Hybrid Approaches for Stocks Price Prediction: A New Institutive Way of Neural Architecture Design

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***Abstract*—Stock price prediction is a critical aspect of financial decision-making for both individual investors and institutions. Traditional methods such as ARIMA and deep learning techniques like ANNs, LSTM, and GRU have demonstrated effectiveness in forecasting stock prices but suffer from inherent limitations. In recent years, hybrid models have emerged as a promising approach to address these shortcomings. This research paper introduces and evaluates three novel hybrid models for stock price prediction. First model integrates GRU, LSTM, and attention mechanisms to leverage the strengths of each component. By employing attention mechanisms, the model can focus on relevant information, thereby enhancing prediction accuracy. The second model combines GRU and LSTM networks with attention mechanisms, incorporating additional architectural elements to further refine predictive capabilities. The third proposed model is a fusion of the first two, augmented with additional features and enhancements to achieve superior performance in stock price prediction tasks. Evaluation of these proposed models utilizes commonly used metrics to assess predictive accuracy and generalizability. The results demonstrate the effectiveness of the proposed hybrid approaches in improving stock price prediction performance. This research contributes to the advancement of stock price prediction methodologies by proposing innovative hybrid models, offering valuable tools for researchers and practitioners in the finance industry seeking enhanced forecasting accuracy and decision-making capabilities.**

Keywords—ANN, LSTM, GRU, RNN, soft computing, Stock Price Prediction, Hybrid approaches, Self-Attention

I. Introduction

The prediction of stock prices has been an area of research interest for many years, with implications for both individual investors and financial institutions. Accurate predictions can help investors make better investment decisions, while also helping financial institutions to manage their portfolios more effectively. Traditional approaches to stock price prediction, such as technical analysis and fundamental analysis, have limitations, and in recent years, researchers have turned to machine learning and artificial intelligence techniques to develop more accurate and reliable models.

Stock prediction is the process of using various statistical and machine-learning techniques to forecast the future behaviour of financial markets and individual stocks. The stock market is known for its volatility, which makes it difficult to predict with certainty. However, investors and traders rely on stock predictions to decide when to buy or sell stocks. There are two primary approaches to stock prediction: fundamental analysis and technical analysis. In fundamental analysis, there is a cross-examination of a company's financial statements, its management, and industry trends to find the intrinsic value. Technical analysis, on the other hand, relies on past stock price and volume data to identify patterns and trends that can be used to forecast coming price movements.

In recent times, machine learning algorithms have become progressively popular for stock forecasting due to their capability to identify complex patterns and connections in large datasets. These algorithms use a variety of ways, including neural networks, decision trees, and support vector machines, to learn from true request data and induce prognostications for coming price movements. Despite the advancements in machine learning and artificial intelligence, stock prediction remains challenging and uncertain. Many factors, including economic conditions, political events, and unexpected company news, can influence stock prices. As such, it is important to use caution when making investment decisions based on stock predictions and to consult with a financial advisor before making any major investment decisions. Machine learning techniques, such as support vector machines, and decision trees, have been used to build predictive models that can learn patterns and relationships from historical data. These models can then be used to make predictions on future stock prices. In recent years, hybrid models that combine multiple machine-learning techniques have emerged as promising solutions.

Stock price forecasting is a problem that comes under time series prognostication and deep learning models, similar to recurrent neural networks (RNNs) and long-short-term memory (LSTM) networks, have been shown to be effective in time series forecasting due to their capability to capture temporal dependencies in the data. RNNs and LSTMs aim to handle successional data and can model tangled patterns in time series data. In a typical time, series forecasting using deep learning, the historical values of the time series are used as inputs to the neural network, and this learns to prognosticate by recognizing the secret patterns in the data. The accuracy of the predictions is evaluated using metrics such as mean squared error or mean absolute error. One important aspect of time series prediction using deep learning is data preprocessing. The data may need to be scaled, normalized, or transformed to meet the requirements of the chosen neural network model. Additionally, the time series data may need to be split into training and testing sets, and the model may need to be trained using various hyperparameters to optimize its performance. To reduce these preprocessing efforts deep learning was introduced, these methods were good but and can't cooperated with the volatility of the data after an extent in order to solve this issue hybridization is introduced, it has given more satisfactory results in comparison to previous approaches. Stock Price Prediction is a vast scope for study on stock price prediction, as accurate predictions can have significant benefits for investors and financial markets. Here are some potential areas for research:

- Comparison of different machine learning algorithms: There are various machine learning algorithms that can be used for stock price prediction, including decision trees, support vector machines, and neural networks. A study could compare the performance of different algorithms to identify which one is most accurate for predicting stock prices.

- Use of alternative data sources: In addition to traditional financial data, there is a growing interest in using alternative data sources such as social media sentiment, news articles, and web traffic data to predict stock prices. A study could explore the effectiveness of incorporating these data sources into stock price prediction models.

- Time series analysis: Time series analysis can be used to identify patterns in historical stock prices and to forecast future prices. A study could explore the use of different time series models, such as ARIMA or exponential smoothing, for predicting stock prices. Overall, there is a wide range of research opportunities for stock price prediction and advances in machine learning, data analytics, and alternative data sources are likely to continue to drive innovation in this area. There are different types of stock recommenders with different scopes of application.

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II. Literature Review

The paper presents an ensembled LSTM model for predicting the KSE-100 index of the Pakistan Stock Exchange, employing Akima spline interpolation and IMFs with single monotone residue to handle noise. In Comparison to popular techniques like SVM and Decision Tree, the proposed method is found more efficient.[1] This paper examines machine learning algorithms like ANN, SVM, and LSTM for stock price prediction, highlighting ANN's 90% efficiency and accuracy, but highlighting the need for revolutionization due to dynamic change in stocks data.[2] Stock predictions have been published using various approaches, including LSTM, SVM, and ANN. The most popular year for stock market prediction using ML was 2013, despite a high number of papers published in 2015-2017.[3] The paper compares popular models ARIMA and LSTM for predicting Apple's stock price from 2016-2020. LSTM outperforms ARIMA due to its low rmse of 0.237, but the major shortcoming is its neglect of external factors like news and revenue. Further research is suggested to combine LSTM with other models.[4]

In this paper the proposed IIFI-based model solves traditional fuzzy systems' dependency for stock price prediction, offering a membership method for fuzzification and defuzzification, addressing CSI 300 and 500 stocks.[5] The research presents a hybrid approach for long-term stock market price trend prediction, utilizing raw and social media data for creating the indexes of stock, butterfly optimization, Feature Extraction, and Brown Planthopper Optimization is used for data preprocessing. The Deep Neural Network integrates firefly-induced extreme learning with DNN, comparing performance with 11 global stock market indices. The proposed network outperforms in terms of accuracy, F-measures and precision in comparison to trendy models.[6]

The paper presents a deep learning neural network for predicting stock prices using S&P 500 data, comparing it to SVM, linear regression, multilayer perception, and RNN.[7] A Hybrid model of CNN and Bidirectional GRU is proposed in this paper where feature selection is applied then CNN collects the local features. This model is also compared with CNN based, GRU based, and with the hybrid of CNN and LSTM and the proposed model is proven better with the least mape of 1.42.[8] The paper compares 8 proposed LSTM and GRU-based architectures for stock market predictions. The four-block neural network architecture is tested using mean absolute percentage error, root mean squared percentage error, and root mean dimensional percentage accuracy. The stock count is restricted to 4, GRU based performs well in terms of used metrics on the other hand from boxplot whisker test LSTM models have found to be least deviated in terms of accuracy.[9] The survey studied 86 papers from 2015-2021 on stock price prediction, forex movement prediction, models like CNN, LSTM, RNN, Reinforcement Learning, HAN, and NLP based, revealing promising results but highlighting limited work on hybrid models.[10] The paper presents a three-step procedure for data preprocessing, including phase space reconstruction and data structuring partitioning with a time window. The Deep Neural LSTM-based architecture is trained and compared to existing models using metrics like RMSE, Direction Accuracy, MAPE, and Correlation Coefficient, revealing a superior prediction performance.[11] The research utilized RNN and LSTM-based neural networks to predict stock prices for Nike (NKE) and Google (GOOGL). The model, consisting of 4 LSTM layers with dropouts after each dense layer, was trained for different epochs. Results showed GOOGL stock experienced losses of 0.0011 and -16.0019 for 12 epochs on NKE and 0.5 and 0.874 for 100 epochs respectively.[12]

The paper proposes a new GAN based stock prediction method using a multi-layer perceptron as a discriminator, outperforming other algorithms like LSTM, ANN, and SVR over the S&P 500 dataset.[13] The article explores the optimal model for daily buying and selling strategy for S&P 500 index stocks, comparing GRU and LSTM models. The GRU model, with an R2_score of 0.94, is the best performer, capable of handling extreme price dips and spikes. Factors like interest rate and GDP growth inflation can enhance the model's performance in future.[14] Using financial features, DNNs predict daily return direction of SPDR S&P 500 ETF using PCA transformation. Pre-processed data performs better than other algorithms, with 31 components providing the best accurate results.[15] The research presents a hybrid approach to stock prediction using Adaline Neural Nets and a modified PSO, achieving an average accuracy of 98.9%, outperforming Bayesian ANN, and CMSPOS in predicting the open price of the Bombay stock exchange.[16] The research presents a new deep learning method with RBFFNN and RNN, demonstrating a 4.8% accuracy increase in total returns and rmse. The best suitable window size is 20 and 10x10 component size.[17] The proposed model utilizes CNN, LSTM, and RNN for stock price prediction, with Infosys being the only stock trained. The model outperformed other models, with RNN 5.12, LSTM 5.31, and CNN 4.98, so CNN is best despite of its high percentage error for TCS.[18] LSTM, RNN, SVR, and MLP are all profitable models for profit gains in five industries: Transport Equipment, Pharmaceutical, Machinery, Electronics, and Wholesale Trade. LSTM outperforms all other methods, with a profit of 1211.90, demonstrating its superior performance in textual or new articles.[19]

III. Proposed Methodology

In this paper there are three neural architectures are proposed using layers like gated-recurrent-unit, long-short term memory, attention layers and dense layer. The steps that are followed while generating the relevant features is shown below in Figure 1.

In this pipeline initially OHCL per minute data of nifty 50 stocks from 2015 to 2024, and then from this data the selected data indicators will be calculated that includes MACD, RSI, Price Spread, Bolling Bands, Stochastic oscillators, and ATR. For each indicators the best parameters will be calculated using exhaustive grid search way and the selection of parameters is based on correlation of them with the target value that is close price. In the below Table 1 the indicators and their best parameters are shown. In the next step these indicators are taken, and their distribution is analysed as a result of that it has been observed that there are 2 skewed features those are price spread and stochastic oscillator. There distribution is shown below in Figure 2.

In the above distribution plot, it is clearly visible that price spread is right skewed while on the other hand the stochastic oscillator is left skewed. For preprocessing the skewed and non-skewed the following pipeline is followed shown in Figure 3. In the above pipeline the data indicators are taken then the null values are dropped in order to maintain the consistency. Now, these Cleaned data is analysed using histogram and split into two parts skewed and non-skewed features. In the next step scaling is applied in order to make the data distribution close to the gaussian distribution, and for this on skewed features log transformation is applied while on non-skewed robust scaling is applied. In the next step deep-neural architectures are constructed using the below deep learning pipeline shown in the below In above pipeline first data indicators are feed directly, and from the closing price time features are generated by lookback way and now these both are integrated and feed to the neural network which is designed using brainstorming and these models is based on functional approaches like skip block, inception block, etc. once it is ready then training begins in which all the features are feed with the target into it and while training we split it with 80-20 for training and validation where total records are 7,90,788. The metrics used in order to monitor the model performance are mean absolute error and mean absolute percentage error. At last model saved. In this research paper 2 models are created then 3rd model created where output of these models are feed to model 3 as input and to improve learning, and generalization. Those two model architectures are shown below in Figure 5 and 5 Next is the third architecture that is integration of both above architectures with some additional layers i.e. shown below in Figure 5.

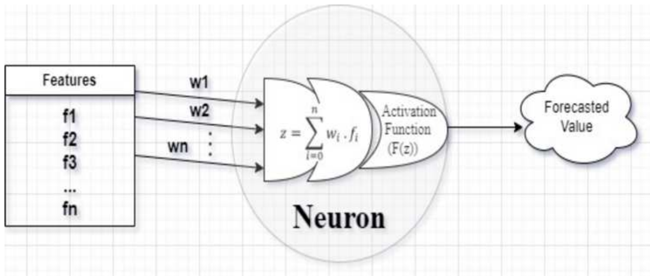

Fig. 1. Structure of Neuron in ANN.

TABLE I. Paramerts for Data Indicators

Data Indicators	*Best Parameters*
MACD	Factor: 32 days (In minutes) this factor is multiply with the default values of short, and long window-size and also with signal with default values of 12, 26, and 9
RSI	Window-Size: 7 and 32 days (In minutes)
Price Spread	No Parameters needed
Bolling Bands	Window-Size: 30 minutes
Stochastic Oscillator	K-periods: 32 days
Average True Range	ATR-periods: 32 days

This is the First Functional architecture proposed in this paper shown in Figure 5, and this model takes the input as a combination of both data indicators and 25 past time slice of close prices, now this feed to Attention layer that computes the scores for each feature using the concept of self-attention then these attention scores are dot product with the features($\sum$(Scores)i .(Features)i) as prod. Then this is further feed to a cascading cross connection network that works on 1-4 & 2-3 approach means the prod is feed sequentially to LSTM & GRU layers in a alternate fashion then first and the fourth layer is combined using Add operation(named as l14) while second and third layer combine by Multiply operation(named as l23), now further these l14 and l23 is feed to LSTM & GRU layer respectively and then further each followed by Layer Normalization. Now the final output of both feed to the Attention layer to compute the scores(sc1), then these both outputs are combined using Add(), then both score(sc1) and the output combined using add is feed to a Multiply() then further feed to Layer Normalization then to a LSTM block then to Batch-Normalization at last to the output Dense Neuron to give the prediction. This is the Second Functional architecture proposed in this paper shown in Figure 6, and this model takes input as a combination of both data indicators and 20 past time slice of close prices now this is feed to LSTM layer now the output of previous layer is feed to two different GRU layer followed by a LSTM layer then we will do cross Add() and Multiply of the outputs of both the simultaneous subnetworks, then further the respective output is Dot Product with each other. This dot product output is feed to Layer Normalization followed by LSTM then at last to the final Output Dense Neuron to give the prediction. This the third proposed architecture shown in Figure 7 which is a hybridization of previous two architectures it simply takes the output of each model, then it is feed to a Dense layer with 16 neurons, then its output is to two different layers simultaneously one having only one dense layer with 4 neurons and another with 2 dense layers sequentially with 8 and 4 neurons respectively. The outputs of both concurrent layers is combined with Add() layer then at last feed to the final Output Dense Neuron to give the prediction.

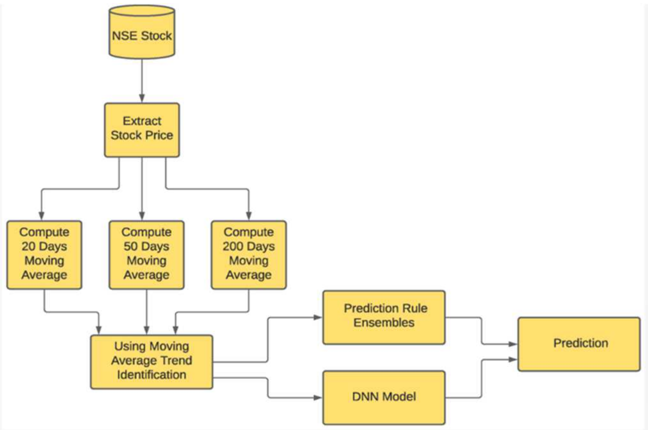

Fig. 2. Architecture of Data Processing robust scaling.

The process followed in the building pipeline procedure is as followed. • Data is collected with various sources this data is heterogenous in nature because it can include the OHCL data of stocks, news, etc. • Then as per the data the preprocessing techniques are applied for example for the OHCL there is a common approach that is moving average for removing the seasonality and remove the noises from it, similarly for each data there is different preprocessing approaches. • Then this data is split into two parts that are Training + Validation Set and Testing Set. • Then for Each type of data a model is trained with the Training and Validation Set respectively, this training is continued until we get an optimal success rate. • As soon as we reach to the optimal training and validation accuracy then the Test set is used in order to verify the models separately. Since, the above procedure in Fig 2 gives various models trained and verified now these models will we utilized in the recommendation pipeline, in-order to get the optimal stocks as per the user-need and that procedure.

IV. Result and Discussions

After analysing the papers, the comparison of various approaches with proposed approach using metrics like mape, mae, etc. is shown below using Table 2.

TABLE II. Comparative Analysis of Stock Price Prediction Approaches

References	***Year of Publishing***	***Methods***	***Metrics of Success***
[1]	2023	LSTM based Network	RMSE: 0.237
		ARIMA based model	RMSE: 3.261
[2]	2022	FEL-DNN	Avg-Accuracy: 83.66 Avg-F1-Score: 84.38
[3]	2022	DFNN	MAE: 0.78
[4]	2022	FS+CNN+BGRU	MAPE: 1.4325 R^2score: 0.983808
[5]	2022	LSTM based Model	MAPE: 96.98% RMPSE: 95.95% RMDPSE: 82.58%
[6]	2022	GRU based Model	MAPE: 96.84% RMPSE: 96.04% RMDPSE: 85.10%
[7]	2021	LSTM based Model	MAE: 6.85E-4
[8]	2019	Gan Based Model	MAE: 3.04 RMSE: 4.10 MAPE: 0.0137
[9]	2019	LSTM based Model	RMSE: 0.000428 R^2 Score: 0.94
		GRU based Model	RMSE: 0.000511 R^2 Score: 0.93
[10]	2019	ANN (with PC's =31)	MSE: 0.3011
[11]	2018	Proposed Hybrid Model	Accuracy: 98% MAPE: 1.1
[12]	2017	RBFNN (Radial Bias Function NN)	MAPE: 0.080059 RMSE: 0.00674

Proposed Method	2024	Proposed Model 1	MAE: 330 MAPE: 2.08

The table above, Table 2, vividly demonstrates the advancements achieved by the proposed models. Notably, Model 2 starts with a MAPE of 1836, which significantly decreases to 330 for Model 1, and further drops to 111 for the hybrid model. Similarly, the trend persists for MAPE, with values descending from 18.5 for Model 2, to 2.08 for Model 1, and further down to 0.89 for the hybrid model. To offer a clearer understanding, visualizations are provided in Figures 8 and 9. These visual aids complement the numerical data, enhancing comprehension of the models' performance improvements over successive iterations is shown. In the above vertical bar chart, the models are compared based on mean absolute percentage error and the best performance is shown by the 3rd model while the worst performance among them is shown by 2nd model.

This above horizontal bar chart compares the proposed models based on mean absolute error this also proves that the 3rd model is the best performer with MAE value of 111 while the 2nd model is the worst performer among them with MAE value 1.84k.

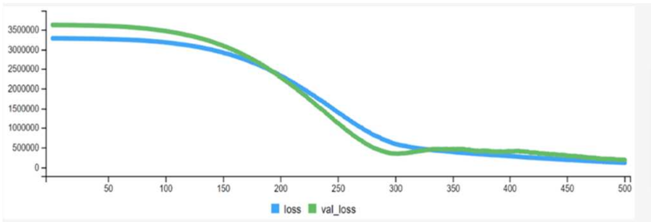

Fig. 3. Models Comparison Based On MAE

A. Soft Computing

It is a type of computing in which the goal is not to compute the exact but here the goal is to reach as close as possible to each solution. It includes techniques like fuzzy sets, genetic algorithms, neural networks, probability-based algorithms. This ability of approximation of soft computing makes it very useful in the world of prediction.

B. ANN

It stands for Artificial Neural Nets it is a technique for prediction that is based on weighted computation, since it is inspired from human brain way of working as we humans analysed the situation and based on that set importance of something, in a similar way in this techniques each feature is assigned with a decimal value that decides its contribution in the decision and goal of these algorithm is to find the optimal weights and bias such that it minimizes the residuals for current as well as future predictions. A neural network is a collection of various neurons arranged in a manner such that each neuron can be represented as shown in Figure10. In the above Figure 10 the f1,f2,..,fn represents the features or the attributes over which the decision depends upon and w1,w2,..wn represents their corresponding importance value. Each neuron follows 2 steps first calculate the the Weighted Sum of the feature values and their corresponding weights and then that sum is feed to a special function known as activation function that gives the final value computed by the neuron some of the renowned activation functions are relu, linear, leaky relu, etc.

C. LSTM

It is a algorithm that is used when we have a problem where there is an inter-dependency of current output on the previous outputs, it is preferred when there is a long dependency means current output need various previous outputs. This algorithm based on basically three gates that are Input (that takes the input), Output (that gives the forecast), and forgot (that helps in removing the unnecessary details from memory). Due to this ability to forget its name come as Long term and Short term Memory (LSTM).

D. GRU

It is another algorithm that deals with sequential data just like LSTM, the major difference is that they have two gates that are Update and Reset gate. In this update gate decides which inputs need to be sustained, on the other hand reset gate is responsible for discarding inputs. It requires less computation than LSTM and less parameters that reduces the chances of overfitting.

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