Survey on AI-Powered Simulations to Elevate Financial Literacy in Real-Time

Jakkula Sneha[1], Ponkam Chandrasekhar[2], Ponneri Muthupriya[3], Shaik Hussain Basha[4], Duvvuru Nishwanth[5]
IV B. Tech Dept of CSE, Gokula Krishna College of Engineering, Sullurpet, AP, India.

***Abstract*—This research explores the application of advanced machine learning techniques, particularly deep learning, to improve stock market prediction accuracy. The studies investigate novel models, including stock sequence array convolutional neural networks (CNNs), long short-term memory (LSTM) networks, recurrent neural networks (RNNs), and deep reinforcement learning (DRL), for analyzing financial time series data and forecasting price trends. These models aim to capture complex, non-linear market patterns that traditional statistical methods often fail to recognize. The research emphasizes the importance of feature extraction, turning point identification, and hyperparameter optimization in achieving accurate predictions. Results demonstrate promising performance, with some models reporting prediction accuracies exceeding 99%. The studies highlight the potential of these AI-driven approaches to provide investors with more reliable forecasts, ultimately aiding in informed trading decisions and risk management. Furthermore, the use of both historical and leading indicator data is explored to enhance the model's predictive capabilities.**

***Keywords*—Artificial Intelligence, Stock Market Analysis, Stock Prediction , CNN, Deep Neural Networks, Reinforcement Learning, Machine Learning, Investment guide.**

INTRODUCTION

Financial literacy encompasses the ability to understand and effectively use various financial skills, including personal financial management, budgeting, and investing. A lack of financial literacy can lead to poor financial decisions, increased vulnerability to financial fraud, and reduced participation in wealth-building activities.

The rapid pace of change in financial markets, driven by technological advancements and globalization, presents a challenge for individuals seeking to maintain financial literacy. Real-time information and analysis are becoming increasingly important for making informed financial decisions.

Accurate stock market prediction is of significant interest to investors, traders, and financial institutions. However, the dynamic and noisy nature of the stock market, influenced by various economic, political, and social factors, makes it difficult to forecast its behavior Machine learning (ML) and deep learning (DL) techniques have emerged as powerful tools for analyzing complex datasets and identifying patterns that may be useful for prediction. These techniques offer the potential to improve the accuracy and reliability of stock market forecasts, ultimately aiding in investment decision-making. This survey paper provides an overview of recent research on stock market prediction using ML and DL. It explores the different types of models, data sources, and evaluation metrics employed in this field. The paper also discusses the challenges and future directions of research in this area.

The unpredictable nature of financial markets stems from various factors, including economic policies, geopolitical events, company-specific news, investor sentiment, and even social media trends. Traditional economic models often fail to account for these dynamic influences, leading to inaccurate predictions. To overcome these challenges, researchers have explored hybrid models that integrate multiple deep learning techniques. A particularly promising approach involves combining LSTM with CNN to leverage both temporal and spatial data patterns. This hybrid model focuses on identifying key market trends rather than just daily fluctuations, allowing for more robust decision-making. In addition, reinforcement learning (RL) techniques, particularly deep reinforcement learning (DRL), have been applied to stock market prediction by modeling the market as an environment where an AI agent interacts, learns from market conditions, and optimizes trading strategies. DRL has demonstrated success in other domains such as robotics, autonomous driving, and gaming, and its application in finance has the potential to improve market predictions and automate trading strategies effectively.

Despite advancements in AI-driven stock market forecasting, significant challenges remain, including the need for high-quality data, the risk of overfitting, and the difficulty of generalizing models across different financial conditions. Market fluctuations are not always governed by fixed patterns, making it difficult to achieve consistently high prediction accuracy. However, by integrating deep learning and reinforcement learning, researchers aim to develop models that can adapt to ever-changing market conditions. The objective of this research is to propose an AI-based LSTM-CNN model that enhances stock market prediction accuracy, enabling investors to make informed decisions. By analyzing crucial trading signals such as the golden cross, death cross, and market sentiment indicators, this approach seeks to maximize investment returns while minimizing risk. The integration of big data, AI, and hybrid deep learning techniques represents a significant step forward in financial market analysis, providing a more systematic and data-driven approach to stock price forecasting.

LITERATURE REVIEW

Literature survey which is related to the work adopted in this investigation is presented in this chapter.

Ran et al. introduced a clustering model for the generation of time series and was able to aid in the prediction of futures value for an indicated time series. Chen et al. proposed an optimization algorithm that focused on a few evolutionary based algorithms and models [4]. Selection as well as feature extraction are crucial in forecasting stock prices. ML (machine learning) and traditional statistical methods have often been used for financial sequence modelling as well as for prediction of stock prices.

Raghav Nandakumar, Uttamraj K. R, Vishal R, and Y. V. Lokeswari (2018) , explores the application of Long Short-Term Memory (LSTM) networks for stock price prediction. LSTM, a type of recurrent neural network (RNN), to capture the temporal dependencies in stock market data. It acknowledges that stock prices are influenced by various factors, making accurate prediction challenging.

Mathanprasad L and Gunasekaran have discussed about The study concentrates on estimating stock prices using regression and machine learning methods based on LSTM [11].

Roy, S. study employs the Auto-ARIMA and Holt-Winters models to forecast future stock prices. Additionally, linear programming is utilized for portfolio optimization. By constantly training the model with upto-date market data, it becomes capable of capturing the latest market trends, making it applicable to a wider range of portfolios in the future. The obtained trend analysis can aid in predicting better investment strategies in the stock market, enabling investors to make optimal decisions based on current market analysis. This approach aims to maximize returns and minimize losses, ultimately helping investors make informed investment choices.

Zahera, S. A., & Bansal, R. have discussed about The study of financial markets previously dominated a new era of understanding human emotions, behaviours, and attitudes . Additionally, this field is gaining interest from a variety of corporate entities, as well as financial intermediaries which increases its significance.

METHODOLOGY

Jimmy Ming-Tai Wu, Gautam Srivastava, Jaroslav Frnda, have discussed about Firstly, there are many historical data sources (historical price, futures)that can be used for stocks and used to create an input image for our model. Second, we make use of a function for normalization that we introduce here in this paper for the modification of the input data.

This normalization function that is used can make the designed approach to have a closer focusing on trend analysis (prices) instead of or in place of the actual values.

A. Datasets Preparation

Prior to any stock forecasts, we can define an index sequence $y1, y2, ..., yt$ which is generated and also set as input. This index sequence may include historical data of both prices as well as futures (leading index) of the stocks used. In our experimental analysis, TSM (Taiwanese stock market) stocks were used and was the focus of this paper. However, the methodology may just as easily be tested and used on other stock markets including but not limited to the New York Stock Exchange (NYSE) and National Association of Securities Dealers Automated Quotations

(NASDAQ). Any stock that has a leading indicator that may be used in economics to help assist the future economic development of the parties involved. Analysts of the stock market analysts use such indicators to predict future economic directions and these indicators may also have an influence on exchange rates. In those paper, the index as well as stock prices are defined as the characteristics of every sample. Five stocks from theTSM in Taiwan are used. The stock's attributes will include historical data as well as the attributes of the stock's futures.

B. Normalization

For proper training of the DL network, all input values are normalized in the developed methodology. We limit the pre-processed data into a specific range that can be used to remove any adverse effects that may be caused by singular data. If normalization does not occur then the difference between values of different features within the feature vector leads to a "flat"objective function.Training data may in actuality have a large range in prices inside test data. Hence, if we normalize input values we can make sure price's trend of stock data. Equation gives the function used for normalization.

$$X^{\cdot}\ t = \frac{Xt - mean}{max - min}$$

where Xt is defined as the indexes vector for time t (*open*, *high*, *low*, *close*...), $X^{\cdot}\ t$ is defined as the indexes vector after normalization. The *max*, *min* and *meam* are maximal value, minimum value and average value, maximal value and minimal value of the indexes vector in a certain period, respectively. Through the experimental analysis, data is always collected using days set to 120 for establishing the input array. Based on Equation (1), the mean of the property is taken for 120 days and from that the normalized value is 0.390278 as calculated.

Stock Indexes and The Input Image

Futures can be treated the same as stocks, and the actual sale is not for a real product, however it is treated as a fixed contract for future transactions. Getting involved in what is called two-way trading is also a good way to make money even if the overall situations in the market are not favourable. In actuality, it is very different from the spot, which can be viewed as a tangible tradable commodity. Futures are usually not regarded as a commodity, however a standardized tradable contract which is based on popular items such as soybeans, cotton, oil, and financial assets(bonds, stocks) are available. Hence, we can also implement our model on commodities (such as crude oil, gold, and products, etc). The usual attributes that are included in futures are *open position, volume, opening price, highest price, basis, lowest price, settlement price, price, ups, downs.*

y								
244.5	248.5	250.5	245.5	248	240	...	228	227.5
246.5	252	251	246.5	248	241	...	235.5	234
243	248.5	243	241	242	232.5	...	227	226.5
246.5	250	245	246	242	234.5	...	234.5	231
6198	5082	2853	4459	5522	9433	...	5491	4338
1	2	3	4	5	6	...	29	30 X

Fig. 3.1: An example of the input image.

In this work, we produce input images by collecting index vectors for 30 days of stock data. In Fig. 1, we give an example of this. In this research direction, an image is created using textual data tha yt can be treated as an input vector. From which, a predicted value will be created in our designed model. Through the experiments, the width of a sliding window is pre-defined set to 30 days in sequences of known stock indexes. Each and every window can be used in the generation of an input image and then moved on to the next window by simply shifting a singular date, and then establishing the (next) following image. Lastly, the method can be used to get the sequence of input images. Let us define that sequence as being expressed as y1, y2,...,yt. 2 adjacent images will indicate clearly that the 2 adjacent images' sliding windows are placed in different directions by 1 day.

Advanced Optimization Framework of the Developed Model: Since there is clearly various factors that can influence stock markets, it is extremely hard to find trading signals. Up to now, a conventional approach is used to establish trading signals with important indicators using trading strategies as demonstrated in. With the development of DL neural networks as well as (CNN) convolutional neural network have both become powerful tools in stock market analysis as was. Using CNN, our algorithm as designed primarily transforms data into an image using a CNN (convolutional neural network)

Other than using the concept of pooling, this work also makes use of other techniques such as *dropout* and *norm*. Since dropout is used for the avoidance of what is called "too deep" learning, in training phase, we only need to sample parameters randomly in the weight layer according to some certain probability *p*. We also take this sub-network as a target network for the updating process. Therefore, if the entire network contains *n* parameters, then and only then should the number of available sub-networks be calculated to be 2*n*. Furthermore, if *n* is deemed to be large, the sub-networks that are used for each and every iterative update should not be implemented repetitively. This allows the model to avoid unnecessarily fitting a certain network into the training set.The "norm" layer can be used to standardize the local input area to achieve the "side suppression" effect. Furthermore, our designed approach can transfer the stock index values within a period to an image sequence. These transferred images would then be used as CNN technique input images. Therefore, the input data can be referred to as the indexes vector for stocks in thirty days × the variables for each day. Then, the resulting data can be considered as the "input image" in the convolutional layer; pool layer, dropout layer, as well as the norm layer that will initially loop this sequence 3×.

We note here that the convolutional layer, the pool layer, the dropout layer, as well as the norm layer can be considered as a unique disjoint "layer" in our developed model. While focusing on our experimental analysis, when the CNN is used for image recognition, we notice that the best results are obtained where the size of the convolutional kernel is set to 3 × 3. Similarly, the size of pooling layer should be set to 2 × 2. Hence, to achieve highest Accuracy, we use a convolution kernel size and pooling layer set to 3 × 3, and2 × 2, respectively. Lastly, for input in the full connection layer as well as in the last full connection layer, we add in the softmax function. Here, the probability for each output can be analyzed with the softmax function and then set as a label for input images.

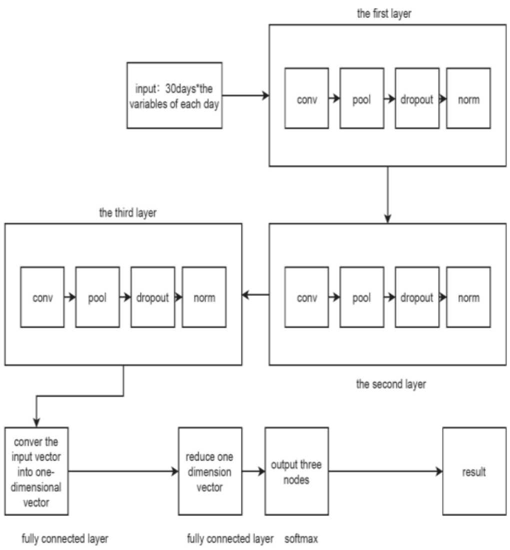

Fig. 3.2: The designed framework for stock trading prediction.

Mingze Shi, Qiangfu Zhao, have discussed about-

A. Strategy and Turing point

100 percent accuracy prediction of stock price change is impossible. If a program can predict the stock price change with 100 percent accuracy, it means that the program as an investor will always be the winner. Therefore, to make this kind of program the starting point of the research should be game theory. The winner should be familiar with every other player and have the absolute winning strategy. The purpose of this research is not to make a 100 percent correct prediction in the future but to analyze the trend of stock price change. Comparing with the traditional prediction of how many percent the stock price will change in the next several days, The targets in this research are turning points that have a period of over 2 weeks.

B. Golden cross and Death cross

This research mainly concentrates on 2 elements that influence stock price change. The first one is the normal law of price change in the stock market which will be simplistically treated as golden crosses and death crosses. The second one is independent events such as Top News. Those events are single points and have strong influences on short-time stock price changes.

Fig. 3.3: Turing point

Fig. 3.4: Golden cross and death cross

The golden cross as a bullish signal is the point where the short-term moving average just crosses above the longterm moving average. The death cross as an indicator of the potential major selloff is the point where the short-term moving average just crosses below the long-term moving average.

Sahith Addagalla, Surya Koppuravuri, Rithvik Krosuri, Mohan Sai Kunapareddy, have discussed about

A. The Proposed Work's main attributes

The data collection process will be carried out initially through Web-based API-Quandl, which supplies many sources of stock data from multiple sources. The facts of the feature extraction data Using Web worker techniques, previously extracted stock market data is transformed into information needed for machine learning categorization techniques. Then, using historical data, the peak start, peak end, and The typical fluctuation of stock price changes are classified using machine learning methods. Using machine learning classification approaches like The accuracy, sensitivity, and specificity of the recommended algorithms, Random Forest, Support Vector Machine, and Neural Network, were compared. Long Short-Term Memory uses Constant error carousels(CECs),CECs are linear storage units that can be used to store data endlessly. Cells with a number of multiplicative units (gates)attached to them contain CECs. Other cells that control the CEC's activation's decay or "forgetting"(forget gate) include input gates that control when fresh information enters the CEC and output gates that control when the CEC's activation is sent to the rest of the network.

B. User Interface

WebSocket is a protocol that enables bidirectional communication between a client (such as a web browser)and a server over the web. It is designed to provide a persistent, low-latency connection for real-time communication and is widely used in applications such as online gaming, chat, and financial trading.

WebSocket is often used in conjunction with other technologies, such as HTTP, to provide a rich, interactive user experience in web apps.

Django [21] is a open-source web framework in Python. It is designed to help developers build and deploy web applications quickly and efficiently. Some key features of Django include:

MVC [21] (Model-View-Controller) architecture: Django follows the MVC architectural pattern, which separates the application logic, data, and presentation layers into distinct components. This makes it easier to develop and maintain complex web applications.

ORM (Object-Relational Mapping): Django includes an ORM (Object-Relational Mapping) layer that allows developers to interact with a database using Python objects rather than raw SQL queries. This simplifies the process of working with databases and reduces the risk of injection attacks.

Templating [21] : Django provides a powerful templating system that allows developers to define the structure of a webpage and populate it with data from the application. This makes it easy to create consistent, dynamic web pages without having to write a lot of boilerplate code.

Security: Django includes several security features out of the box, such as cross-site request forgery (CSRF)protection and clickjacking prevention. This helps to reduce the risk of common web vulnerabilities in Django based applications.

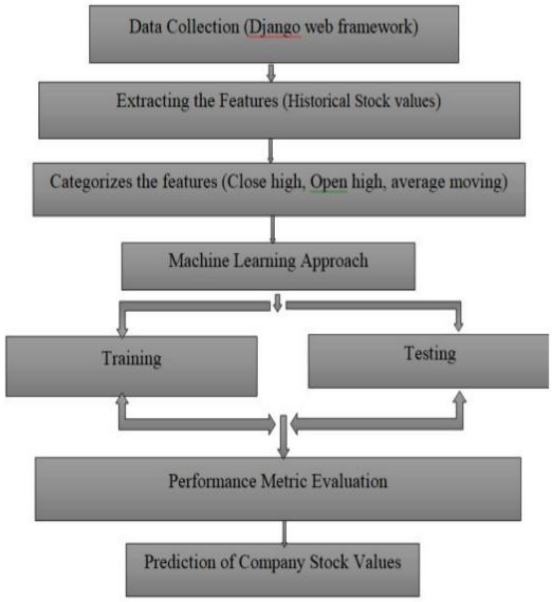

Fig. 3.5: Architecture Method

Scalability [21] : Django is designed to be scalable and can handle high traffic sites. It includes support for caching ,load balancing, and other performance optimization techniques to help developers build high performance web applications. Django is widely used to build a variety of web applications, including content management systems, social media platforms, and e-commerce sites. It is known for its simplicity, reliability, and flexibility, making it a popular choice among developers.

Django is widely used to build a variety of web applications, including content management systems, social media platforms, and e-commerce sites. It is known for its simplicity, reliability, and flexibility, making it a popular choice among developers.

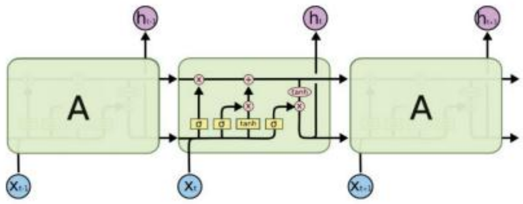

Fig. 3.6: Long Short Term Memory

Razib Hayat Khan, Jonayet Miah, Md Minhazur Rahman, Md Maruf Hasan, Muntasir Mamun, have discussed about

In reinforcement learning, an agent gathers data from its surroundings and modifies its behavior in response to the environment's state. Each action has an impact on the environment and alters the overall reward points, and the agent chooses actions depending on connected rewards. The new status is instantly considered when updating rewards and punishments for activities. The agent and environment continue to interact until the agent discovers a decision-making method that maximizes total return. Rewards and environment are two of the four crucial elements that influence reinforcement learning, according to Sutton and Barto. Policies in reinforcement learning are like self-imposed rules that guide the agent's behavior within the environment. In the training process, the primary objective is the reward function, which represents the ultimate goal to be achieved. On the other hand, the value function evaluates the long-term desirability of states or state-action pairs in terms of their overall goodness.

A. Data Collection and Processing

It is the initial process of this work we have done the most struggling work. Acquiring high-quality financial data can be costly, and free sharing of such data is rare. However, we have successfully collected comprehensive historical daily price and volume data for all US-based stocks and ETFs traded on the NYSE, NASDAQ, and NYSE MKT, making it one of the most valuable datasets available in this domain. The collected data is then preprocessed to prepare it for further analysis. This can involve cleaning the data by handling missing values, correcting errors, and normalizing or standardizing the data to a common scale. Data preprocessing also includes feature engineering, which involves selecting relevant features or indicators that are expected to have predictive power for stock price movements. After preprocessing the data, the training, validation, and testing sets are created. During the training process, the validation set is utilized to adjust hyperparameters and assess the model's performance. In contrast, the testing set is reserved for evaluating the final trained model's performance, while the training set is used to train the reinforcement learning algorithm. Overall, the data collection process for stock price prediction using reinforcement learning involves gathering historical stock price data, preprocessing the data, defining the environment, splitting the data into training, validation, and testing sets, collecting data during training and evaluation, analyzing the collected data, and iterating the process to refine the model's performance. The flowchart, presented in Figure 1, outlines the procedure of reinforcement learning (RL) for agent-environment interaction in a concise manner. On this event, the agent takes an action response to the current state, and because of this action, the system receives a signal, known as a reward (Rt+1), which guides the By employing the probability function f(at, st), the state is updated in the subsequent time step to reflect the behavior of the chosen action.

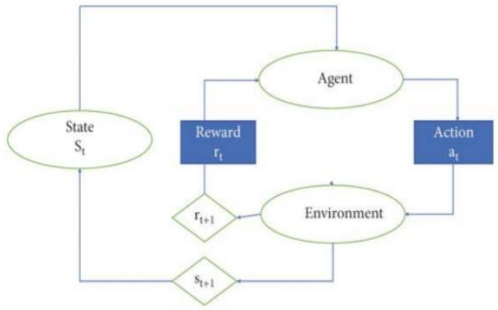

Fig. 3.7: The Full process of reinforcement learning (RL) for agent-environment interaction.

B. A value function-based approach to deep reinforcement learning

Convolutional neural networks (CNNs) from deep learning and the Q learning algorithm from conventional reinforcement learning are combined in Minh's novel deep Q network (DQN) model. This model stands out for its use of convolutional layers, which significantly improve learning effectiveness and performance. Four previously processed photos that come before the current moment are used as input in the DQN model. These images undergo a nonlinear modification after being passed through numerous convolutional layers and fully linked layers. The Q value corresponding to each action is generated by the output layer.

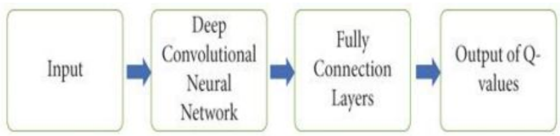

Fig. 3.8: The structure of the DQN model

Our research employed a single-agent training technique that focuses on how quickly the price of a particular stock fluctuates in the market. By focusing on the rate of change, the training method aims to increase the capacity to forecast changes in the stock price. We assumed that the data would encompass all relevant market information, such as information about the surrounding area and the current condition of the stock. Despite the complex and dynamic nature of the market and the fact that the market price is influenced by the behaviors of multiple investors, we believe that after a prolonged reinforcement learning the results might offer a thorough reflection of the data present in the market during the reinforcement learning (RL) training period. It is appropriate to think about this assumption as a result. The state parameter is a crucial component in the policy equation, as it influences the decision-making process. In our analysis, we assumed that all investors have rigid policies and that their choice of action is solely determined by the current state. In this context, the policies of other investors can be considered as a representation of the state of the market, especially when analyzing data in a 5-minute time frame. The stock information indicators we considered in our research include Six state indicators for the stock market that reflect several data points, such as the starting and closing prices of a day, the highest and lowest prices reached, the day's average price, and the number of profitable trades executed. These metrics are essential for comprehending a stock's performance on a particular day.

Bayan Albaooth have discussed about

A. Artificial Intelligence-based Prediction Models

To predict the stock market values, the origin architecture, and Long Short-Term Memory (LSTM) model are used for the processing of prediction [10]. The mechanism of feature extraction using CNN model and LSTM model for the prediction of the stock market is applied in this prediction model for investors' decisions. LSTM, CNN, RNN, and MLP were the four main deep-learning model types that were used. Each of these models was trained using information given by Tata Motors [11]. The models after the training and testing phase are used for forecasting the stock values in the future after initialization and training. Even in other stock markets, the algorithms could identify patterns in stock movement, which made it possible to obtain successful results. By considering the fax and the d planning models suggested for the understanding of dynamics, CNN-LSTM is demonstrated to be superior to the other three models.

B. Dataset

The dataset is taken from the global technology Apple Inc which promotes manufacturers and develops a wide range of electronics that include wearables, smartphones, tablets, accessories, and personal computers of the company trade in the Stock Exchange under the code name AAPL. The dataset includes the historical information of shares in the stock market of Apple Inc for two years period and it is accessed on an everyday basis. The currency used is USD where 70% of the dataset is used as a training set and 30% of the data is used for the testing and validation set.

C. Data Normalization

The approach of data scaling for making the data into a particular interval when it is utilized in vast amounts is known as normalization. It improves the accuracy and speed of the gradient descent. Normalization of minimum and maximum are used for data scaling among the specific ranges which is applied in the initial data of linear transformation. The highest value and lowest value of the attributes or denoted as notations such as correspondingly. The value of XS map is the value for computation and determining the difference between the two values.

D. Prediction process

Convolution Neural Network (CNN) model

The purpose of CNN model is to perform the feature extraction for capturing the topology. For achieving this the groups of data are utilized by the filters. CNN has a wide range of domains that include time series analysis speech recognition and image processing for capturing the special and sequential input. There are 4 layers in CNN such as convolution layer, pooling layer, input layer, and output layer as shown in Figure.

Long Short-Term Memory (LSTM) model

LSTM model works based on a recurrent neural network, and it is utilized in many cases for the prediction of investors' decisions in the stock market for playing a substantial role in training and testing face. LSTM can be achieved throw the addition of a forget gate and input gate. current cell gate and output gate which allows the LSTM to retain information about the dependencies at a certain amount of time. The key benefit of LSTM using forgotten gates for teaching the model when it can forget.

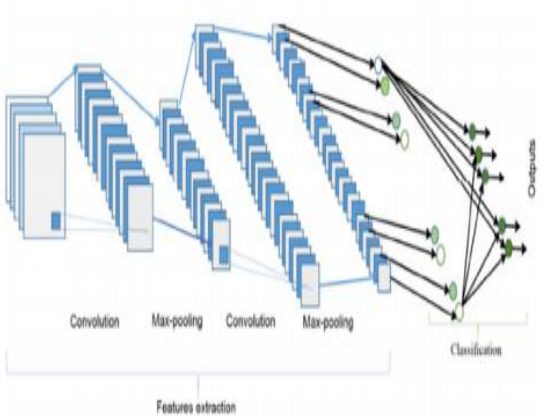

Fig. 3.9: Convolution Neural Network (CNN) Architecture.

There is no limit to the amount of value that is saved in the memory cell. LSTM is more effective in recognizing the patterns in the time series during the unknown duration and for the generation of predictions.

RESULTS AND DISCUSSION

The experimental design focuses on selecting stock attributes (historical prices and futures) and classifying market trends using five algorithms: CNNpred, CNN-corr, NN, SVM, and the proposed model. The tests are divided into two parts—one using historical data and the other using futures data. Notably, this study is the first to use futures as input for prediction. Due to its use of candlestick charts, CNN-corr was only evaluated with historical data.Results from the Taiwanese stock market (TSM) show that the proposed model outperforms all others in both tests. While traditional NN performs relatively well with historical data, CNNpred and CNN-corr are more prone to noise, and SVM shows lower accuracy.

The authors evaluated three different neural network architectures for stock market trend prediction:

Model	Accuracy (Directional Prediction)
MLP	55.4%
CNN	57.5%
LSTM	60.3%

LSTM outperformed the other in predicting the correct direction of stock market movement.

They tested a simulated trading strategy based on the predictions made by the models.

Here are the outcomes over a + 4-month period:

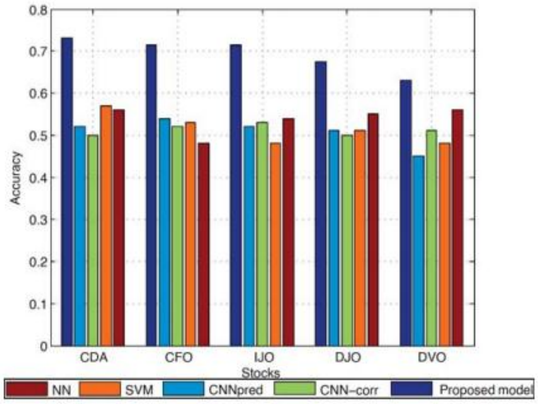

Fig .4.1 : The prediction accuracy of all five models including NN, SVM, CNNpred, CNN-corr, and the designed model by the conducted historical data.

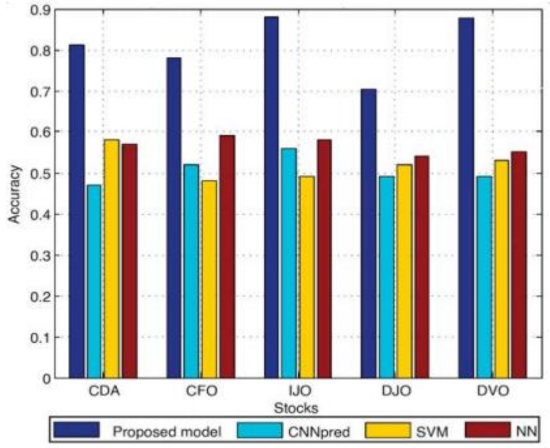

Fig. 4.2: The prediction accuracy for all four model specifications including the developed model, CNNpred, SVM, and NN, using the futures data.

Again, the LSTM model led to the highest returns, showing better performance than the traditional buy-and-hold strategy. LSTM's ability to remember long-term dependencies makes it better suited for time series forecasting in stock markets. The deep learning- based trading strategy significantly outperformed the benchmark buy-and-hold strategy.

Accuracy above 60 % can already produce profitable investment strategies when used consistently.

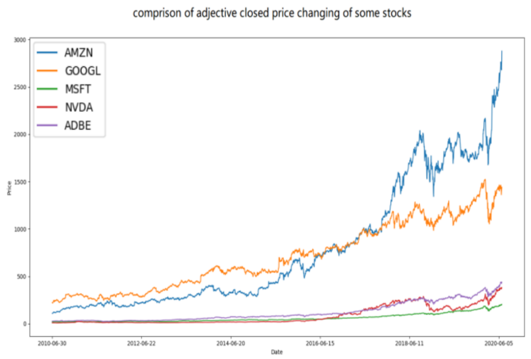

Fig. 4.3: Comparison of some stocks in samples

The suggested technique is trained and evaluated Using TATA stock data from Yahoo Finance [22], the proposed approach is trained and assessed. It is divided into two sets those are training and testing, and after running through multiple models, it yields the findings shown below: Figure shows a data visualization with 512 batch sizes and 90 epochs. the current tendency is depicted using a line which is coloured blue, while the forecast is displayed by a green line. The close closeness of these two lines demonstrates the power of the LSTM-based model. Figure displays the TATA market datavisualisation. A blue line represents the real trend, while a red line shows the forecast. When a significant period of time has passed, the projection approaches the current tendency. The system will generate more accurate results the more training it gets. Figure 4.33 shows User interface of the website and this is how it actually looks like.

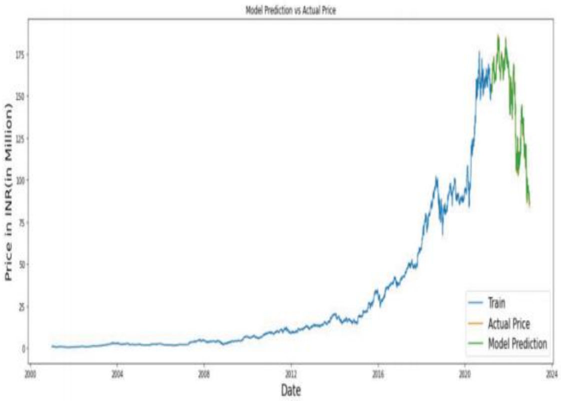

Fig . 4.4: TATA stock prediction by LSTM.

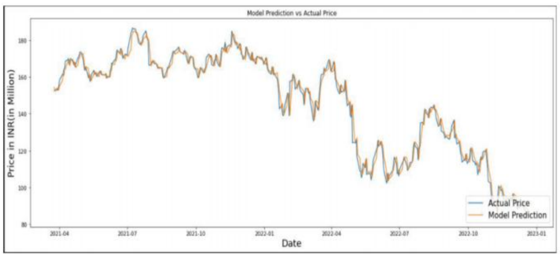

Fig. 4.5: TATA stock prediction by RNN.

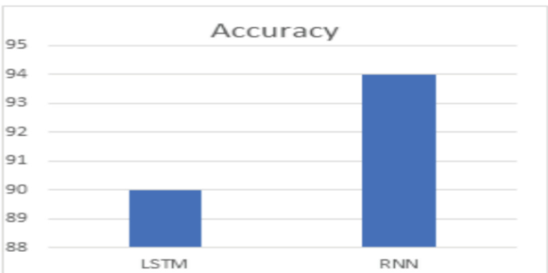

Fig. 4.6: Model Accuracy

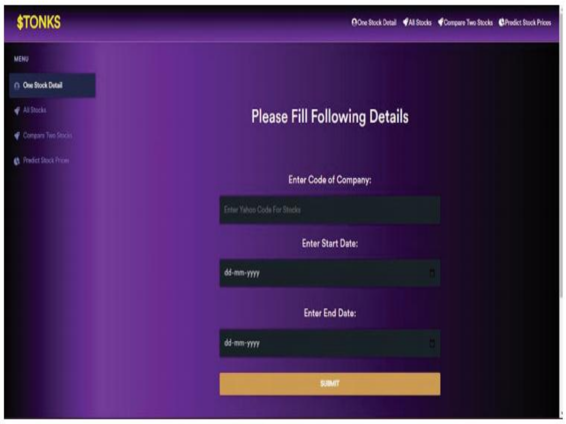

Fig. 4.7: User Interface

The proposed DRL model was trained using U.S. stock and ETF data from July 2013 to January 2016 and tested on data from January 2016 to July 2018. Results show a strong match between predicted and actual prices. During training, the loss function steadily decreased, reaching its minimum around 10 epochs . Reward values fluctuated initially but stabilized over time, indicating effective training. Finally, the DQN-based method showed improved accuracy in predicting stock trends, with faster reward stabilization despite some initial loss fluctuations.

Fig. 4.8: Testing and training data result

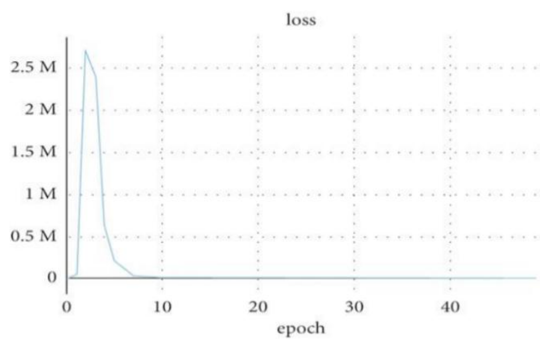

Fig 4.9: Loss function simulation

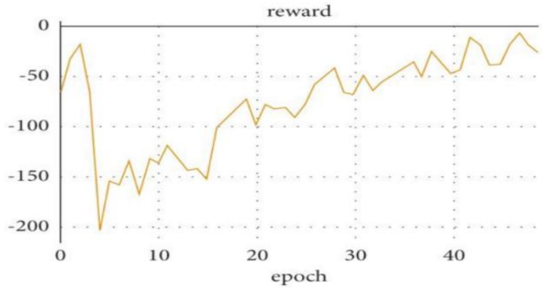

Fig.4.10: Reward Convergence flow

Fig.4.11: DQN training and testing results.

For prediction of the stock market and investor interest in the closing price of Apple Inc is decided using deep learning models. 70% of the data obtained from the dataset is used for the training phase. The LSTM - CNN model achieved the prediction according to the metrics of MSE.

Table I presents the results of investors decisions perditions based on LSTM and LSTM-CNN model.

AI Model	RMSE	MSE	NRMSE	Accuracy
LSTM	0.01453	0.0001621	0.04290	98.32
LSTM-CNN	0.00643	4.4387x 10^-5	0.02075	99.98

Table II shows a comparative performance evaluation of the applied prediction models along with existing models. The results show that the developed model outperformed existing models with high percentages.

REFERENCES	DATASET	PREDICTION TYPE	RESULTS
Shen et al., (2012)	Indices & Commodities	Daily, Monthly	77.16%
Wang et al., (2012)	DJOA Index	Weekly	70%
Tiwari et al., (2010)	Sensex Stocks	Daily	92.1%
Developed Model	Apple Inc	Daily, Weekly	99.98%

CONCLUSION

This survey paper presents a comprehensive overview of various deep learning approaches applied to stock market prediction, including CNNs, LSTMs, RNNs, DRL, and hybrid models. Across the studies, it is evident that deep learning models significantly outperform traditional statistical methods in capturing complex patterns and temporal dependencies within financial time-series data.

CNN-based models have shown promising performance in extracting important features from historical stock data and leading indicators like futures. LSTMs and RNNs, known for handling sequential data, have been widely used for their ability to model long-term dependencies. While LSTMs are particularly powerful for capturing extended temporal patterns, RNNs offer simplicity and faster training in certain cases.

Deep Reinforcement Learning (DRL), especially when enhanced with policy gradient methods, has emerged as a forward-looking approach. These models adapt based on reward signals and are suitable for dynamic trading environments. However, they require large datasets and careful tuning of hyperparameters to ensure stability and performance. Experimental results across the base papers confirm that deep learning-based strategies not only improve the accuracy of trend predictions but also support investment strategies such as identifying golden crosses, optimizing trading thresholds, and maximizing returns with reduced risk. Moreover, hybrid models like LSTM-CNN and implementations with advanced UI for user interactions further emphasize practical applications. Despite the promising outcomes, challenges such as market volatility, overfitting, generalizability across timeframes, and real-time processing persist. The conclusions suggest that shorter interval predictions (e.g., 1-minute or 5-minute) and inclusion of sentiment analysis could enhance predictive power.

In conclusion, deep learning models, particularly when hybridized or coupled with reinforcement learning, are proving to be transformative tools in financial forecasting. Their continued evolution, combined with real-time data collection and expanded datasets, holds great potential to empower investors with more informed, accurate, and timely decision-making tools.

REFERENCES

[1] W. Bao, J. Yue, and Y. Rao, "A deep learning framework for financial time series using stacked autoencoders and long-short term memory," *PloS one*, vol. 12(7), e0180944, 2017.

[2] X. Cai, S. Hu, and X. Lin, "Feature extraction using restricted Boltzmann machine for stock price prediction," *The International Conference on Computer Science and Automation Engineering*, 80–83, 2012.

[3] E. Hoseinzade and S. Haratizadeh, "CNNpred: CNN-based stock market prediction using a diverse set of variables," *Expert Systems with Applications*, vol. 129, 273–285, 2019.

[4] C. H. Chen and C. Y. Hsieh, "Actionable stock portfolio mining by using genetic algorithms," *Journal of Information Science and Engineering*, vol. 32(6), 1657–167, 2016.

[5] C. H. Chen and C. H. Yu, "A series-based group stock portfolio optimization approach using the grouping genetic algorithm with symbolic aggregate approximations," *Knowledge-Based Systems* vol. 125, 146– 163, 2017.

[6] Junming Yang, Yaoqi Li, Xuanyu Chen, Jiahang Cao and Kangkang Jiang, Pierpaolo, "Deep Learning for Stock Selection Based on High Frequency Price-Volume Data", arXiv:1911.02502v1 [q-fin.CP] 6 Nov 2019

[7] Zhichao Zou, Zihao Qu, "Using LSTM in Stock prediction and Quantitative Trading", CS230: Deep Learning, Winter 2020,.

[8] Raghav Nandakumar, Uttamraj K. R, Vishal R, Y. V. Lokeswari, "Stock Price Prediction Using Long Short Term Memory",Page 3342, IRJET, Mar 2018

[9] Pang X., Zhou Y., Wang P., Lin W. and Chang V., "Stock Market Prediction based on Deep Long Short Term Memory Neural Network", DOI: 10.5220/0006749901020108,COMPLEXIS 2018, pages 102-108

[10] Feature fusion LSTM-CNN model using different representations of the same data", PLOS ONE— https://doi.org/10.1371/journal.pone.0212320 February 15, 2019.

[11] Mathanprasad L and Gunasekaran Analysing the Trend of Stock Market Evaluate the performance of Market Prediction using Machine Learning Approach, 2022 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI), DOI: 10.1109/ACCAI53970.2022.9752616.

[12] IshitaParmar, Stock Market Prediction Using Machine Learning, DOI: 10.1109/ICSCCC.2018.8703332.

[13] Adil Moghar, Mhamed HAMICHE, Stock Market Prediction Using LSTM and Neural Network,International Workshop on Statistical Methods, and Artificial Intelligence (IWSMAI 2020), DOI: 10.1016/j.procs.2020.03.049.

[14] Selvin, Sreelekshmy, et al. "Stock price prediction using LSTM, RNN and CNN-sliding window model." 2017 international conference on advances in computing, communications and informatics (icacci). IEEE, 2017.

[15] Mehtab, Sidra, and Jaydip Sen. "Stock price prediction using convolutional neural networks on a multivariate timeseries." arXiv preprint arXiv:2001.09769 (2020).

[16] F. Agostinelli, S. Mcaleer, A. Shmakov, and P. Baldi, "Solving the Rubik's cube with deep reinforcement learning and search", Nature Machine Intelligence, vol. 1, no. 8, pp. 356–363, 2019

[17] R. Hafner and M. Riedmiller, "Reinforcement learning in feedback control", Machine Learning, vol. 84, no. 1-2, pp. 137–169, 2011

[18] V. Konda and J. Tsitsiklis, "Actor-critic algorithms," Advances in Neural Information Processing Systems, vol. 12, 1999

[19] M. P. Naeini, H. Taremian, and H. B. Hashemi, "Stock market value prediction using neural networks," In Proceedings of the 2010 International Conference on Computer Information Systems and Industrial Management Applications, pp. 132– 136, IEEE, 2010.

[20] J. W. Lee, E. Hong, and J. Park, "A Q-Learning Based Approach to Design of Intelligent Stock Trading Agents," In Proceedings of the 2004 IEEE International Engineering Management Conference, pp. 1289–1292, 2004

[21] Shah, D., Isah, H., & Zulkernine, F. (2019). Stock market analysis: A review and taxonomy of prediction techniques. International Journal of Financial Studies, 7(2), 26.

[22] Thakkar, A., & Chaudhari, K. (2021). A comprehensive survey on deep neural networks for stock market: The need, challenges, and future directions. Expert Systems with Applications, 177, 114800

[23] Lee, T. K., Cho, J. H., Kwon, D. S., & Sohn, S.

Y. (2019). Global stock market investment strategies based on financial network indicators using machine learning techniques. Expert Systems with Applications, 117, 228-242.

[24] Zahera, S. A., & Bansal, R. (2018). Do investors exhibit behavioral biases in investment decision making? A systematic review. Qualitative Research in Financial Markets.

[25] Parveen, S., Satti, Z. W., Subhan, Q. A., & Jamil, S. (2020). Exploring market overreaction, investors' sentiments and investment decisions in an emerging stock market. Borsa Istanbul Review, 20(3), 224-235.