ISSN: 2633-4828 Vol. 5 No. S6, (Oct - Dec 2023)

International Journal of Applied Engineering & Technology

PREDICTING DYNAMIC STOCK MARKETS WITH INTEGRATED CNN AND LSTM MODELS

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ABSTRACT

Knowing how to accurately forecast a stock's price helps in analysing market patterns and, more crucially, provides investors with crucial insight into what the future holds. Researchers are increasingly relying on past stock data and various financial variables to enhance prediction accuracy, thanks to the rapid rise of machine learning and data science. In contrast to all previous methods, this study presents a fresh, future-oriented strategy for the stock market. To venture a guess as to what the national stock exchange-listed companies' stock values might be, we'll employ CNN, LSTM, and a CNN-LSTM hybrid model. In order to visualise prediction models and capture vividly complicated market dynamics, the methodology places an emphasis on visual analytics and makes use of graphical tools like edge graphs and animated colour graphs. In order to provide stakeholders with a fresh, potent analytical framework for improved financial market decision-making, the study thoroughly describes such methods.

Keywords: *Predictive Analytics, Stock Market, LSTM, CNN, Hybrid LSTM-CNN, machine Learning*

1. INTRODUCTION

Stock price prediction is an important undertaking since the stock market offers investors the chance to make big gains [1]. Effective strategies to maximise returns while limiting risks are in high demand due to the increasing popularity of trading and investment activities. The two most important stock markets in India are the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE). Major indices like the Nifty and the Sensex attract a lot of trading activity on both exchanges [2]. The unpredictable nature of the market, however, makes accurate stock price forecasting difficult. In order to accurately anticipate future market patterns, a number of forecasting models have evolved. One of these is Time Series Analysis, which employs patterns and trends found in past data to predict future market changes [3]. Contrarily, Warren Buffett and other value investors rely on financial indicators like the Price-to-Earnings (P/E) ratio in their Fundamental Analysis[4] evaluations of stocks. Fundamental Analysis looks at the bigger picture, evaluating a company's financial health and market position, as opposed to Technical Analysis's short-term concentration on past price trends to forecast future moves.

2. LITERATURE REVIEW

Ongoing research in machine learning for stock price prediction, with a focus on Long Short-Term Memory (LSTM), aims to capture stock price variations over certain timeframes in order to estimate future stock prices. Because of its superior performance with sequential data, LSTM has quickly become a go-to method in this area. A machine learning strategy for predicting stock prices was suggested in a recent study[8], drawing attention to the significance of data normalisation. Yahoo! Finance provided the information, which included about 900,000 stock price records with details like date, symbol, open price, closing price, low price, high price, and volume. As part of the data preparation procedure, we used Python's Pandas data frame to import the CSV file, and then we normalised the data using the sklearn module. Next, we split the dataset in half, setting aside 20% for testing and the other half for training. Two architectural paradigms, LSTM and regression-based models, were investigated in the study. While LSTM is great at spotting changes in trends over time, regression-based models use linear functions to forecast continuous values. Findings demonstrated that LSTM was superior to competing models, demonstrating how well it can mine stock market data for previously unseen patterns. With the ever-changing stock market, LSTM's capacity to analyse real-time data and discover cycles and patterns gives investors a leg up in navigating market ups and downs and finding lucrative opportunities.

This paper[9] uses LSTM, SARIMA, and Facebook Prophet models, along with financial time series analysis and machine learning approaches, to predict Bitcoin price and volatility. With lower MSE and MAE, LSTM predicts Bitcoin prices better than SARIMA and Facebook Prophet. The study finds that legislation and social media have a big influence on Bitcoin's high volatility, and it also finds weekly and yearly trends that may be predicted. The results provide light on the impact of global market dynamics in the midst of geopolitical and pandemic-related events, as well as rules pertaining to cryptocurrencies, which is crucial information for managers and investors. Using machine learning methods such as SARIMA, Facebook Prophet, and LSTM, this paper[10] investigates how to forecast the price and volatility of Bitcoin. With lower MSE and MAE, LSTM outperforms SARIMA and Facebook Prophet in price prediction. Finding weekly and yearly sea-sonality patterns, the study emphasises how legislation and social media trends contribute to Bitcoin's high volatility. In light of geopolitical and pandemic factors, it sheds light on the regulation of cryptocurrencies, the developments of the worldwide market, and the consequences for fund managers and investors.

In order to forecast stock values in the halal tourism industry, this research[11] looks at how deep learning and natural language processing can be applied. Using text analysis as its foundation, it presents the World Halal Tourism Composite Sentiment Index (WHTCSI) and concludes that CNNs are the most effective model for predicting stock prices. The study highlights the importance of sentiment analysis for improving forecasting accuracy, shedding light on industry herding effects and illogical investing behaviours. This research will help analysts, investors, and portfolio managers better understand the halal tourism industry and make informed decisions.

In the ever-changing and intricate financial sector, this study[12] investigates LSTM networks as a potential tool for stock price prediction. Leveraging copious data for trend research, it tackles issues brought forth by economic conditions and world events. Across a range of forecasting tasks, the empirical results show that LSTM is more effective than traditional approaches, with a reduction in MAE of 23.4%. LSTM outperforms baseline models in financial markets, achieving an average forecast accuracy of 89.7 percent. Improving asset valuation through the analysis of past market data for more accurate price pattern prediction is the goal of the research.

To solve the problems of nonlinearity and nonstationarity in financial time series, this study[13] introduces a hybrid model that combines multi-input LSTM with Wavelet Transform (WT) to forecast SSE Composite Index movements. The model achieves a 72.19% accuracy rate by utilising WT for noise reduction and includes numerous data inputs, such as technical indicators, data from the Chinese and US stock markets, and more. By outperforming decision trees, random forests, Support Vector Machines (SVMs), and XGBoost models, it proves that WT + LSTM improves stock market forecasting.

The purpose of this research is to examine the feasibility of using three deep learning models—HMM, Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM)—to forecast the stock price of ICICI Bank [14]. In order to find hidden patterns in financial data, the study presents a model-independent method. LSTM outperforms HMM and RNN, achieving a lower error rate of 2.36% compared to 7.32% and 3.94%, respectively, making it the most effective model. In dynamic investment environments, LSTM has the capacity to accurately estimate stock prices by capturing shifting trends.

In order to enhance stock price prediction, this paper[15] presents the Time-series Recurrent Neural Network (TRNN) as a new tool for big data analysts to use in data pre-processing. The training efficiency of traditional models is a problem. This includes BP, RNN, and LSTM. In order to process time series data, TRNN incorporates sliding windows and trading volume. This allows it to extract market-specific patterns and inflection points. The two-dimensional RNN enhances the price-volume connection, making it more accurate and efficient. Potentially applicable in a variety of fields, including larger time-series compression, TRNN surpasses RNN and LSTM in terms of efficiency and accuracy, according to comparative studies.

In order to forecast changes in stock prices, this research[16] presents a hybrid information mixing module that combines stock and news data. This method uses multilayer perceptron models to examine how textual features and time-series pricing data interact with one another.The module's efficacy in predicting price variations in unpredictable stock markets is validated by evaluation measures such as Matthew's correlation coefficient (MCC), F1 score, and accuracy.

This compilation of research shows that LSTM works well in a variety of contexts by investigating several deep learning methods for predicting the values of Bitcoin and stock markets. In terms of accuracy and efficiency, LSTM models often surpass conventional methods as well as other deep learning approaches like as SARIMA, Facebook Prophet, and CNNs. Important for reliable stock price predictions, the research show that LSTM can grasp intricate market dynamics and temporal relationships in financial time series data. These results demonstrate the value of LSTM in unpredictable markets, providing information about investor actions, the effects of regulations, and worldwide economic tendencies; as a result, stakeholders in the cryptocurrency and financial industries may make better decisions.

3. PLANNED APPROACH

Getting a good read on how much stocks and other financial assets traded on the stock exchange will be worth in the future is the basic goal of stock market prediction. By doing so, they can optimise their investing plans for optimal returns and acquire the knowledge to make educated judgements, which could lead to substantial financial benefits. The ultimate goal of this endeavour is to predict the movement of stock values in several industries, including business, finance, and others. Accurate forecasts help stakeholders successfully traverse complicated markets, directing strategic decisions that boost profits and guarantee economic stability in the long run. Figure 1 shows the system's planned workflow, which includes five essential modules:

1. Dataset Input: Extracting essential properties like open, high, low, close, and adjusted close prices is the first step in using a complete dataset.
2. To guarantee data consistency and quality, the extracted characteristics go through stringent pre-processing procedures, such as normalisation and one-hot encoding.
3. Split the dataset in half lengthwise, with half going into training and half into testing. This 80:20 split is crucial for validating and training models.
4. Building and Training Models: Three different approaches are utilised to construct predictive models, utilising LSTM, CNN, and a Hybrid LSTM+CNN approach. Each methodology draws upon its own capabilities to identify underlying patterns in the data.
5. Finally, the system uses the trained models to provide anticipated outcomes, which are the fifth and final output. To ensure trustworthy insights for decision-making, evaluation metrics such as Root Mean Square Error (RMSE) are utilised to measure the correctness and efficacy of each module.

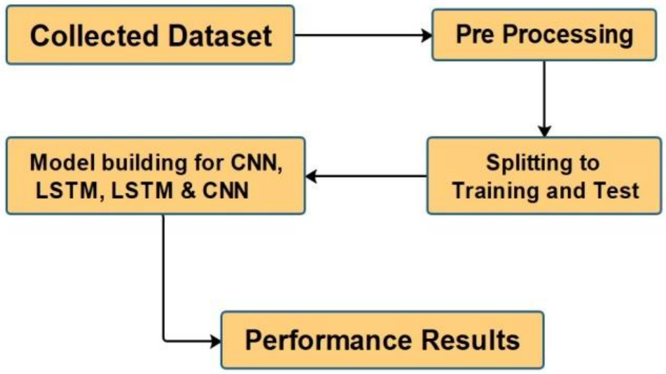

Fig1. Proposed Framework

When it comes to stock market forecasting, a systematic method is necessary to handle data comprehensively, construct models rigorously, and have precise prediction capabilities.

3.1 Functioning of LSTM Model

Long Short-Term Memory (LSTM) is a major improvement in recurrent neural networks (RNNs) [17]. In contrast to its forerunners, LSTM takes on the problem of dealing with the long-term dependencies that are intrinsic to sequential data. Traditional RNNs have a hard time remembering details over long periods of time, which makes it hard for them to make reliable predictions [18]. A contrast to this is LSTM's architecture, which allows it to accurately process, forecast, and categorise time-series data by capturing and using historical context. This figure 2 shows how the LSTM model works.

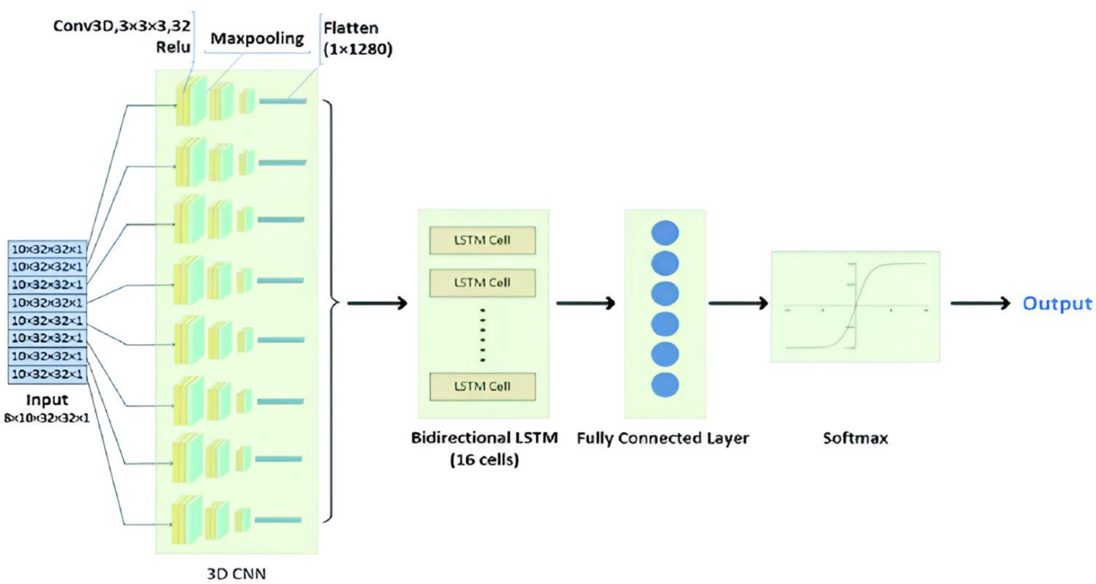

Fig 2. Architecture of LSTM

The memory structure of LSTM is an important part of the model. It consists of neural networks that are coupled to each other and specialised memory units called cells [19]. The memory cell is the brainstem of LSTM; it controls data storage and allows for RW&F processes. There are three primary gating mechanisms in an LSTM. The first, the input gate, regulates the insertion of new data into the memory cell. The second, the forget gate, determines which data to discard and which to retain. Lastly, the output gate, regulates the utilisation of stored data to produce the final output. The efficient processing of sequential data by LSTM is made possible by these parts working in tandem. Long Short-Term Memory's (LSTM) sturdy architecture and sophisticated gating mechanisms make it relevant across numerous disciplines [20]. Language modelling relies on it to generate coherent text sequences, and machine translation relies on it to facilitate correct translations between languages, among many other applications. Furthermore, LSTM plays a crucial role in both the development of meaningful captions for photographs and the generation of hand-writing by mimicking patterns seen in humans. Additionally, it improves chatbots that answer questions by giving smart answers depending on context. A must-have for sophisticated AI and ML applications, these features demonstrate LSTM's mastery of sequential data with nuanced understanding [21].

3.2 Functioning of CNN Model

The CNN (Convolutional Neural Network) model functions through a sequence of specialized layers designed to extract and process significant features from input data, making it particularly effective for tasks such as image analysis and pattern recognition.[22]. The operation of the CNN model is illustrated in this figure 3.

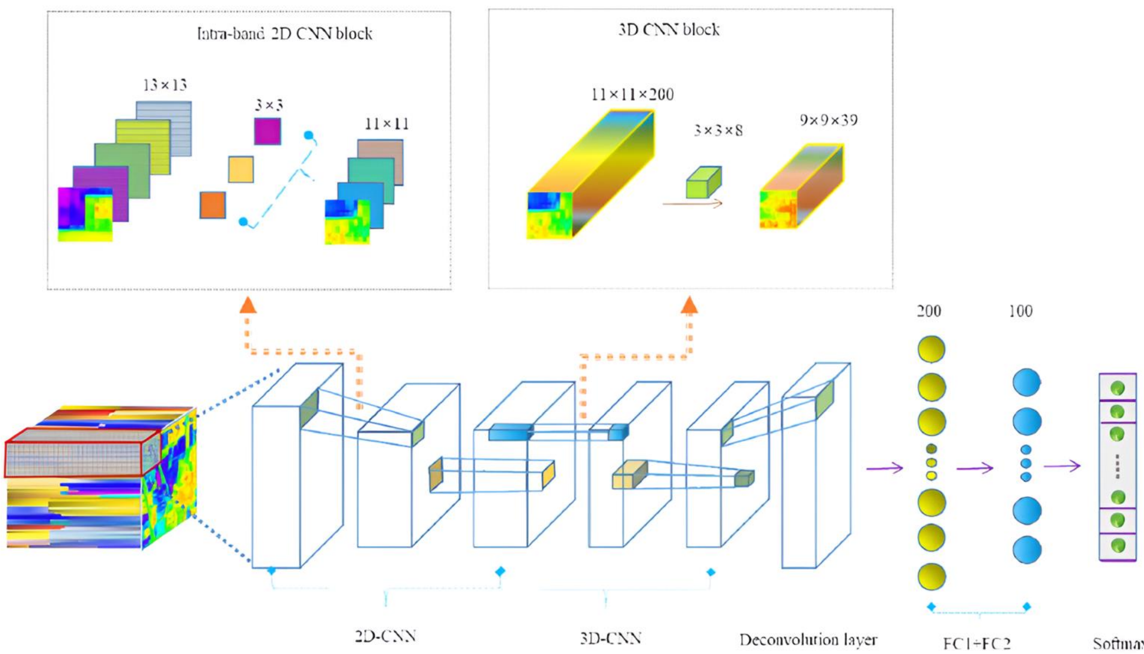

Fig 3. Architecture of the CNN

A CNN model relies on a number of essential procedures to function. To begin feature extraction, convolution convolves filters over input data, resulting in a feature extraction matrix [23]. By finding the highest values inside feature map segments, MAX pooling can reduce dimensionality and consolidate important information. By inadvertently turning off neurones during training, dropout improves generalisability, prevents overfitting, and boosts robust model performance. As a prerequisite for fully connected layers, the flatten layer reduces the multidimensional output of earlier layers to a flat vector. Dense (completely connected) layers use weights to synthesise complicated features by establishing connections between each neurone in successive levels. Lastly, activation functions, such as sigmoid, transform raw outputs into practical predictions, usually shown as probabilities ranging from 0 to 1. Facial recognition and document analysis are two examples of CNN's practical uses[24]. Facial recognition uses CNN to identify and verify people based on facial traits, while document analysis uses CNN to extract and process information for categorisation from textual and graphic content. The CNN is crucial in many areas of computer vision and artificial intelligence due to its hierarchical structure and specialised layers, which enable it to perform very well on complicated tasks requiring sophisticated feature extraction and pattern identification.

3.3 Hybrid LSTM + CNN Approach

Hybrid Long Short-Term Memory (LSTM) + Convolutional Neural Networks (CNN) methods greatly improve prediction accuracy by combining the powerful features of both types of networks [25]. This method captures intricate patterns in sequential data and efficiently manages complex datasets by combining the strengths of the two models. The hybrid model relies on a number of essential procedures to function. To begin, convolutional neural networks (CNNs) are vital for jobs in computer vision and natural language processing because they extract crucial characteristics from input layers using complex filters. After these filters iterate over the input matrix to produce a variety of feature maps, max-pooling layers pick out the most important data and refine them. After that, LSTM networks are fed the output of the CNN's max-pooling layer, which allows for the examination of long-term dependencies in sequential data. Long short-term memories (LSTMs) are great at catching temporal dynamics because they process data from previous layers to improve their grasp of sequential patterns and because they remember past knowledge through specialised memory cells. Last but not least, fully connected layers compute complex input-output interactions by combining the LSTM layers' outputs into a single matrix. This makes it easier to use the sigmoid function in the last classification step, which optimises the model's performance in classification tasks by converting the data into predictions between 0 and 1.By combining the strengths of both LSTMs and CNNs, the hybrid LSTM + CNN method achieves better prediction accuracy in many different domains, including healthcare, autonomous systems, and the financial sector [26]. Together, CNNs and LSTMs improve the model's performance by extracting complex features and capturing temporal dependencies. Applications requiring accurate sequential learning and strong feature extraction capabilities can be empowered by this hybrid technique, which is a state-of-the-art predictive modelling solution.

4. DATASET OVERVIEW

The National Stock Exchange (NSE) is the primary source of the dataset's vast historical stock data, which covers a wide variety of industries vital to the global financial system. Included in these records are crucial indicators including trade volume, adjusted closing price, opening price, lowest price, and closing price for the day.

Table 1: Details of the Dataset

Sector	Stock Name
Software	Infosys
Banking	HDFC Bank
Pharma	Cipla
Petroleum	ONGC

Table 1 gives a high-level overview of the dataset, showing which industries are included and which stocks are part of each industry. In order to analyse and comprehend the scope and depth of the dataset, it is used as a basic reference.

4.1 Technological Framework

Using Python's strengths across multiple important aspects, this study establishes Python as the basic tool. First, it has a strong community behind it, which means that problems can be solved quickly and knowledge can be shared easily. This is shown on sites like Stack Overflow. Researchers are equipped with robust tools for efficiently performing sophisticated numerical computations and data manipulations with Python's suite of advanced scientific computing modules, which includes NumPy, Pandas, and SciPy. Its user-friendly syntax makes it simple to put theoretical ideas into practice, which speeds up development and prototyping in many different fields. Careful consideration while implementation is required because Python's dynamic typing could cause unexpected behaviours with some packages. Regardless of these details, Python is still a go-to because of its clarity, flexibility, and the many libraries available for use within it, such as Scikit-learn for machine learning, TensorFlow for scalable computation, and Keras for quick neural network prototyping. With the help of environments like Jupyter Notebook for collaborative data exploration and analysis and Anaconda for simplified package management, these technologies propel innovation in data science and machine learning..

4.2 Results Overview

In order to begin analysing stock market data, we looked at historical records from different sectors. We missed certain important indicators such starting and closing prices, highs and lows, adjusted close values, and trade volumes (Table 4). After thoroughly exploring the dataset, crucial information was carefully consumed and prepared for additional research, yielding a wealth of 4,274 data points per organisation, as shown in Table 5.

```
<class 'pandas. core. frame. DataFrame'>
RangeIndex: 2020 entries, 0 to 2019
Data columns     2020   non-null object
Date             2014   non-null float64
Open             2014   non-null float64
High             2014   non-null float64
Low              2014   non-null float64
Close            2014   non-null float64
adj_close             2014   non-null float64
dtypes:  float64(6), object (1)
memory usage: 109.9+ KB
```

Fig 4. Overview of Insights from Stock Dataset

	Date	Open	High	Low	close	adj_close	volume
0	23-04-2023	64.099988	67.849988	64.099998	65.250000	65.250000	3945.0
1	24-04-2023	63.099998	67.099998	64.099998	66.849998	66.849998	4195.0
2	25-04-2023	64.099998	68.000000	64.099998	66.199997	66.199997	3874.0
3	28-04-2023	62.299999	68.949997	62.299999	66.750000	66.750000	6522.0
4	29-04-2023	63.049999	67.849998	63.049999	66.750000	66.750000	2678.0

Fig 5. Dataset Ingestion and Initial Examination

The changing patterns in closing prices over time were brought to light by visual representations, which offered a clear picture of the market's dynamics (Figure 6).

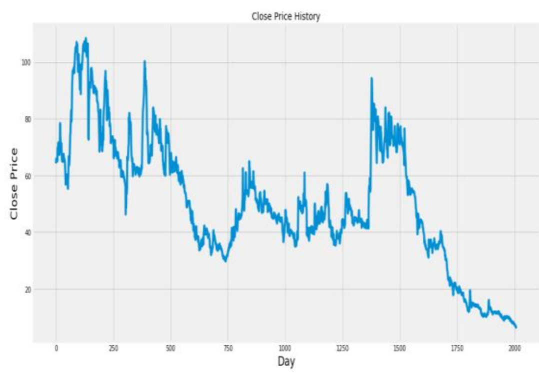

Fig 6. Historical Trends in Close Prices

```
array ([[0.56722278],
        [0.58292443],
        [0.57654561],
        ...,
        [0.00147203],
        [0.        ],
        [0.00294406]])
```

Fig 7. Data Scaling Analysis

As shown in Figure 7, the dataset was refined using techniques including normalisation with the Min-Max Scaler after subsequent data pre-processing procedures minimised noise and assured homogeneity. Figure 8 shows the results of dividing the dataset into a training set and a testing set after preparation. The training set received 80% of the dataset, while the testing set received 20%. Extensive research was conducted to identify the best architectures for model development and training. Various approaches were considered, including convolutional neural networks (CNN), long short-term memory (LSTM), and a hybrid LSTM + CNN method .To make sure the model was robustly developed, we kept a tight watch on the training progress, making sure to validate and batch process well. The next step was to create and analyse forecasted closure prices for various sectors and stock names. Along with this, insightful RMSE assessments were conducted to measure the accuracy and effectiveness of the model (Figure 8).

	close	predictions
1620	277.399994	288.1493353
1621	276.950012	285.368256
1622	277.600006	284.209137
1623	279.399994	284.209137
1624	277.100006	286.001678
1625	272.799988	283.681885
1626	272.750000	280.047577
1627	270.799988	278.311981
1628	268.600006	279.174744
1629	268.549988	277.969299
1630	272.299988	274.473358
1631	275.250000	277.308990
1632	274.899994	279.147766
1633	264.49994	280.531006
1634	258.850006	271.17551
1635	263.549988	266.927856
1636	267.549988	270.736115

	close	predictions
2001	408.000000	402.654297
2002	405.399994	411.530182
2003	395.500000	413.619385
2004	397.500000	404.025146
2005	402.100006	405.862488
2006	396.399994	410.270325
2007	408.200012	407.446960
2008	408.500000	413.991180
2009	396.549988	416.177673
2010	402.799988	409.181976
2012	402.299988	411.930969
2013	387.500000	412.304718
2014	383.200012	403.517517
2015	382.200012	396.869690
2016	386.100006	396.898712
2017	377.299988	399.567047
2018	381.399994	390.333130
2019	383.000000	391.759949

Fig 8. Predicted Close Price

The models' predictive potential is illustrated by visualisations of the expected results, which offer practical insights into market behaviour and investment strategies (Figure 9-23). In Table 2 you can see all the sectors' accuracy details.

Table 2: Accuracy Summary

Industry Classification	Stock Identifier	RMSE (LSTM)	RMSE (CNN)	RMSE (LSTM+CNN)
Banking	HDFC Bank	23.5309	9.1599	10.1597
Pharma	Cipla	20.4290	17.2115	17.0616
Petroleum	ONGC	6.4296	7.6578	5.6235
Software	Infosys	5.7052	4.7176	2.0623
Textiles	Vardmn Ploy	2.3809	3.5974	3.2952

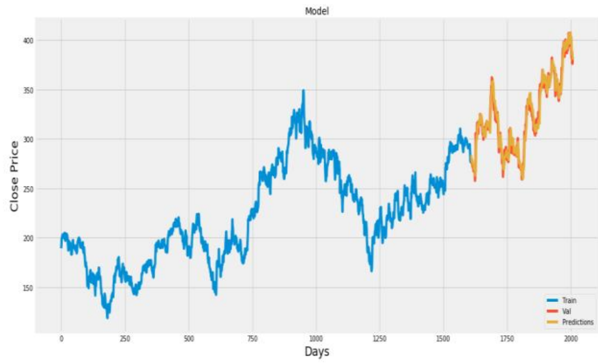

Fig9. Plot of HDFC Bank's Actual and Predicted Values Using LSTM + CNN

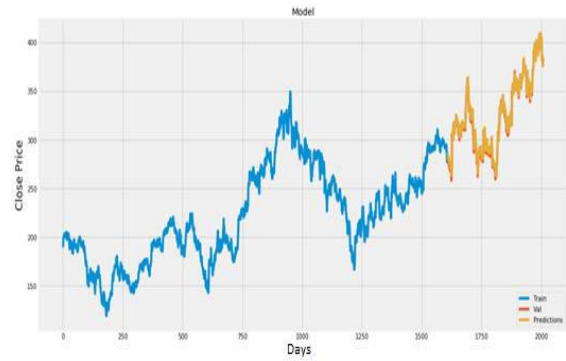

Fig10. LSTM + CNN Plot of Cipla's Actual vs. Predicted Values

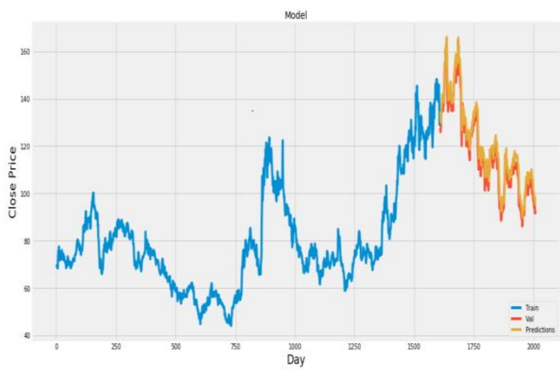

Fig11. Plotting ONGC's Actual vs. Predicted Values using LSTM + CNN

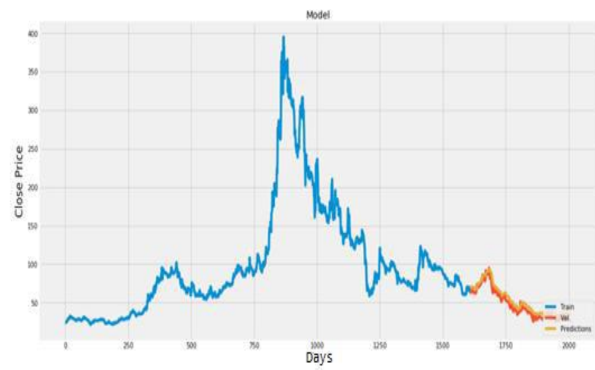

Fig12. Plot of Infosys Actual vs. Predicted Values Using CNN + LSTM

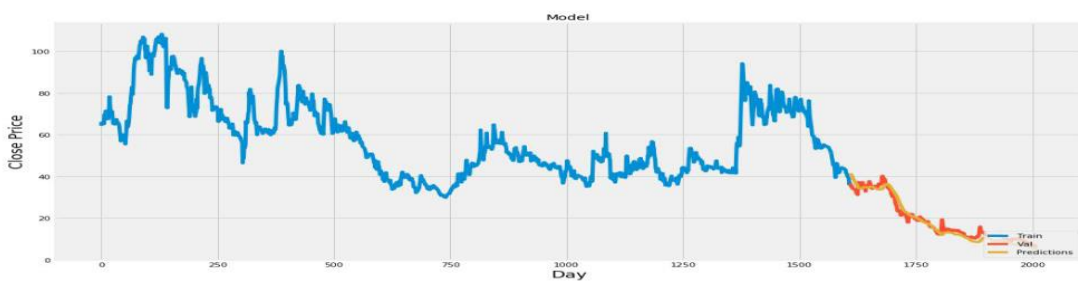

Fig13. Plot of Vardhman Polytex's Actual vs. Predicted Values Using LSTM + CNN

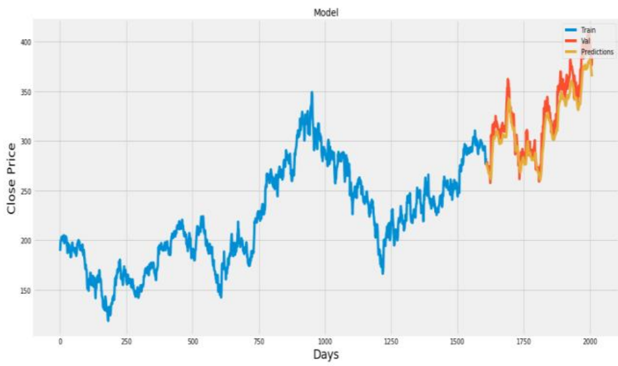

Fig14. Plot of HDFC Bank's Actual and Predicted Values Using LSTM

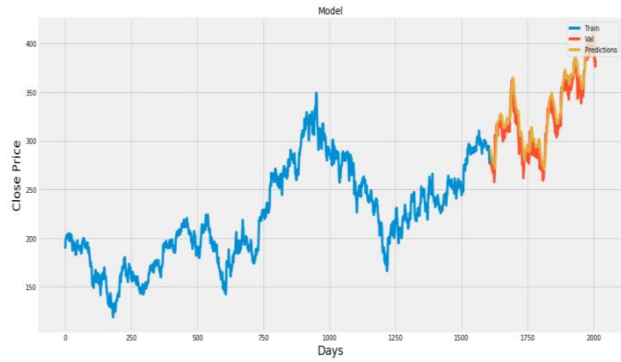

Fig15. Plot of Cipla's Actual and Predicted Values Using LSTM

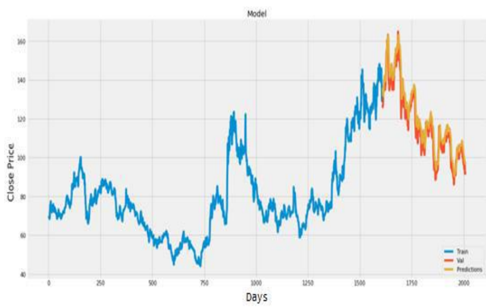

Fig16. Plotting Actual vs. Forecasted ONGC Values using LSTM

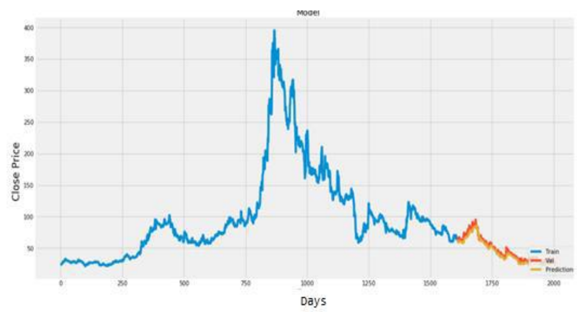

Fig17. Plot of Infosys's Actual and Predicted Values Using LSTM

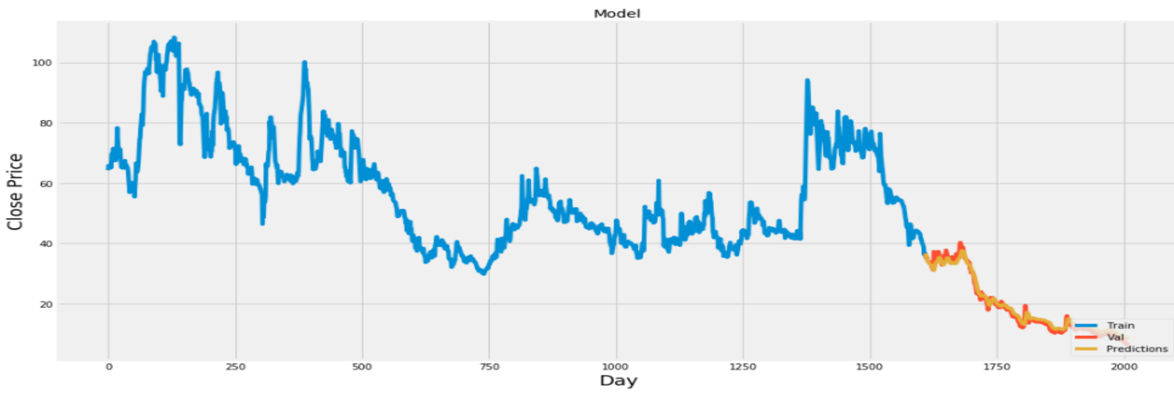

Fig18. Plot of Vardhman Polytex's Actual vs. Predicted Values Using LSTM

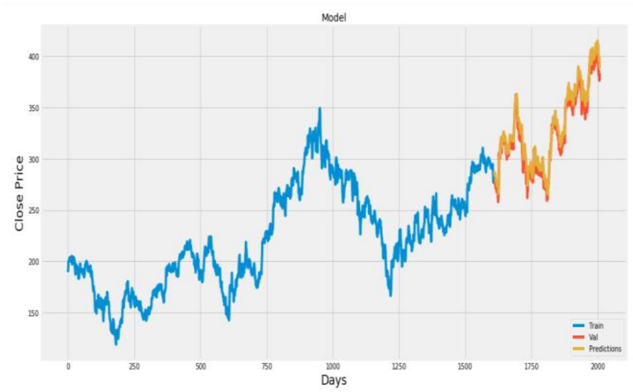

Fig19. CNN Plot of HDFC Bank's Actual vs. Predicted Values

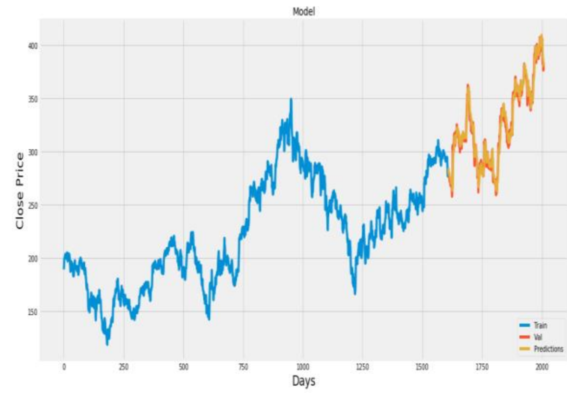

Fig20. CNN Plot of Cipla's Actual vs. Predicted Values

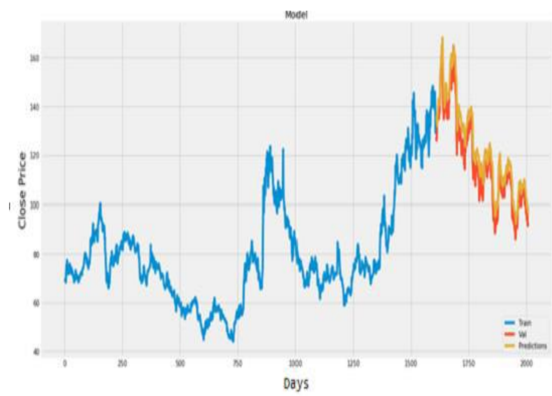

Fig21. CNN Plot of ONGC's Actual vs. Predicted Values

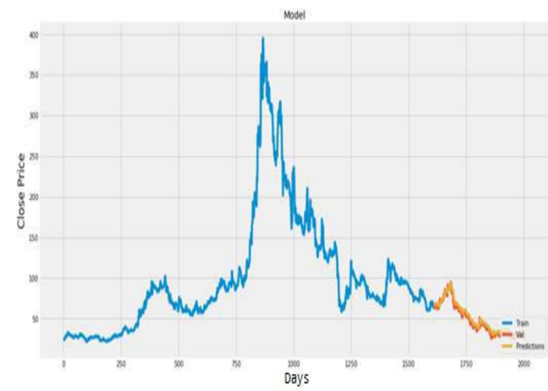

Fig22. Plot of Infosys's Actual and Predicted Values Using CNN

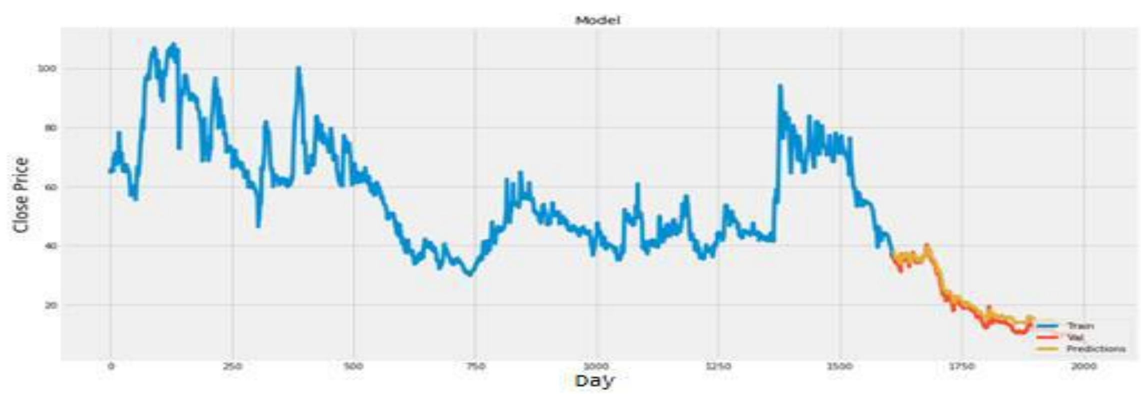

Fig 23. CNN Plot of Vardhman Polytex's Actual vs. Predicted Values

5. CONCLUSION AND PROSPECTIVE DEVELOPMENTS

Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and a hybrid LSTM-CNN technique were employed in this study to predict future stock values based on data from NSE-listed businesses. Our results show that our method successfully extracts important variables from the dataset. The ability to integrate inputs efficiently allowed the hybrid LSTM-CNN model to outperform LSTM and CNN alone in capturing market dynamics. When it came to handling the fast and irregular changes that are endemic to the stock market—which differ greatly across sectors—the hybrid architecture was more effective than the conventional LSTM and CNN models. If in-vestors want to optimise their investing strategy and successfully handle market volatility, they must understand these subtleties. More advanced models with better forecasting skills could be developed in the future by enriching training datasets and investigating alternative algorithms in addition to our hybrid approach.

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