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Advanced Stock Price Prediction: A Comprehensive Study Using Lstm and Gru- Based Machine Learning Techniques

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Abstract—**The purpose of this paper is to develop an advanced hybrid stock price prediction model by integrating the advantages and benefits of Long Short-Term Memory Model (LSTM) and Gated Recurrent Units (GRU) to facilitate the users in stock market, papers aim is to create an integrated one step solution for stock market prediction. LSTM is highly recommended to capture long-term dependent trends in sequential historical price of a stock whereas GRU handles short-term dependencies and effective in smaller datasets. This paper tries to combine these two models and make a hybrid model for better accuracy and reliability. This hybrid model improves the prediction capability and addresses the limitation which occurs in traditional methods.**

Index Terms—**Stock Market Prediction, LSTM, GRU, Hybrid Model, Normalization, Multi-Layer Perceptron.**

1 BACKGROUND

Financial sector is highly dynamic and unpredictable, especially Stock market price variation due to its highly volatile, non-linear and complex changes. Many factors such as variable global market, geopolitical conditions, behaviors of investor and many more affects the price. According to recent reports and statistics, around 3% of the Indian population are actively participating in stock investment and over 120 mil- lion investors registered on the National Stock Exchange (NSE) in period of 2019 to 2024 which has increased in 2025. Traditional stock market prediction system such as CNN and statistical data models normally are not sufficient enough to capture and predict many of these variable factors, therefore unable to precisely understand and predict the prices of stock of companies. To facilitate this huge crowd, we need to have a highly complex and reliable models.

This paper aims to provide models that are highly accurate and reliable in predicting the price of stock by incorporating LSTM and GRU model into a single model. LSTM is a specialized RNN which is efficient in time series data and can capture long term dependencies. LSTM has three gates namely Input, Output and Forget gates which takes input from series data and memorizes it and based on this predicts the future values. It is highly advantageous in preventing overfitting, vanishing gradient and

enhances the pattern recognition with improved memory retention. GRU is the updat- ed and simplified version of LSTM model with fewer gates which reduces the compu- tational complexities of the time series data. It is highly recommended when there should be balance between the output value and time taken. This hybrid model ap- proaches the ability of machine learning model to learn dynamic market. This model takes advantages of both the models and predicts the pattern which matches the actual pattern, maximum. Thus, integration of machine learning models with financial sec- tors helps us to predict the long-term dependencies of data points which in turn helps investors, bankers and business market to take calculated guess about the price of any company's stock.

2 MOTIVATION

Stock price is highly volatile and complex to predict so, one of the primary motiva- tions behind this paper started with the need to optimize and increase the accuracy of the time-series data. Improvement of the model that can predict data in more reliable manner would be helpful for the investors, small businesses and many financial bro- kerage firms. Financial sectors are moving towards data-driven decision making in almost all the fields. Advent of big data analytics, machine learning algorithms and data science techniques many firms and even the individual investors are looking for advance tools and techniques that can provide them accurate results which they can use for calculated decisions.

Another thing is combining of two changing and trendy domains which is financial market and machine learning techniques. Both this domain is continuously evolving and changing which needs continuous replenishment of acquired knowledge with new and trendy facts. Our paper's goal is to make a robust advanced hybrid model that would be helpful in this field. Moreover, the real-world impact which is possible in financial market with this approach would minimize the risk and maximize the de- sired output. Practical implementation and working with real data include understand- ing data, feature extraction of time-dependent stock price and handling anomalies with pre-processing, model tuning and testing its validity with various evaluation methods. No model can be perfectly accurate with hundred percent accuracy, while goal of the paper is to push the capacity of the existing models to as accurate as possi- ble and explore how new models, by manipulating its structure could help in enhanc- ing the price prediction ability of a stock. By addressing its limitations, paper contrib- utes in making AI-Based stock price prediction more suitable for broader audience who doesn't have much financial knowledge and experience. Professional investors may have the capacity to prediction based on their experiences and knowledge but small retail investors often relied on limited knowledge base and tools. This hybrid model would help and cater them with automated data driven prediction value which even helps smaller retail investor to take informed decisions.

3 RELATED WORK

Applying the LSTM network to predict future market values of company stocks based on the past stock data. RMSE and MSE tests performed in the study confirm the accu- racy of stock prediction with the application of LSTM as a model of choice to predict financial markets with the aid of a computer [1]. The experiment findings are validat- ed by the uses of support vector machine and random forest analysis different mar- kets. If the S&P BMV IPC Index was discovered to be a very excellent one among them, the authors would like to propose that the NASDAQ can be more fascinating with the real-time data. The capability of AI in investment was broached in the study [2]. Steps utilized in the cyclical application of the random neural network (RNN), focusing on forecasting data flow data. This new method of prediction from a series of data points within the time domain was adapted from a model taken from the struc- ture of the human brain. The asset prices within different sectors such as equities, real estate, and digital currencies were considered to confirm the effectiveness of the mod- el against the performance results illustrated by the LSTM and linear regression methods.[3]

The research paper proposed a new stock forecasting optimization model that com- bined the investor sentiments and technical indicators with the financial data. Authors reduced the dimension for all these variables by combining deep learning methods like LASSO and PCA. Researchers compared different configurations of LSTM and GRU and found that models of both types with LASSO performed better than PCA in predicting the stock price [4]. The research proposed a new hybrid Recurrent Neural-Network model, where each of the models, i.e. Bidirectional Long Short-Term Memory (Bi-LSTM), Gated Recurrent Unit (GRU), and stacked Long Short-Term Memory (sLSTM) was applied for the prediction of the stock price in the optimal manner [5]. Another paper is the application of a CNN-LSTM model that pairs fea- ture extraction by the CNN layer with a memory by the LSTM layer for time series forecasting in the application to stock price forecasting [6].

CNN has been used to extract deep features, while BiLSTM was used to predict and analyses the stock price. For improved attention to important features, a novel module Efficient Channel Attention (ECA) was proposed [7]. A system was developed an LSTM model with two layers followed by two dense layers. via the use of Adam optimizer and the minimization of the mean squared error as the loss function, the model illustrated that besides the complexity of the stock prices, it turned out to be proficient predict most accurately [8]. Another dimension can be, by establishing the superiority of the single-layer LSTM model over the multi-layer models using RMSE, MAPE, and Correlation Coefficient measures, which confirmed that these models had a lower error and higher predictability fit [9].

Convolutional Neural Network method for the aim of portfolio risk forecasting that includes forecasting the risk of several assets at the same time. From the outcome, it was found that the CNN model is much more efficient in the prediction of accuracy and resilience, especially in the case of markets in the extreme state [10]. The re-

search employed a set of fundamental concepts from technical analysis and global indices as inputs for the machine learning models, namely RNN, LSTM, GRU, CNN, and XGBoost. In particular, the research determined that XGBoost and GRU possess characteristics that are uniquely advantageous for complicated time series such as stock prices [11]. Forecasting method, which combines LSTM networks with GARCH models. The research considered the problems of non-stationarity and non-linearity of the stock index futures price series [12].
A model test demonstration has shown that it is the hybrid MULTI-GARCH-LSTM model that is overall more efficient than any of the separate models [13]. Novel hy- brid forecasting method with LSTM networks that were hybridized with several GARCH. The hybrid method was a response to solve the issues pertaining to the non- stationarity and nonlinear nature of a stock index. Based on the conclusions of the study, the MULTIGARCH-LSTM hybrid model outperformed its individual building block models under gold futures tests [14]. Time series representation model (TSRM) for automatic stock price prediction using temporal and relational data. The model first uses transaction data to cluster stocks with K-means clustering, then examines stock relationships. By combining time series data with Long Short-Term Memory (LSTM) networks and relationship data with a graph convolutional network, the TSRM was used in empirical studies and performance of the model has demonstrated better performance [15].

4 ARCHITECTURAL DESIGN

4.1 Proposed System

Paper emphasizes on model that starts with techniques using both LSTM and GRU, initially the sequential previous stock price data from the desired company is taken, then cleaning of the provided data using appropriate preprocessing techniques like outlier detection, addressing the null values and many more for quality and complete- ness check. Then to normalize the data so that it can be feed into hybrid machine learning model which help features to be in a common scale. Once we have a stand- ardized data, we can implement feature engineering for understanding data, features of the stock value and relevant information. This featured engineered data can be holistically be used as inputs that can help in precisely predicting the time-series data.
This pre-proposed dataset is then divided into training and testing modules which is divided into 80:20 ratio i.e. 80 percentage is used as training dataset and rest 20 per- centage is used as testing dataset which helps model to learn dataset properly and rest are used for efficient evaluation process. This split data is then introduced to the hy- brid model. Advantage of choosing LSTM is to capture long-term dependent patterns and price values which is used to control the information flow whereas GRU layer helps to recognize the short-term dependent data as well as reduction of the complex architecture by merging forget and input gate into single advanced gate. The output is then fed into series of dense neural network which eventually provides result with single neuron which can predict stock price. The model is then fed into evaluation

algorithm that use to provide efficiency and reflects optimized results. Testing process ensures knowledge gained by training data is providing appropriate pattern that matches the output as much as possible with maximum accuracy and precision.

Various methods such as MSE, RMSE and MEA is used to quantify the accuracy of output. Finally, this data can be used in fresh unseen dataset that helps stakeholder for decision-making processes Thus this project emphasis on providing capacity of LSTM and GRU combined model in predicting which helps in integrating AI in fi- nance sector.

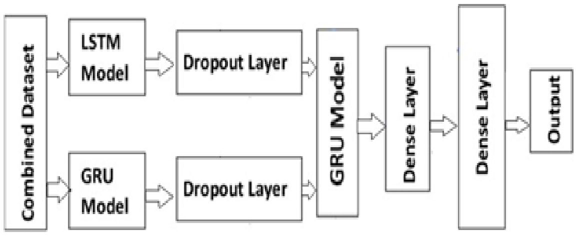

Fig. 1. Proposed architecture illustrating the system's core components and data flow

4.2 System modelling

LSTM is one type of recurrent neural network; this networking models can rearrange the weight parameters of each neuron and can be used effectively in models that need predictions and pattern analysis. However, RNN can only be effective for short-term dependence data and is prone to gradient disappearance and gradient explosion, that is long-term dependency. In order to solve this problem LSTM was been proposed for long-term dependency data to improve. It can be used widely in various field and have yielded impressive results and outcomes.

Compared to RNN model, LSTM introduces cell state (Ct) and use three gates input gate (it), forget gate (ft) and output gate (Ot). These three gates are used in various phases and are having different functions that maintains and controls information. Let's assume time t, then xt is input data, ht is current output, ct is value from input gate tan(h) is hyperbolic tangent function and, σ as sigmoid function, W represents matrix weight and b is bias. Therefore, operation formula of LSTM is:

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f)$$
$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i)$$
$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o)$$
$$c_t = f_t \circ c_{t-1} + i_t \circ \sigma_c(W_c x_t + U_c h_{t-1} + b_c)$$
$$h_t = o_t \circ \sigma_h(c_t)$$

LSTM is mostly popular in financial forecasting because it deals with redundancy of the relevant historical data. Additionally, GRU is one more variant of RNN model,

this model is introduced by changing gating structure. It solves problem that deals with even short-term dependent data. Compared to LSTM, GRU is simplified and only have update gate (Zt) and reset gate (rt) are introduced. In GRU input gate i.e. update gate decides how input (xt) and previous output (ht-1) is to be passed into next cell and function of reset gate is to determine which past data need to be forgotten. The current memory content ensures that relevant information should be carry for- warded for next iteration, which is determined by weight W. The main operation of GRU is governed as follows formula:

$$z = \sigma(W_z \cdot x_t + U_z \cdot h_{(t-1)} + b_z)$$
$$r = \sigma(W_r \cdot x_t + U_r \cdot h_{(t-1)} + b_r)$$
$$\tilde{h} = tanh(W_h \cdot x_t + r * U_h \cdot h_{(t-1)} + b_z)$$
$$h = z * h_{(t-1)} + (1 - z) * \tilde{h}$$

System model also includes structured presentation of system's data flow and interac- tions. It will help in understanding systems workflow and sequence. This project in- volves a modular approach that contains various phases starting from data collection till visualization.

- Data Collection Module: This project takes historical price value of a particular company listed in stock market using API, Yahoo Finance, this module takes se- quential streaming updated data and store for feature engineering.
- Data preprocessing Module: That contains all cleaning and filtering process includ- ing removal of noise, missing value, and inconsistent data. This module also in- cludes process of normalization, feature selection and transforming the input data for better processing and better performance.
- Machine leaning Module: Project incorporates LSTM and GRU neural network for predicting time dependent data. This module learns from the historical patterns and learn complex pattern out of it and generate result that is highly accurate.
- Training and Optimization module: project that trains historical stock price data with hyperparameter tuning and various optimization methods to improve accura- cy. System also emphasis on providing investors, traders, and financial analysts with market trends and market fluctuations with investment opportunity.
- Evaluation and visualization matrix: Project evaluate model based on various metrices such as RMSE, R2, MAE, MSE to access the performance

of each mod- ule. With this we have provided interactive visualization graphs and charts that provide and immersive experience for the customer with essential details.

Overall, system ensures efficient functioning and provide well-structured, user friend- ly, reliable and scalable AI-driven financial system for financial inclusion of every person whether in financial field or not, this system will be helpful.

4.3 Methodology

This paper focuses on training historical stock price data for Reliance Industries (RELIANCE.NS) from 1st of January 2010 till 26th of March 2025, for this we have used a library yfinance that takes data from Yahoo Finance API, this streaming data includes all necessary details including such as Opening Price, High Price, Low Price, Closing Price and Volume of reliance stock data. Next, preprocessing steps includes removing null and missing values and then analyzing some of the properties of the attributes involved in it, with this, first step ends. Next step involves understanding of the reliance stock data by visualizing of Closing Price of market for each day, also includes analysis of trade volume pattern, correlation matrices, daily percentage change with moving averages (both 50-day and 200 day) as important indicator for feature engineering.

Selecting closing price as our projects primary target feature with normalization of data using MinMaxScaler to range 0 to 1 to facilitate model training. This step also includes creation of sequential dataset so that it can be easily processed in the training model with time step 60 which means using past 60 days to predict the next day's price value. Another aspect that involves in this phase is reshaping input data which is essential for recurrent networks. Lastly splitting of dataset into 80:20 ratio for train and testing respectively. Model fed last 60 days normalized data to predict future day's value. This model includes many processing branches include LSTM branch which has 100 units with sequence and 20% data is dropout for better training pro- cess, similarly, GRU branch contains 300 units with same sequence and 20% data is dropout for better training process. Later these two branches are fused together. Other than we have additional layers including 500 units of GRU branch that takes these combined data, then they are fed into 50 units of Dense layer with ReLU activation function. This training process has 300 epochs with 32 batch size using Adam opti- mizer. Comparative visualization of actual price data and predicted price data for performance check along with testing data to evaluate model accuracy.

Generating future prediction of reliance stock market data for different time stamps (30, 90, 180 days). Each prediction involves previous forecasted data in rolling win- dow approach. This are visualized using Plotly, which is an interactive time-series plot. Forecasting using intervals and range sliders for detail examination of price for a specific time duration. Evaluating of a system is one of the important phases of devel- opment, keeping this in mind many performances evaluation metrices are performed such as MAE, MSE, RMSE, R2 with some additional information such as confusion metrics, loss function value graphs and others using visualization tools. This whole methodology combining technical indicators, statistical component and art of devel- oping deep learning techniques helps in completing this project that could help users to have a detailed understanding of stocks and also cater them to have informed deci- sion using forecasting capabilities.

5 SYSTEM ARCHITECTURE

In the detailed system architecture of Stock price prediction model, the whole system can be broken down in various different components. Each of this component are having their own functionality. Here is the description of each module along with its architecture. LSTM module is specialized type of RNN which is dealing with time series data and effective for handling sequential data while it helps in overcoming vanishing gradient challenge which is usually faced by traditional methods. LSTM have various application including speech recognition, and language processing. In stock prediction historical data is very important as historical data influence future trend, which makes LSTM an ideal choice for capturing long-term dependencies of the data. Usually, RNN models are incapable of identifying long sequence data due to inability to remember past information, however LSTM has memory cell that remem- bers essential data that helps in identifying patterns and trends. LSTM contains three gates in each memory cells i.e. Forget Gate, Input Gate, Output Gate. Function of Forget Gate is to decide which information or data should be discarded, as its not useful in capturing patterns. Similarly, we have Input Gate and Output Gate for de- termining which information is used and stored in memory and which information should be passed to the next time step respectively. This cell acts as the memory that carries information in each step, ensuring relevant information is passed forward for effective future prediction. This interaction among gates ensures that crucial data is maintained and filtering all noise. Therefore, LSTM works effective in stock price prediction where past patterns influence future trends. Now listing some of the ad- vantage of LSTM model is memory retention which help model to retain lang-term dependent historical stock data making it suitable for stock prediction, along with this it solves the problem of vanishing gradient problem that traditional models face, pre- venting of shrinking during backward iteration for effective learning. Another ad- vantage is it handle volatility by capturing variations which best suits it for extreme fluctuating market. Lastly this model is adaptive to learn by updating its weights dy- namically.

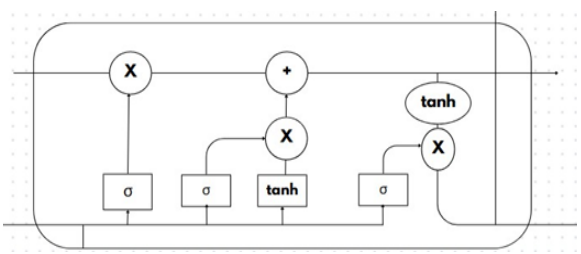

Fig. 2. Illustration of the LSTM network architecture showcasing its gate mechanisms

LSTM is a powerful deep learning tool, its unique architecture allows it to store relevant and discard irrelevant values, making it efficient in capturing time series data. This project incorporates LSTM model as its one of the components of architec-

ture to improve prediction, providing an effective tool for users to make an informed decision regarding their investments.

GRU is also one of the advanced RNN designed to capture sequential data more effi- ciently. It also addresses the problem of vanishing gradient which traditional network unable to capture. GRU is similar to LSTM network in simplified architecture making it more computable helps in capturing even short-term dependencies. Due to their ability to capture patterns and trends making it appropriate for time-series data, GRU is used in different fields like stock price prediction, speech recognition and natural language processing. GRU uses fewer parameters than LSTM leading faster computa- tion and maintains performance. GRU also consists of various gates that regulate information sequence through various networks. GRU has only two gates, Unlike LSTM which has three gates however mechanism is mostly same. These two gates help in regulating the flow of data for effective prediction, it consists of Reset Gate which determines how historical data can be forgotten and Update Gate that controls the retention function facilitating how much of previous information should be recap- tured. Additionally, GRU do not have a cell state like LSTM instead it directly han- dles hidden state to store dependencies making them more memory efficient. Ad- vantages of GRU is, its simpler to make and requires fewer parameter making it faster than other computational models. Other advantages of GRU are its efficient memory usage. No separate cell state reducing computation overhead, elimination the extra memory cells. Faster to train while achieving almost similar result as LSTM, handles long-term dependencies and can also capture shorter patterns and trends. GRU is best model by providing balanced between performance and efficiency.

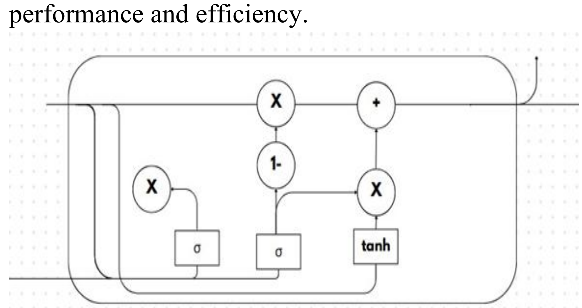

Fig. 3. GRU architecture showcasing update and reset gates for efficient sequence modeling

GRU is an excellent alternative to LSTM but if it is combined by LSTM the whole architecture becomes efficient as it balances the advantages of both the models into a single hybrid model making an ideal for real-world application. Dropout layer is a regularization technique used in machine learning technique which prevent model from overfitting by randomly dropping out some of the neurons and connected layers.

Dropout layer improves generalization by ensuring whether the model do not learn general pattern i.e. become overly reliant on single neuron. This helps in learning robust patterns and features making it efficient for stock price prediction, if no drop- out layer is incorporated the model leads to poor performance on unseen market data.

In stock price forecasting model, dropout is applied on different models to reduce dependency and stability of the model.

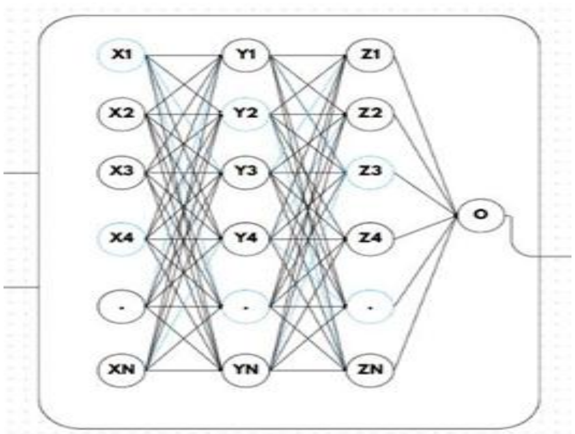

Fig. 4. Dropout layer illustrating random neuron deactivation to prevent overfitting.

Role of Dropout layer is primarily used in LSTM or GRU or fully connected layers to prevent overfitting by memorizing patterns that often has noisy and volatile which do not generalize well, improve model that rely on multiple neurons instead of some dominant ones making it effective for fluctuating market. Lastly Dropout enhances robustness which is important for learning patterns, leading more stable prediction and reduce computation cost.

Dense Layer also known as fully connected layer is a fundamental block in neural network, it connects neurons from last layer and every layer is connected through a weighted connections ensuring effective feature extraction and transformation. Dense Layer receives input from all the neurons from previous layers, each layer is intercon- nected with some weights, these weights are computed and some bias is added to it. These are then passed through activation functions; adjustment of weights is done when backpropagated.

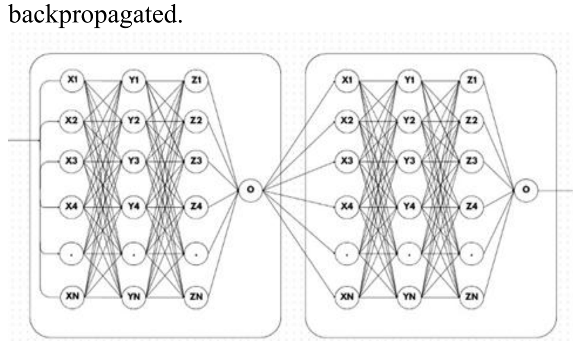

Fig. 5. Stacked dense layers demonstrating fully connected neurons for feature learning

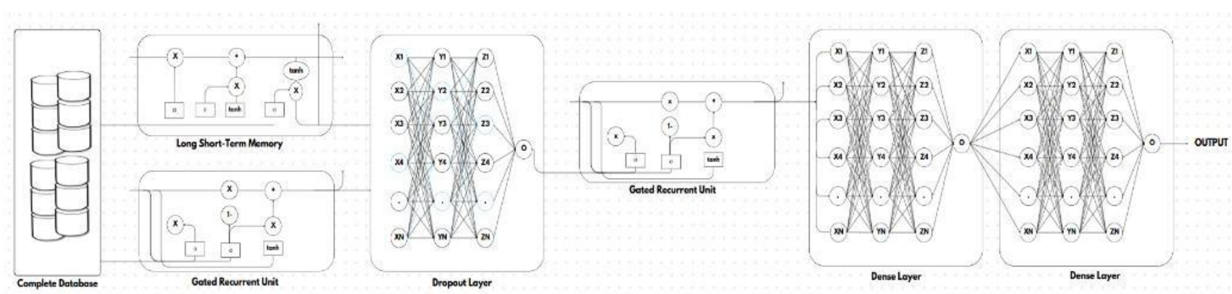

Fig. 6. Overall architecture of the hybrid LSTM-GRU system

6 RESULTS

6.1 Performance Evaluation

Hybrid LSTM-GRU model has provided good result as compared to using them sepa- rately on Reliance Industry stock market data. The model had provided consistent performance with respect to stock price market, suggesting generalization capabilities without much overfitting. Closeness between the predicted value and actual value showcases the accuracy and predictable ability of the model.

Metrices	LSTM	GRU	Hybrid
MAE	32.1164	13.9217	13.2336
MSE	1497.8762	351.5659	301.3012
RMSE	38.7024	18.7501	17.3580
R^2	0.9505	0.9884	0.9984

Table 1. Performance evaluation of Single LSTM, GRU and Hybrid model

Hybrid LSTM-GRU model had outpowered accuracy for single LSTM Model and single GRU model. Below are some performance evaluations of each of these forms using MAE, MSE, RMSE, R2

6.2 Outputs and Graphs

The proposed system with stock markets continuously prone to frequent changes and having a handful of factors affecting them, thereby, exposes users to a situation of the system being the way of finding out what is likely to transpire with the stock and thus makes the right choice on the point of investing or not. Through using the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, the system excellently discovers sequential dependencies in stock price data, thus, it works better in predicting future trends. The employment of the Dropout layers guards against overfitting, while the Dense layers succeed in making more precise predictions and hence raise the certainty of the model.

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 60, 1)	0	-
lstm (LSTM)	(None, 60, 100)	40,800	input_layer[0][0]
gru (GRU)	(None, 60, 300)	272,700	input_layer[0][0]
dropout (Dropout)	(None, 60, 100)	0	lstm[0][0]
dropout_1 (Dropout)	(None, 60, 300)	0	gru[0][0]
concatenate (Concatenate)	(None, 60, 400)	0	dropout[0][0], dropout_1[0][0]
gru_1 (GRU)	(None, 500)	1,353,000	concatenate[0][0]
dense (Dense)	(None, 50)	25,050	gru_1[0][0]
dense_1 (Dense)	(None, 1)	51	dense[0][0]

Total params: 1,691,601 (6.45 MB)
Trainable params: 1,691,601 (6.45 MB)
Non-trainable params: 0 (0.00 B)

Fig. 7. Model Summary

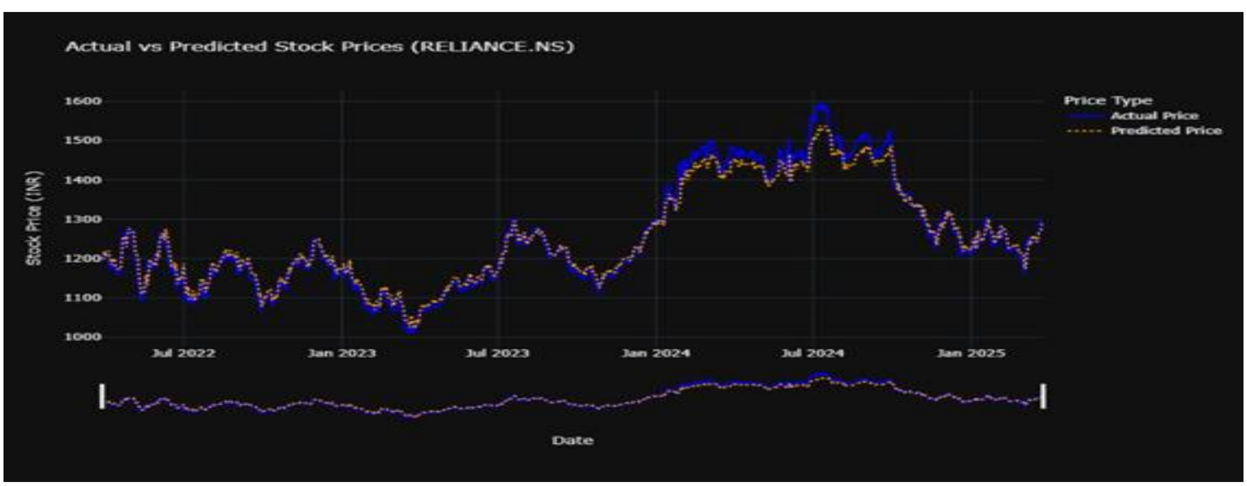

Fig. 8. Prediction of Testing Price Values

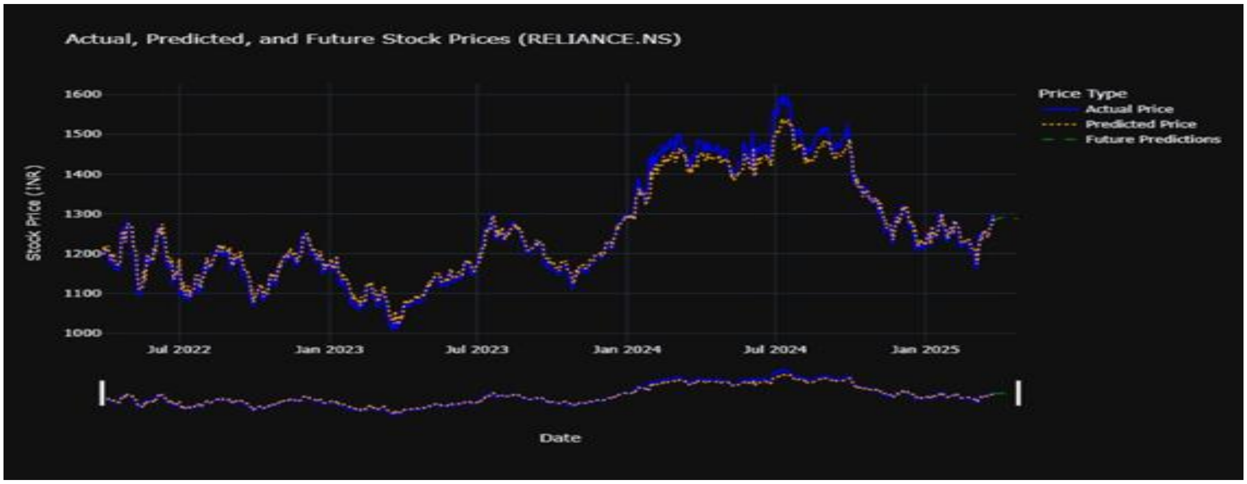

Fig. 9. Prediction of Future 30 days

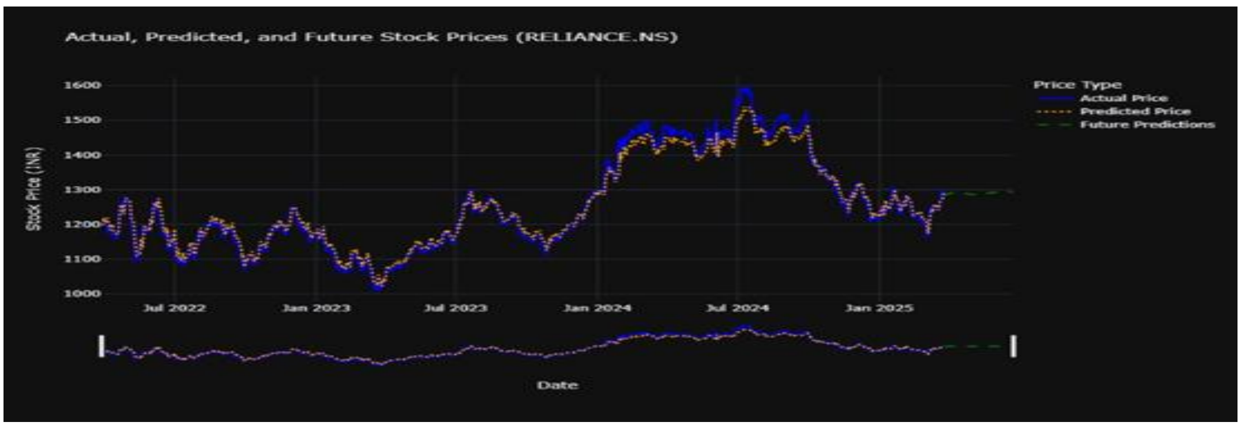

Fig. 10. Prediction of Future 90 days

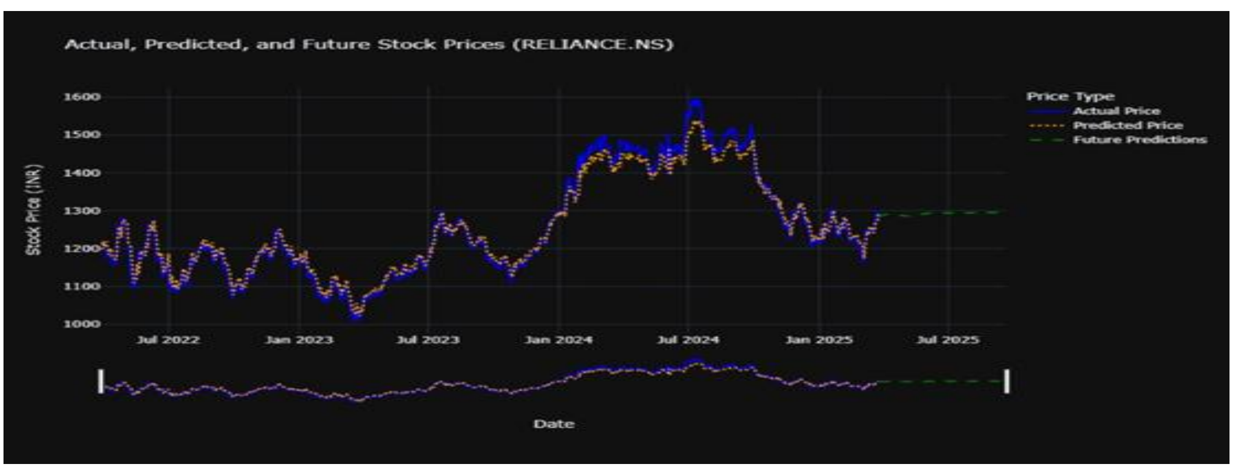

Fig. 11. Prediction of Future 180 days

7 CONCLUSION

The paper titled "Advanced Stock Price Prediction: A Comprehensive Study Using LSTM and GRU-Based Machine Learning Techniques" manages to solve the one of the problems of financial markets by realizing precise and data-driven stock price prediction. The proposed system with stock markets continuously prone to frequent changes and having a handful of factors affecting them, thereby, exposes users to a situation of the system being the way of finding out what is likely to transpire with the stock and thus makes the right choice on the point of investing or not. Through using the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks,

the system excellently discovers sequential dependencies in stock price data, thus, it works better in predicting future trends. The employment of the Dropout layers guards against overfitting, while the Dense layers succeed in making more precise predictions and hence raise the certainty of the model. The utilization of model ap- praisals such as trends such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) are good indicators of the model's real-world practicality. Systematically, the primary role of the project is to show us the capability of deep learning in stock market prediction solely for the sole purpose of untold futures that could entail real-time financial indicators, sentiment analysis, and ensemble learning approaches.

REFERENCES

[1] Kalyoncu, S., Jamil, A., Karataş, E., Rasheed, J., Djeddi, C.: Stock Market Value Predic- tion using Deep Learning. In: 3rd International Conference on Data Science and Applica- tions (ICONDATA’20), Istanbul, Turkey (2020).

[2] Valle-Cruz, D., Fernandez, V., Lopez-Chau, A., Rojas-Hernández, R.: Stock Market Pre- diction with Artificial Intelligence Techniques in Recession Times. In: Applied Machine Learning and Data Analytics, Communications in Computer and Information Science, vol. xxx, pp. 246–263. Springer, Heidelberg (2024).

[3] Serrano, W.: The Random Neural Network in Price Predictions. Neural Computing and Application (2022).

[4] Gao, Y., Wang, R., Zhou, E.: Stock Prediction Based on Optimized LSTM and GRU Mod- els. Scientific Program. (2021).

[5] John, A., Latha, T.: Stock Market Prediction Based on Deep Hybrid RNN Model and Sen- timent Analysis (2023)

[6] Lu, W., Li, J., Li, Y., Sun, A., Wang, J.: A CNN-LSTM Based Model to Forecast Stock Prices (2020).

[7] Chen, Y., Fang, R., Liang, T., Sha, Z., Li, S., Yi, Y., Zhou, W., Song, H.: Stock Forecast Based on CNN-BiLSTM-ECA Model (2021).

[8] Moghar, A., Hamiche, M.: Stock Market Prediction Using LSTM Recurrent Neural Net- work. In: International Workshop on Statistical Methods and Artificial Intelligence (IWSMAI 2020), Warsaw, Poland, pp. xxx-xxx (2020). Elsevier.

[9] Li, Z., Yu, H., Xu, J., Liu, J.: Stock Market Analysis and Prediction Using LSTM: A Case Study on Technology Stocks. In: Innovations in Applied Engineering and Technology (2023).

[10] Bhandari, H.N., Rimal, B., Pokhrel, N.R., Rimal, R., Dahal, K.R., Khatri, R.K.C.: Predict- ing Stock Market Index Using LSTM. Machine Learning with Application, (2022).

[11] Hu, Z., Lei, F., Fan, Y., Ke, Z., Shi, G., Li, Z.: Research on Financial Multi-Asset Portfo- lio Risk Prediction Model Based on Convolutional Neural Networks and Image Processing (2024).

[12] Teixeira, D.M., Barbosa, R.S.: Stock Price Prediction in the Financial Market Using Ma- chine Learning Models. Computation (2024).

[13] Sonkavde, G., Dharrao, D.S., Bongale, A.M., Deokate, S.T., Doreswamy, D., Bhat, S.K.: Forecasting Stock Market Prices Using Machine Learning and Deep Learning Models: A Systematic Review, Performance Analysis and Discussion of Implications (2023).

[14] Pan, H., Tang, Y., Wang, G.: A Stock Index Futures Price Prediction Approach Based on MULTI-GARCH-LSTM Mixed Model. Mathematics (2024).

[15] Zhao, C., Hu, P., Liu, X., Lan, X., Zhang, H.: Stock Market Analysis Using Time Series Relational Models for Stock Price Prediction. Mathematics (2023).