Stock Price Prediction Using Machine Learning And Deep Learning Techniques

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Abstract- *Since stock values are intrinsically complicated, it has never been easy to anticipate how they will move. In recent years, deep learning techniques have shown promising results in recognising complex patterns in financial time series data. This research proposes two novel architectures for stock price prediction: GRU-CNN and MLP-GRU. Together, convolutional neural networks (CNNs) and gated recurrent units (GRUs) can extract short-term relationships and spatial patterns from the input data. GRUs are used by the model to capture sequential dependencies, and CNNs are used to extract spatial features from the input time series data. The MLP-GRU design integrates the Multi-Layer Perceptron (MLP) and GRU network to enable the model to learn complex nonlinear correlations within the data. The MLP layers allow the GRU network to focus on temporal connections by providing it with greater flexibility in detecting higher-order correlations. Both systems are evaluated using historical stock price data from several financial markets. The trials' results demonstrate that the recommended models outperform baseline methods and traditional deep learning architectures in terms of prediction accuracy and robustness. When all is said and done, the GRU-CNN and MLP-GRU architectures offer feasible routes to improved stock price prediction, providing investors and financial analysts with crucial data that they can utilise to make informed choices in unpredictable market conditions.*

Keywords- MLP-SVM,CNN-GRU, Stock Price, Deep Learning

I. INTRODUCTION

Predicting stock prices with accuracy is a crucial yet challenging undertaking in the financial markets. It is difficult to predict stock values accurately since they are dynamic and affected by many different factors, such asgeopolitical developments, market mood, and economic statistics. Traditional approaches typically rely on statistical methods or oversimplified models, which may not be able to adequately capture the complex underlying patterns found in financial time series data. The advent of deep learning techniques has revolutionised the field of stock price prediction and offers new avenues for developing more accurate and dependable forecasting models. As deep learning models can automatically discover complicated patterns from raw data, they have surpassed older methods in many domains, such as natural language processing, computer vision, and speech recognition.In this research, two novel deep learning architectures for stock price prediction are proposed: GRU-CNN and MLP-GRU. These architectures make use of the advantages of recurrent neural networks (RNNs), convolutional neural networks (CNNs), and multi-layer perceptrons (MLPs) to capture temporal dependencies and spatial patterns within the input data. The first proposed architecture, known as GRU-CNN, combines Gated Recurrent Units (GRUs) and Convolutional Neural Networks (CNNs), taking advantage of the complementing advantages of both architectures. GRUs excel with sequential dependencies throughout time, while CNNs are adept at extracting spatial features from multidimensional data. By combining these two components, the GRU-CNN modelaims to increase its ability to recognise complex patterns in the financial time series data. The second proposed design, known as MLP-GRU, combines a Multi-Layer Perceptron (MLP) with a GRU network to find nonlinear correlations in the data. The MLP layers provide greater modelling flexibility for correlations of a higher degree, allowing the GRU network to focus on effectively capturing temporal dependencies. This research aims to investigate the predictive power of these proposed architectures for stock prices across different time horizons and market conditions. The models' performance and resilience will be assessed experimentally against baseline methods and traditional deep learning architectures using historical stock price data from several financial markets.

In short, the proposed GRU-CNN and MLP-GRU architectures are promising advancements in the field of stock price prediction since they can improve accuracy and reliability. These models have significant implications for investors, financial analysts, and regulators since they provide valuable insights for decision-making in dynamic and volatile market conditions.

II. METHODOLOGY

In order to predict stock prices, the process starts with preprocessing historical data and dividing it into training and testing sets. An MLP-SVM model learns complicated associations for prediction, whereas a CNN-GRU model extracts sequential features to capture short-term trends. The outputs of the models are aggregated, possibly using a meta-learner or weighted by performance. Performance is evaluated using measures like MAPE, MSE, or accuracy, and architectures and parameters are adjusted for maximum efficiency. The generalisation ability of the model is then verified by testing it with untested data. By combining CNN-GRU's skill in recognising temporal patterns with MLP-SVM's ability to understand complex relationships, the hybrid technique seeks to improve prediction accuracy. By combining these models, the methodology aims to lessen the drawbacks of separate strategies and provide a thorough foundation for accurate stock price predictions.

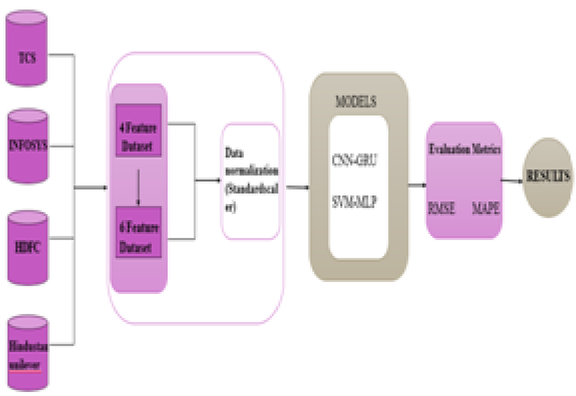

Fig. 1. Architecture of the system

III. ALGORITHM USED

Convolutional neural networks and Gated Recurrent Units (CNN-GRU):

CNN-GRU work together to create a powerful framework for handling sequential data, such as stock prices. With the use of convolutional filters applied at various time steps, CNNs in this hybrid architecture are particularly good at extracting spatial information from the sequential input data. The network can identify local patterns and dependencies in the sequential data thanks to these filters. The GRU units, which are intended to identify long-range and temporal dependencies in sequential data, receive the output from the CNN layers after that. Because GRUs are recurrent, they can process fresh input while retaining a recollection of previously processed data, which makes it easier to mimic the intricate temporal dynamics included in stock price fluctuations. The model is able to capture the temporal and spatial aspects in the data by merging CNNs and GRUs. The network can learn complex patterns and correlations across many time scales thanks to this combination of spatial and temporal processing powers, which improves its predictive performance on tasks like stock price prediction. All things considered, the CNN-GRU combination provides an effective and adaptable method for evaluating sequential data by utilising the complimentary advantages of GRUs for temporal modelling and CNNs for spatial feature extraction to produce higher predicted accuracy. Additionally, the combination of CNNs and GRUs has a number of benefits, including as robustness against noisy and irregularly sampled data, scalability to handle huge datasets, and the capacity to catch both short- and long-term trends in the data.The hybrid design can also automatically pick up hierarchical data representations, which enables it to adjust to the dynamic and complicated nature of financial markets. In general, the amalgamation of CNNs and GRUs furnishes an efficacious and adaptable structure for evaluating consecutive data, exhibiting enhanced efficacy in assignments like stock price forecasting when juxtaposed with the utilisation of either architecture in isolation.

Multilayer Perceptron and Support Vector Machine (MLP-SVM):

By combining the advantages of both models, the Support Vector Machine (SVM) and Multilayer Perceptron (MLP) offer a strong foundation for stock price prediction. Support Vector Machines (SVMs) are robust classifiers that are well-known for their capacity to manage intricate, high-dimensional data and their efficiency in capturing nonlinear correlations. MLPs, on the other hand, are adaptable neural networks with many layers of connected neurons that enable them to discover complex patterns and relationships in data. The SVM functions as a feature extractor in this hybrid architecture, converting the input data into a higher-dimensional space that allows for efficient separation into distinct classes or regression goals. SVMs achieve this by finding a hyperplane that, within a maximum margin of separation, maximally separates data points from various classes or targets.

The MLP further refines the retrieved characteristics and discovers intricate correlations between them using the SVM's output as input. The MLP is made up of several layers of neurons, each of which modifies the input data in a nonlinear way. The MLP modifies its weights to reduce the error between the expected and actual stock prices through a forward and backward propagation mechanism. The model gains from the combination of SVM and MLP by utilising the former's power to extract discriminative features and the latter's ability to understand complex correlations between these features. Comparing this hybrid technique to utilising SVM or MLP alone, the model is better able to identify both global and local trends in the data, improving its predicted accuracy. Additionally, because the SVM serves as a regularisation technique for the MLP by giving it a reduced representation of the input data, the combination of SVM and MLP offers robustness to various types of data and helps mitigate overfitting. All things considered, this hybrid architecture offers an excellent framework for stock price prediction that can capture the intricate relationships present in financial markets.

IV. SYSTEM ARCHITECTURE

The various datasets of various organizations are obtained from Kaggle. Dataset contains features such as Date, High, Close, Open, Low, Adjacent close, Volume of the following companies-TCS, INFOSYS, HDFC, HINDUSTAN UNILEVER. The values present in the datasets are preprocessed to check and eliminate the missing values and fill the null values.Data preprocessing is crucial for ensuring data quality and reliability. The appropriate algorithm is applied to the collected dataset. The most important features are extracted using appropriate feature extraction techniques.In our approach to stock price prediction, we utilize a variety of models specialized in distinct aspects. For the system, the combination of CNN-GRU and MLP-SVM are used. The preprocessed data is fed into the combination of algorithms chosen. Further, the dataset is divided into training, validation, and testing sets after the models are chosen. The training data is used to train the models and validation data is used to check whether the algorithm is works correctly. From the test data, performance of the system for the algorithm is obtained. From the results obtained the system is compared and evaluated by comparing both the algorithms used. And the most accurate predicting algorithm will be taken into consideration.

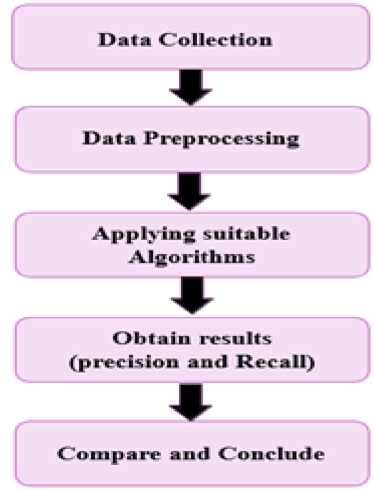

Fig.2. Working of the system

V. OUTPUT

Using MLP-SVM the Combined Root Mean Squared Error value and Mean Absolute Percentage Error values are obtained for the datasets used.

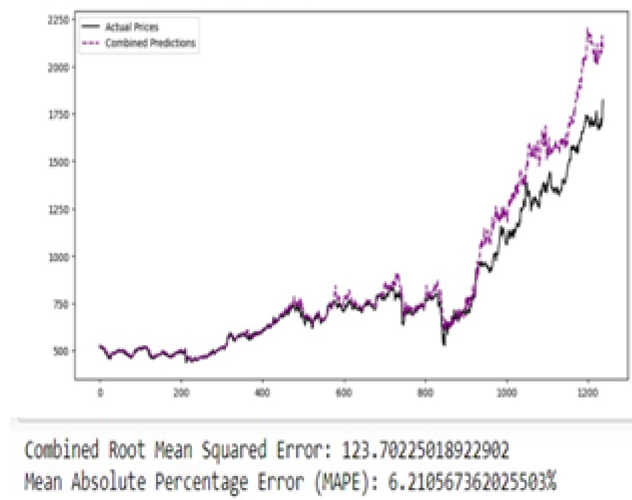

Fig.3. Output of Infosys dataset using MLP-SVM

The evaluation metrics for Infosys stock price prediction model showcase promising results. With an RMSE of 123.702, the predictions exhibit an average deviation of approximately 123.702 units from the actual values. Additionally, the MAPE value of 6.21 reflects an average percentage error of around 6.21%, indicating a relatively accurate forecasting performance.

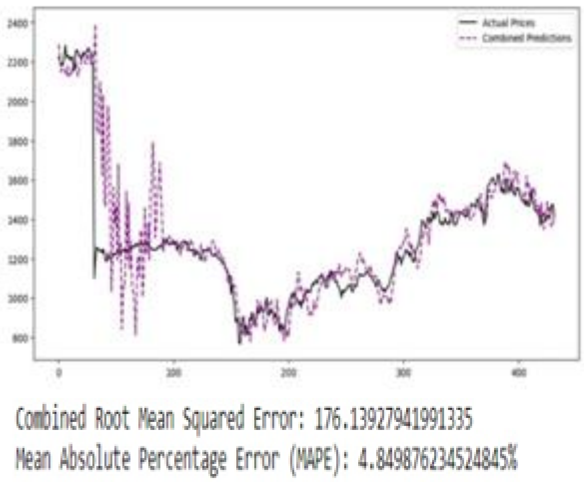

Fig. 4. Output of HDFC dataset using MLP-SVM

For the HDFC dataset, the achieved RMSE is 163.964, indicating an average prediction error of around 163.964 units. The accompanying MAPE value of 7.17 implies an average percentage deviation of approximately 7.17%. These metrics suggest a reasonable level of accuracy in the stock price predictions, highlighting the model's performance in capturing the dynamics of HDFC stock prices.

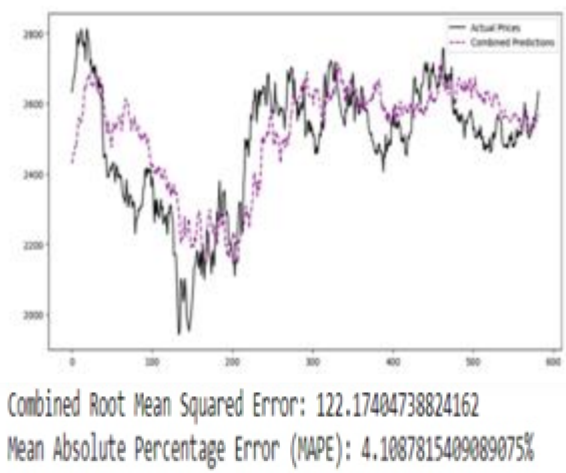

Fig. 5. Output of Hindustan Unilever dataset using MLP-SVM

In the context of the Hindustan Unilever dataset, the stock price prediction model exhibited strong performance, as reflected by an RMSE of 122.174 and a MAPE of 4.108. These metrics indicate a relatively low average prediction error of approximately 122.174 units and an average percentage deviation of around 4.108%. The results affirm the model's accuracy and effectiveness in capturing the dynamics of Hindustan Unilever's stock prices

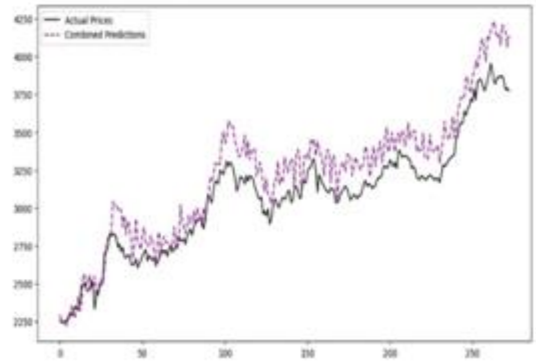

Fig. 6. Output of TCS dataset using MLP-SVM

In the TCS dataset, the model demonstrated a performance with an RMSE of 176.13, indicating an average prediction error of approximately 176.13 units. The corresponding MAPE value of 4.84 suggests an average percentage deviation of around 4.84%. Despite a somewhat higher RMSE, the low MAPE underscores the model’s effectiveness in accurately predicting TCS stock prices.

Using CNN-GRU the Combined Root Mean Squared Error value and Mean Absolute Percentage Error values are obtained for the datasets used.

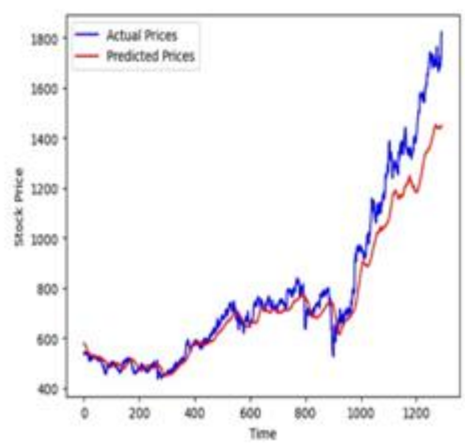

Fig. 7. Output of Infosys dataset using CNN-GRU

For the Infosys dataset, the CNN-GRU model exhibited a performance with an RMSE of 431.11, indicating an average prediction error of approximately 431.11 units. The corresponding MAPE value of 6.70 suggests an average percentage deviation of around 6.70%. While the RMSE is relatively higher compared to previous models, the moderate MAPE value indicates a reasonable accuracy in predicting Infosys stock prices with the CNN-GRU architecture.

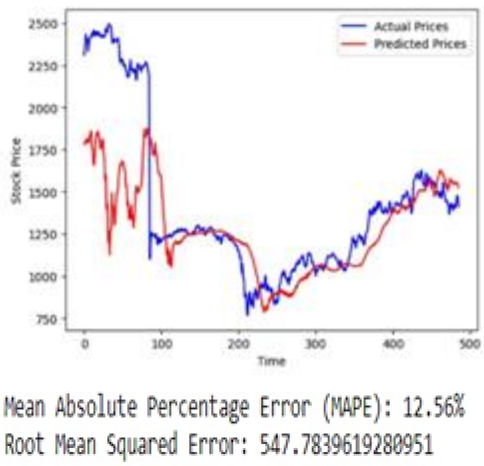

Fig. 8. Output of HDFC dataset using CNN-GRU

For the HDFC dataset, the CNN-GRU model demonstrated a performance with an RMSE of 547.78, implying an average prediction error of approximately 547.78 units. The accompanying MAPE value of 12.56 suggests an average percentage deviation of around 12.56%. These metrics indicate a higher level of prediction error compared to previous models, highlighting the potential challenges in accurately forecasting HDFC stock prices with the CNN-GRU architecture.

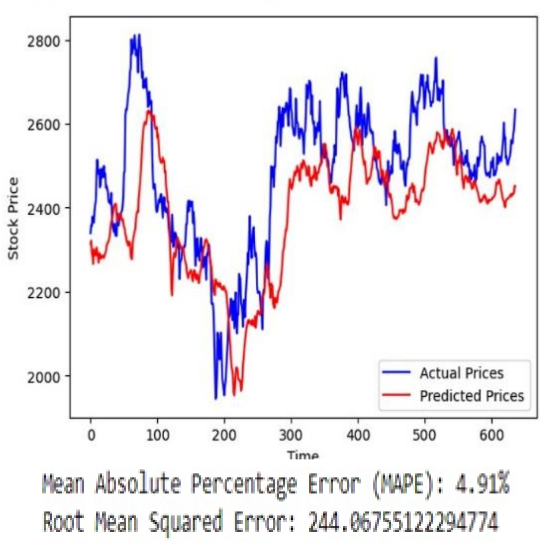

Fig. 9. Output of Hindustan Unilever dataset using CNN-GRU

In the context of the Hindustan Unilever dataset, the CNN-GRU model exhibited performance metrics with an RMSE of 244.067, implying an average prediction error of around 244.067 units. The accompanying MAPE value of 4.91 suggests an average percentage deviation of approximately 4.91%. These results indicate a satisfactory accuracy level in forecasting Hindustan Unilever stock prices using the CNN-GRU architecture, with a moderate RMSE and a relatively low MAPE.

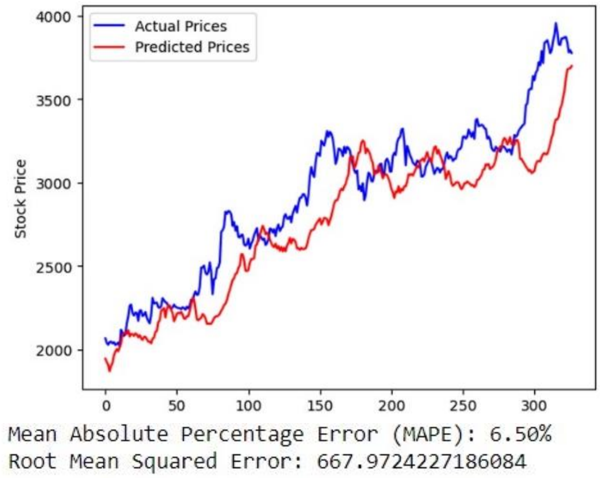

Fig. 10. Output of TCS dataset using CNN-GRU

In the case of the TCS dataset, the CNN-GRU model yielded performance metrics with an RMSE of 667.97, signifying an average prediction error of around 667.97 units. The associated MAPE value of 6.50 suggests an average percentage deviation of approximately 6.50%. These findings indicate a moderate level of accuracy in predicting TCS stock prices using the CNN-GRU architecture, featuring a higher RMSE but a relatively low MAPE.

VI. CONCLUSION

The objective of this project is to forecast stock prices by utilizing deep learning and machine learning models. This is a challenging and uncertain task. We used a wide range of models, each having special qualities and abilities. We have gained important insights from the analysis of these models using metrics like Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). According to the results obtained, the MLP-SVM model performed exceptionally well, attaining the lowest MAPE and RMSE while still demonstrating remarkable accuracy and precision. It is evidence of how successful this conventional machine learning methodology is when it comes to stock price forecasting.

In conclusion, the analysis we have done on deep learning and machine learning for stock price prediction has produced optimistic results. These findings underscore the diversity of approaches that can be applied to tackle this complex and dynamic task. However, we must be mindful of the inherent challenges and uncertainties in financial markets. Continuous model monitoring and adaptation to changing conditions are essential to maintain and improve predictive capabilities. The foundation this project provides for future study and advancement in the area of stock price prediction is invaluable. Looking ahead, there is a lot of potential for understanding the complexities of financial markets and giving traders and investors precise insights.

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