results, the proposed model outperformed the state-of art models when considering the evaluation results. As conclusion the proposed model can be used for minute wise stock market prediction generally other companies as well.

Comparison based on different time-windows

In this research, I have used time-window approach when training the model. So, time-window parameter was needed to set when developing the model, considering the model performance. The proposed model was trained considering different time windows, and their results are shown in table 4.6.

TABLE 4.6: VALIDATION RESULTS BASED ON DIFFERENT TIME-WINDOWS

	Apple			Amazon			Google		
Metric (min)	60	30	15	60	30	15	60	30	15
RMSE	0.1846	0.1874	**0.1562**	4.5768	4.4361	**3.7780**	3.2500	2.9900	**2.5381**
MAPE %	0.0776	0.0773	**0.0653**	0.1075	0.1040	**0.0879**	0.0911	0.0852	**0.0772**

According to table 4.6, when proposed model training by setting time-window parameter to 60 minutes, 30 minutes and 15 minutes for Apple dataset, RMSE values were recorded as 0.1846, 0.1874 and 0.1562. MAPE value reported as 0.776, 0.0773 and 0.0653 respectively for each time window. And when time-window parameter was set to 60 minutes, 30 minutes, and 15 minutes for Amazon dataset, RMSE values were recorded as 4.5768, 4.4361 and 3.7780. MAPE value reported as 0.1075, 0.1040 and 0.0879 respectively for each time window for Amazon dataset. Furthermore, when time-window parameter was set to 60 minutes, 30 minutes, and 15 minutes for Google dataset, RMSE values were recorded as 3.2500, 2.9900 and 2.5381. MAPE value reported as 0.0911, 0.0852 and 0.0772 respectively for each time window for Google dataset.

According to these results, the proposed model has been provided the best results when time-window parameter was set to 15 minutes. When considering the Apple dataset, 0.1562 RMSE value was recorded when time-window was 15 minutes. RMSE value for 60 minutes was 0.1846, which was higher than the 15 minutes model. Amazon and Google datasets-based models also provided the best results when time-window parameter was set to 15 minutes. Overall, when time-window parameter was set to 15 minutes, the proposed model provided the lowest error while providing the highest performance.

Comparisons based on different model parameters

The proposed model was evaluated by changing different model parameters such as number of hidden neurons and several other models like LSTM and CNN. Table 4.7 shows the evaluation results by changing model parameters as below.

Proposed model:

```
Conv1D(filters=128, kernel_size=2, activation='relu')
MaxPooling1D(pool_size=2)
LSTM(128, return_sequences=True, activation='relu' )
LSTM(64, return_sequences=True, activation='relu' )
LSTM(32, return_sequences=True)
Flatten()
Dense(100, activation='relu')
Dense(1)
```

Model 1:
Conv layers - 128, 64, LSTM - 128, 64, 32, Flatten, Dense 100, 1
Model 2:
Conv layers 64, LSTM 128, 64, 32, Flatten, Dense 100, 1
Model 3:
Conv layers 256, LSTM 128, 64, 32, Flatten, Dense 100, 1
Model 4:
Conv layers 128, LSTM 64, 32, Flatten, Dense 100, 1
Model 5:
Conv layers 128, LSTM 64, Flatten, Dense 100, 1
Model 6:
Conv layers 128, LSTM 128, Flatten, Dense 100, 1
Model 7:
Conv layers 128, LSTM 128, 64, 32, Flatten, Dense 1
Model 8:
LSTM 128, 64, 32, Flatten, Dense 100, 1

Model 9:
CNN 128, Flatten, Dense 100, 1

TABLE 4.7: COMPARISON RESULTS BASED ON DIFFERENT MODEL PARAMETERS

	Apple		Amazon		Google	
Model	RMSE	MAPE%	RMSE	MAPE%	RMSE	MAPE%
Model 1	0.2715	0.1293	5.6708	0.1318	4.7372	0.1518
Model 2	0.2114	0.0955	4.8356	0.1081	4.3636	0.1299
Model 3	0.2501	0.1197	5.2080	0.1337	3.4566	0.0997
Model 4	0.5003	0.2783	7.4200	0.2092	6.4685	0.2079
Model 5	0.1906	0.0799	6.2832	0.1665	4.3603	0.1389
Model 6	0.2664	0.1309	8.8416	0.2574	3.3054	0.0950
Model 7	0.2197	0.1014	7.4006	0.1999	3.4827	0.1016
Model 8	0.1893	0.0928	3.6165	0.0896	3.9044	0.1124
Model 9	0.2762	0.1383	4.9469	0.1150	3.9044	0.1242
Proposed model	**0.1846**	**0.0776**	**4.5768**	**0.1075**	**3.2500**	**0.0911**

In this research, the parameters of proposed model were selected considering the evaluation results by changing parameters of CNN-LSTM model. Table 4.7 represent the evaluation results of models which were implemented by changing model parameters such as number of hidden layers, filters, and number of layers.

According to these results, the proposed model provided the RMSE values 0.1846, 4.5768, 3.2500 for the Apple, Amazon and Google datasets respectively. And also, it provided the 0.0776%, 0.1075% and 0.0911% MAPE values for previously mentioned company datasets. The proposed model contained Convolutional 1D layer (128 filters), max pooling layer, LSTM layers (128, 64, 32 number of hidden neurons), flatten layer and two dense layers. Considering these evaluation results, these model parameters were selected for the proposed model since it provided the less error values.

Comparison of forecasting results

The upcoming 5 minutes stock prices were forecasted from proposed model using different company datasets. Then after those forecasting results of each model were evaluated with the actual prices and calculated the RMSE and MAPE measurements.
The table 4.8 shows the evaluation results for implemented models considering the Apple, Amazon and Google datasets. Forecasting was done by using 5% of collected data which were not use for validation purpose. 95% of collected data were used for training and validation the model.

TABLE 4.8: EVALUATION RESULTS OF FORECASTING

	Apple			Amazon			Google		
Metric (min)	60	30	15	60	30	15	60	30	15
RMSE	0.1010	**0.0972**	0.1059	**1.9447**	2.5009	3.1455	**1.4071**	1.4582	4.6744
MAPE %	0.0477	**0.0443**	0.0496	**0.0529**	0.0660	0.0854	**0.0424**	0.0457	0.1538

According to the results shown in table 4.8, when stock prices were forecasting for apple dataset, in 60 minutes, 30 minutes and 15 minutes time-windows, RMSE values were 0.1010, 0.0972 and 0.1059. And MAPE% values were 0.0477, 0.0443 and 0.0496 respectively. When time window is 30 minutes, model performed better results.

As shown in the results, when stock prices were forecasting for amazon dataset, in 60 minutes, 30 minutes and 15 minutes time-windows, RMSE values were 1.9447, 2.5009 and 3.1455. And MAPE% values were 0.0529, 0.0660 and 0.0854 respectively. When time window is 60 minutes, model performed better results for amazon dataset.

When stock prices were forecasting for google dataset, in 60 minutes, 30 minutes and 15 minutes time-windows, RMSE values were 1.4071, 1.4582 and 4.6744. And MAPE% values were 0.0424, 0.0457 and 0.1538 respectively. When time window is 60 minutes, model performed better results for google dataset as well.

Overall, the models which were developed using Amazon and Google datasets provided better forecasting results, when time-window was taken as 60 minutes. But Apple dataset provided the best forecasting results when time-window was 30 minutes. But in there also evaluation results of 60 minutes is better than the 15 minutes time window. So, we can conclude 60 minutes time window is more suitable for proposed model considering average results.

Parameter Analysis of Benchmark models

When considering the selected benchmark models, those models were developed based on different other datasets. In this research, I have used the same parameters which were used in original research studies, to implement benchmark models. Hence, I have conducted a parameter analysis for those benchmark models considering apple dataset and RMSE and MAPE evaluation measurements were recorded. The following tables contains the evaluation results of parameter analysis of benchmark models.

Benchmark 1

As the benchmark 1, a CNN model has been implemented including convolutional 1D layer, max pooling layer, flatten layer and dense layers. In original model the number of filters and kernel size that have been considered for convolutional 1D layer was 64 and 2. For the parameter analysis, I have changed these number of filters and kernel size and measured the performance. Table 4.9 shows the evaluation results of benchmark 1 model using apple dataset.

TABLE 4.9: EVALUATION RESULTS OF PARAMETER ANALYSIS – BENCHMARK 1

Changed parameters and values	RMSE	MAPE%
Original (kernel = 2 & filters = 64)	0.1702	0.0687
Kernel = 1	0.2585	0.1326
Kernel = 3	0.1788	0.0722
Filters = 128	0.1823	0.0781
Filters = 32	0.2004	0.0906

According to these results, when having the original parameters, model provided 0.1702 RMSE and 0.0687% MAPE values. Those values are better than the other evaluation measurements which were provided when parameters have been changed. So, considering the results, we can conclude that the best performance can be obtained for benchmark 1 model, when having the original parameters.

Benchmark 2

A Univariate encoder-decoder Convolutional LSTM model was implemented as benchmark 2 using CNN and LSTM techniques. This sequential model includes ConvLSTM2d layer, flatten layer, repeat vector layer, one LSTM layer and two dense layers. I have changed the number of filters of CNN layer and number of hidden units of LSTM layer and evaluation results are shown in below (Table 4.10).

TABLE 4.10: EVALUATION RESULTS OF PARAMETER ANALYSIS – BENCHMARK 2

Changed parameters and values	RMSE	MAPE%
Original (CNN filters = 64 & no of hidden units = 200)	0.1969	0.0860
CNN Filters = 128	0.2385	0.1181
CNN Filters = 32	0.2005	0.0881
LSTM no of hidden units = 300	0.2039	0.0956
LSTM no of hidden units = 100	0.2243	0.1031

According to these results, when having the original parameters, model provided 0.1969 RMSE and 0.0860% MAPE values. These results outperform the other evaluation measurements provided when parameters were changed. So, based on the results, we can conclude that the benchmark 2 model performs best when the original parameters are used.

Benchmark 3

As for the benchmark 3, a CNN-LSTM model was developed including CNN and LSTM layers. When parameter analysis was performing, the number of filters in CNN layer and number of hidden units of LSTM layer were changed and recorded the evaluation measures as follows (Table 4.11).

TABLE 4.11: EVALUATION RESULTS OF PARAMETER ANALYSIS – BENCHMARK 3

Changed parameters and values	RMSE	MAPE%
Original (CNN filters = 32 & LSTM hidden units = 64)	0.1337	0.0561
CNN Filters = 64	0.1821	0.0881
CNN Filters = 16	0.1366	0.0572
LSTM hidden units = 128	0.1353	0.0569
LSTM hidden units = 32	0.1626	0.0749

According to these results, when having the original parameters, model provided 0.1337 RMSE and 0.0561% MAPE values. Those values are better than the other evaluation measurements which were provided when parameters have been changed. So, considering the results, we can conclude that the best performance can be obtained for benchmark 3 model, when having the original parameters.

Benchmark 4

Hybrid fast-RNN model was implemented as benchmark 4 and it was developed by combining fast-RNN, Bi-directional LSTM, CNN techniques. Several parameter values were changed in this parameter analysis and measured the performance. Table 4.12 contains the performance results of parameter analysis of benchmark 4 model.

TABLE 4.12: EVALUATION RESULTS OF PARAMETER ANALYSIS – BENCHMARK 4

Changed parameters and values	RMSE	MAPE%
Original (CNN Filters = 300 & LSTM hidden units = 50)	0.1261	0.0535
CNN Filters = 200	0.1397	0.0631
CNN Filters = 400	0.1275	0.0581
LSTM hidden units = 64	0.1285	0.0584
LSTM hidden units = 32	0.1554	0.0736

According to these results, when having the original parameters, model provided 0.1261 RMSE and 0.0535% MAPE values. These results outperform other evaluation measurements that were offered when parameters were altered. Considering the findings, we can therefore say that benchmark 4 model performs at its best, when using the original settings.

Furthermore, all the results were included in a Git repository and following shows the git link for that repository.

Git link: https://github.com/rasikavijithasena/Final_Hybrid_CNNLSTM

4.6 Discussion

In this research, a hybrid CNN-LSTM model was implemented for short term stock price prediction with high accuracy. For the comparison purpose, four benchmark models were implemented which was implemented by other researchers for stock price prediction and evaluated using RMSE and MAPE metrics. The proposed model's goal is to develop an optimized model that gives high performance and outperforms other existing models. Two benchmark models were implemented to predict stock prices minute wise and other two were implemented for predicting daily prices. But in here all models were evaluated under same conditions and used to forecast minute wise prices. Furthermore, these models were executed in a Windows 10 64-bit system where CPU is intel i7, clock speed is 2.80GHz-1.69 GHz, and RAM is 8GB.

According to the table 4.1, 4.2 and 4.3, the proposed model outperforms benchmark models by providing lowest RMSE and MAPE values. For the Apple dataset the hybrid CNN-LSTM model provided the RMSE 0.1956 and MAPE 0.0865%. These results are less than the evaluation results of other benchmark models. When comparing the proposed model with the benchmark models, our proposed model contains simple structure than the Benchmark 2 and 4 models (which consists of ConvLSTM2d + LSTM layers and fast RNN + CNN + Bi-directional LSTM layers respectively). And also, this model includes more LSTM layers than benchmark 3, which is another CNN-LSTM model developed for daily stock price predictions. Furthermore, benchmark 1 consists only CNN technique and proposed model performs well since it includes LSTM layers which provide higher results for time-series predictions.

Although Amazon's and Google's RMSE and MAPE values are somewhat higher than the Apple dataset's values, the proposed model provides the less error values than other four benchmark models. Finally, it is clear that the proposed model was providing better performance with less errors when comparing with other benchmark models.

There are three datasets from the three IT related companies used as the training datasets. Since they are from the same domain, we can clearly see the trend is somewhat same in all three datasets. We can conclude from this, that there is a relationship between the same domain datasets when it comes to stock market patterns. The external and internal factors that effect to the stock market may affect to the same domain companies in equal manner. Furthermore, when there is a sudden change is available in the database, that affect to the model performance as well. When comparing with the Apple, the results of Google and Amazon are low due to the available fluctuations.

The proposed model was tested by using other industry datasets such as banking, auto motive, energy and beverage. The companies that have been selected were JPMorgan Chase & Co. (JPM), General Motors Company (GM), Duke Energy company (DUK) and McDonald Corporation (MCD). The selected datasets were fed to the proposed model and four benchmark models. The overall evaluation results showed that the proposed model outperform the state of art models when feeding these other domain datasets as well. But for JPMorgan Chase company, one of the benchmark models (benchmark 2) provided the better performance than the proposed model. The reason for that might be the parameters that have been used for proposed model is not fine-tuned by considering these datasets. For getting better results, the parameters of machine learning models should be fine-tuned according to the dataset. But for other datasets, the proposed model provided the better results than the benchmark models. Hence, when considering the overall results, the proposed model provided the better performance than the selected benchmark models. Finally, it shows that, the proposed Hybrid CNN-LSTM model achieves the generalizability by providing high performance for different domain datasets.

The model structure was designed with convolutional 1D layer, Max pooling layer, LSTM layers, Flatten layer and Dense layers. This proposed model is a sequential model which pass outputs of one layer to the next layer as input. The input was shaped as three-dimensional data vector when providing to the convolutional layer. Each layers take input vector and provide output according to the configurations that have been provided. Final output value was provided by the second dense layer. ReLU activation function, ADAM optimizer and Mean Square Error loss function were used when training the model. And also, it was trained by providing 16 as the batch size and 20 as the epochs. Different models were implemented by changing models' parameters such as number of hidden units, filters, batch size, and then the best parameter set was selected for this proposed model.

Overall, the experimental results clearly show the proposed hybrid CNN-LSTM model perform well rather than the already available stock market prediction models which were considered as benchmark models in this research. Furthermore, according to RMSE and MAPE results, this optimized proposed model can be applied to predict different company datasets with better accuracy.

4.7 Summary

As described in the previous chapter, this chapter assessed the techniques and presented the evaluation results. The performance results of proposed model on different companies and time-windows were also clearly described in this chapter. Furthermore, proposed model was compared with the four benchmark models as well. The conclusion, future improvements, and limitations of the research study are discussed in the next chapter.

CHAPTER 5 - CONCLUSION

5.1 Introduction

The sixth chapter focuses on providing an overview of the overall study as well as future work for this research study. First, a summary of the research has been provided and then the limitations of the research as well as future works that have been determined to be carried out, were discussed in this chapter.

5.2 Overview of research

Forecasting stock prices is a difficult task due to the dynamic and non-linear price fluctuations. And also need to deal with high volume and high frequency data since prices are changed real-time. Although there are several Machine learning and Deep Learning techniques that have been used to implement prediction algorithms, stock value prediction is challenging because of its changing behavior and high frequency.

Stock market movements can be influenced by economic factors such as change in corporate policy, economic shifts, expectations of investors and government change. When developing a prediction model, these influenced factors need to be considered to get highly accurate results. The successful stock market prediction models result in better decisions and high profits as well.

When considering short term basis stock market dataset, minute-wise data is available to access freely from Yahoo Finance API. Minute-wise stock market prices provide better understanding about stock price behavior within a particular day. Since it is very important to thoroughly analyze stock price behavior to make trading decisions, analyzing and predicting trading trends within a day is very crucial.

Most research studies have been conducted to predict daily, weekly prices. Rather than predicting daily close price, open price or highest average price, if we can predict the next upcoming couple of minutes or hours stock prices with highest accuracy, then it is a great improvement in stock market prediction. In this research I have mainly considered that problem and implemented a better deep learning approach for predicting minute-wise stock prices.

Following have listed the main contributions of this research for the stock market prediction research area.

- A hybrid CNN-LSTM model for implemented for predicting stock prices for short term time basis (minute-wise) with highest performance.

- Evaluating proposed model and different deep neural network models (benchmark models) that used CNN, LSTM and CNN-LSTM technologies for minute-wise stock market prediction.

According to the evaluation results of this research, with proper fine-tuning this hybrid CNN-LSTM model provides better performance (comparing with other models which available in literature) in short-term stock market predicting with highest evaluation results. For the other domain related companies (banking, food, energy and automotive) also proposed model has been provided the best performance comparing with selected benchmark models. And also proposed model consists of simple structure than the other benchmark models. Finally, according to the evaluation results, the proposed model outperforms the selected benchmark models.

5.3 Limitations

According to this study major limitations were the non-linear and dynamic nature of stock market trends. Due to internal and external factors, sudden changes are included in stock price data. Although there were sudden changes included in company datasets, they were not noises because those occurred due to other factors. Since other factors are not considered in this research these models are not capable of identifying that kind of effects when forecasting.

When developing forecasting models, I only considered the close stock price of selected dataset and did not consider other factors (internal and external). Since I have developed regression models to predict close prices, other factors and variables were not considered. And there were not many resources available when it comes to other internal or external factors since minute-wise data is considered in here.

I have used seven-week data to train the model considering my hardware and software resources. The size of the training dataset is also limited due to this matter and performance of model would be increased if the proposed model train with more data.

5.4 Future works

In this study I have chosen IT related worldwide popular companies to fetch datasets, Amazon, Apple and Google. Models were created using historical stock prices and other data sources such as financial news, twitter were not considered. As future work, it is better to consider other facts which effect for stock market movements when implementing the models. For evaluation purposes I considered RMSE and MAPE metrics and came up with conclusions. It is better if these models were trained on more datasets and evaluated with many other evaluation metrics.

5.5 Summary

This chapter finalized the thesis by discussing the solution provided by the Hybrid CNN-LSTM deep learning approach for forecasting minute-by-minute stock prices and how it may be improved further by improving the level of performance in forecasting stock prices considering datasets of various other companies.

REFERENCES

[1] D. Zhang, M. Hu, and Q. Ji, “Financial markets under the global pandemic of COVID-19,” *Finance Research Letters*, vol. 36, p. 101528, Oct. 2020, doi: 10.1016/j.frl.2020.101528.
[2] W. Jiang, “Applications of deep learning in stock market prediction: Recent progress,” *Expert Systems with Applications*, vol. 184, p. 115537, Dec. 2021, doi: 10.1016/j.eswa.2021.115537.
[3] A. Phuyal, A. Pokharel, N. Dahal, and S. Shrestha, “Analysis of Stock Market using Data Mining Techniques,” *Journal of Network Security and Data Mining*, vol. 4, no. 2, Art. no. 2, Jul. 2021, Accessed: Mar. 29, 2022. [Online]. Available: http://hbrppublication.com/OJS/index.php/JNSDM/article/view/1926
[4] E. Endri, M. Rinaldi, D. Arifian, B. Saing, and A. Aminudin, “Oil Price and Stock Return: Evidence of Mining Companies in Indonesia,” *International Journal of Energy Economics and Policy*, vol. 11, pp. 110–114, Feb. 2021, doi: 10.32479/ijeep.10608.
[5] “A Statistical Analysis of Impact of COVID19 on the Global Economy and Stock Index Returns | SpringerLink.” https://link.springer.com/article/10.1007/s42979-020-00410-w (accessed Mar. 29, 2022).
[6] D. Kumar, P. K. Sarangi, and R. Verma, “A systematic review of stock market prediction using machine learning and statistical techniques,” *Materials Today: Proceedings*, vol. 49, pp. 3187–3191, Jan. 2022, doi: 10.1016/j.matpr.2020.11.399.
[7] “Reliance on Artificial Intelligence, Machine Learning and Deep Learning in the Era of Industry 4.0 - Smart Healthcare System Design - Wiley Online Library.” https://onlinelibrary.wiley.com/doi/abs/10.1002/9781119792253.ch12 (accessed Mar. 29, 2022).
[8] P. K. Tiwari, A. Kumar, S. S. Malladi, P. Nuney, and V. K. Verma, “Stock Market Prediction Techniques: A Systematic Review and Taxonomy,” *SPAST Abstracts*, vol. 1, no. 01, Art. no. 01, Oct. 2021, Accessed: Mar. 29, 2022. [Online]. Available: https://spast.org/techrep/article/view/2441
[9] “Stock Market Prediction Using RNN LSTM | IEEE Conference Publication | IEEE Xplore.” https://ieeexplore.ieee.org/abstract/document/9587540/ (accessed Mar. 29, 2022).
[10] I. K. Nti, A. F. Adekoya, and B. A. Weyori, “A systematic review of fundamental and technical analysis of stock market predictions,” *Artif Intell Rev*, vol. 53, no. 4, pp. 3007–3057, Apr. 2020, doi: 10.1007/s10462-019-09754-z.
[11] “Fundamental Analysis of Share Prices in Coal Mining Subsector Companies | Rahayu | Budapest International Research and Critics Institute (BIRCI-Journal): Humanities and Social Sciences.” https://www.bircu-journal.com/index.php/birci/article/view/2371 (accessed Mar. 29, 2022).
[12] R. Dash, P. K. Dash, and R. Bisoi, “A self adaptive differential harmony search based Optimized extreme learning machine for financial time series prediction,” *Swarm and Evolutionary Computation*, vol. 19, Aug. 2014, doi: 10.1016/j.swevo.2014.07.003.

[13] M. Ballings, D. Van den Poel, N. Hespeels, and R. Gryp, “Evaluating multiple classifiers for stock price direction prediction,” *Expert Systems with Applications*, vol. 42, no. 20, pp. 7046–7056, Nov. 2015, doi: 10.1016/j.eswa.2015.05.013.

[14] A. Jadhav, J. Kale, C. Rane, A. Datta, A. Deshpande, and D. D. Ambawade, “Forecasting FAANG Stocks using Hidden Markov Model,” in *2021 6th International Conference for Convergence in Technology (I2CT)*, Apr. 2021, pp. 1–4. doi: 10.1109/I2CT51068.2021.9418216.

[15] A. Verma, K. Maheshwari, S. Gupta, and A. Rana, *Stock Price Prediction using Hidden Markov Models and understanding the nature of underlying Hidden States*. 2021.

[16] “Stock market prediction using Hidden Markov Model | IEEE Conference Publication | IEEE Xplore.” https://ieeexplore.ieee.org/document/7065011 (accessed Mar. 29, 2022).

[17] Md. R. Hassan, “A combination of hidden Markov model and fuzzy model for stock market forecasting,” *Neurocomputing*, vol. 72, no. 16, pp. 3439–3446, Oct. 2009, doi: 10.1016/j.neucom.2008.09.029.

[18] E. K. Ampomah, G. Nyame, Z. Qin, P. C. Addo, E. O. Gyamfi, and M. Gyan, “Stock Market Prediction with Gaussian Naïve Bayes Machine Learning Algorithm,” *Informatica*, vol. 45, no. 2, Art. no. 2, Jun. 2021, doi: 10.31449/inf.v45i2.3407.

[19] Mehar Vijha , Deeksha Chandolab, Vinay Anand Tikkiwalb, Arun Kumar, Stock Closing Price Prediction using Machine Learning Techniques, International Conference on Computational Intelligence and Data Science (ICCIDS 2019)

[20] A. Kurani, P. Doshi, A. Vakharia, and M. Shah, “A Comprehensive Comparative Study of Artificial Neural Network (ANN) and Support Vector Machines (SVM) on Stock Forecasting,” *Ann. Data. Sci.*, Jun. 2021, doi: 10.1007/s40745-021-00344-x.

[21] “Machine Learning in Prediction of Stock Market Indicators Based on Historical Data and Data from Twitter Sentiment Analysis | IEEE Conference Publication | IEEE Xplore.” https://ieeexplore.ieee.org/document/6753954 (accessed Mar. 30, 2022).

[22] Saahil Madge, “Predicting Stock Price Direction using Support Vector Machines,” https://www.cs.princeton.edu/sites/default/files/uploads/saahil_madge.pdf

[23] S. R. Nanda, B. Mahanty, and M. K. Tiwari, “Clustering Indian stock market data for portfolio management,” *Expert Systems with Applications*, vol. 37, no. 12, pp. 8793–8798, Dec. 2010, doi: 10.1016/j.eswa.2010.06.026.

[24] “A hybrid fuzzy time series model based on granular computing for stock price forecasting - ScienceDirect.” https://www.sciencedirect.com/science/article/abs/pii/S0020025514009505 (accessed Mar. 30, 2022).

[25] M. Nabipour, P. Nayyeri, H. Jabani, A. Mosavi, E. Salwana, and S. S., “Deep Learning for Stock Market Prediction,” *Entropy (Basel)*, vol. 22, no. 8, p. 840, Jul. 2020, doi: 10.3390/e22080840.

[26] I. Parmar *et al.*, "Stock Market Prediction Using Machine Learning," in *2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC)*, Dec. 2018, pp. 574–576. doi: 10.1109/ICSCCC.2018.8703332.
[27] J. Tang and X. Chen, "Stock Market Prediction Based on Historic Prices and News Titles," in *Proceedings of the 2018 International Conference on Machine Learning Technologies*, New York, NY, USA, May 2018, pp. 29–34. doi: 10.1145/3231884.3231887.
[28] E. Hoseinzade and S. Haratizadeh, "CNNpred: CNN-based stock market prediction using a diverse set of variables," *Expert Systems with Applications*, vol. 129, pp. 273–285, Sep. 2019, doi: 10.1016/j.eswa.2019.03.029.
[29] P.Naveen , B Diwan, "STOCK MARKET PREDICTIONS USING NEURAL NETWORK MODEL," *Journal of Shanghai Jiaotong University*, Volume 16, Issue7, July. 2020
[30] X. Pang, Y. Zhou, P. Wang, W. Lin, and V. Chang, "Stock market prediction based on deep long short term memory neural network: 3rd International Conference on Complexity, Future Information Systems and Risk," *COMPLEXIS 2018 - Proceedings of the 3rd International Conference on Complexity, Future Information Systems and Risk*, pp. 102–108, Mar. 2018.
[31] Abin Shakya, Anuj Pokhrel, Ashuta Bhattarai, Pinky Sitikhu,Subarna Shakya, "Real-Time Stock Prediction using Neural Network," *International Research Journal of Engineering and Technology (IRJET) – IEEE*, 2018
[32] X.K. Xie, H. Wang, Recurrent neural network for forecasting stock market trend, in: Proceedings of International Conference on Computer Science, Technology and Application, 2017, pp. 397–402.
[33] A. Ghosh, S. Bose, G. Maji, N. Debnath, and S. Sen, "Stock Price Prediction Using LSTM on Indian Share Market," Sep. 2019. doi: 10.29007/qgcz.
[34] N. Unnithan, E. A. Gopalakrishnan, V. Menon, and S. Kp, "A Data-Driven Model Approach for DayWise Stock Prediction," 2019, pp. 149–158. doi: 10.1007/978-981-13-5802-9_14.
[35] W. Lu, J. Li, Y. Li, A. Sun, and J. Wang, "A CNN-LSTM-Based Model to Forecast Stock Prices," *Complexity*, vol. 2020, p. e6622927, Nov. 2020, doi: 10.1155/2020/6622927.
[36] J. Shen and M. O. Shafiq, "Short-term stock market price trend prediction using a comprehensive deep learning system," *Journal of Big Data*, vol. 7, no. 1, p. 66, Aug. 2020, doi: 10.1186/s40537-020-00333-6.
[37] J. Zhao, D. Zeng, S. Liang, H. Kang, and Q. Liu, "Prediction model for stock price trend based on recurrent neural network," *J Ambient Intell Human Comput*, vol. 12, no. 1, pp. 745–753, Jan. 2021, doi: 10.1007/s12652-020-02057-0.
[38] S. Selvin, V. Ravi, E. A. Gopalakrishnan, V. Menon, and S. Kp, "Stock price prediction using LSTM, RNN and CNN-sliding window model," Sep. 2017, pp. 1643–1647. doi: 10.1109/ICACCI.2017.8126078.

[39] D. P. Kuttichira, E. A. Gopalakrishnan, V. K. Menon, and K. P. Soman, "Stock price prediction using dynamic mode decomposition," in *2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, Sep. 2017, pp. 55–60. doi: 10.1109/ICACCI.2017.8125816.
[40] K. Bheemaiah, M. Esposito, and T. Tse, "What is machine learning?," *The Conversation*. http://theconversation.com/what-is-machine-learning-76759 (accessed Mar. 30, 2022).
[41] "Understanding LSTM Networks -- colah's blog." https://colah.github.io/posts/2015-08-Understanding-LSTMs/ (accessed Mar. 30, 2022).
[42] "A Comprehensive Guide to Convolutional Neural Networks — the ELI5 way | by Sumit Saha | Towards Data Science." https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53 (accessed Mar. 30, 2022).
[43] "Convolutional Neural Networks (CNN) with Deep Learning." https://www.happiestminds.com/insights/convolutional-neural-networks-cnns/ (accessed Mar. 30, 2022).
[44] J. Brownlee, "CNN Long Short-Term Memory Networks," *Machine Learning Mastery*, Aug. 20, 2017. https://machinelearningmastery.com/cnn-long-short-term-memory-networks/ (accessed Mar. 30, 2022).
[45] "Root Mean Square Error (RMSE) - C3 AI." https://c3.ai/glossary/data-science/root-mean-square-error-rmse/ (accessed Mar. 30, 2022).
[46] Stephanie, "Mean Absolute Percentage Error (MAPE)," *Statistics How To*, Apr. 25, 2021. https://www.statisticshowto.com/mean-absolute-percentage-error-mape/ (accessed Mar. 30, 2022).
[47] K. Yadav, M. Yadav, and S. Saini, "Stock Market Predictions Using FastRNN, CNN, and Bi-LSTM-Based Hybrid Model," in *Machine Vision and Augmented Intelligence—Theory and Applications*, Singapore, 2021, pp. 1–10. doi: 10.1007/978-981-16-5078-9_1.
[48] Q. Liu, Z. Tao, Y. Tse, and C. Wang, "Stock market prediction with deep learning: The case of China," *Finance Research Letters*, vol. 46, p. 102209, May 2022, doi: 10.1016/j.frl.2021.102209.
[49] D. S. A. Elminaam, A. E. Tanany, M. A. Salam, and M. A. E. Fattah, "CPSMP_ML: Closing price Prediction of Stock Market using Machine Learning Models," in *2022 2nd International Mobile, Intelligent, and Ubiquitous Computing Conference (MIUCC)*, May 2022, pp. 251–255. doi: 10.1109/MIUCC55081.2022.9781756.
[50] I. K. Nti, A. F. Adekoya, and B. A. Weyori, "A novel multi-source information-fusion predictive framework based on deep neural networks for accuracy enhancement in stock market prediction," *Journal of Big Data*, vol. 8, no. 1, p. 17, Jan. 2021, doi: 10.1186/s40537-020-00400-y.

[51] P. Mehta, S. Pandya, and K. Kotecha, "Harvesting social media sentiment analysis to enhance stock market prediction using deep learning," *PeerJ Comput. Sci.*, vol. 7, p. e476, Apr. 2021, doi: 10.7717/peerj-cs.476.
[52] H. Rezaei, H. Faaljou, and G. Mansourfar, "Stock price prediction using deep learning and frequency decomposition," *Expert Systems with Applications*, vol. 169, p. 114332, May 2021, doi: 10.1016/j.eswa.2020.114332.
[53] M. Ghahramani and H. E. Najafabadi, "Compatible deep neural network framework with financial time series data, including data preprocessor, neural network model and trading strategy." arXiv, May 11, 2022. doi: 10.48550/arXiv.2205.08382.
[54] K. Gajamannage and Y. Park, "Real-time Forecasting of Time Series in Financial Markets Using Sequentially Trained Many-to-one LSTMs." arXiv, May 10, 2022. doi: 10.48550/arXiv.2205.04678.
[55] Z. Shi, Y. Hu, G. Mo, and J. Wu, "Attention-based CNN-LSTM and XGBoost hybrid model for stock prediction." arXiv, Apr. 06, 2022. doi: 10.48550/arXiv.2204.02623.