Golden Eagle optimized Hybrid RNN-GRU Model for Stock Price Prediction: A Data-Driven Deep Learning Approach

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***Abstract*--Predicting stock prices accurately remains a formidable challenge due to their volatile and non-linear behavior. Advent of Artificial Intelligence (AI) and Machine Learning (ML) significantly enhanced computational capabilities, improving efficiency in stock price forecasting. This research employs Deep Learning (DL) methods to predict future stock prices, leveraging a Hybrid Recurrent Neural Network (RNN)-Gated Recurrent Unit (GRU) integration to boost prediction accuracy. Hybrid RNN-GRU model effectively captures the complex patterns in stock price deviations across diverse market sectors. The performance of hybrid RNN-GRU model is further enhanced by finely tuning its hyperparameters by optimization algorithms. Golden Eagle Optimization (GEO) approach is utilized which mimics hunting behavior of eagle to explore and exploit optimal solution effectively in predicting stock price trends. Evaluation of the proposed model includes performance metrics such as Mean Square Error (MSE) at 0.1045, Root Mean Square Error (RMSE) at 0.4189, Mean Absolute Error (MAE) at 0.9985, and an R² score of 0.9980. These relatively low error values demonstrate model's high efficiency in predicting stock prices accurately.**

Keywords—Data preprocessing, Feature engineering, Scaling/Normalization, Hybrid RNN-GRU, GEO.

I. INTRODUCTION

Equity capital market serves as a platform for the issuance and trading of shares belonging to publicly listed companies. Stock market allows financial investors to buy or sell shares of an organization, resource, or security, addressing fragmented ownership. People involved in trading stocks and assets are referred to as market participants. These participants are classified into categories such as Non-Residential Indians (NRI), Overseas Citizens of India (OCI), Domestic Asset Management Companies (AMC), or Foreign Investors. Companies go public and issue stocks, which are then traded in secondary markets, commonly known as stock exchanges, to raise funds for business growth or debt repayment [1-2]. Offering shares instead of cash allows the corporation to avoid losses, obligations, and interest payments. Shareholders seek profit and financial gain. Shareholders and investors generate earnings by investing in companies that distribute dividends or by selling their shares at a higher market price than the original purchase price [3].

Stocks are financial assets known for their high risk, high return potential, and flexible trading, making them appealing to numerous investors. With precise predictions, investors achieves substantial returns. Stock market prediction involves forecasting performance of future stocks, market sectors, or whole market. Stock prices are affected by various factors, including market conditions, significant socio-economic events, macroeconomic trends, investor behavior, and company management decisions, making accurate predictions highly challenging [5].

Traditional stock price prediction often relies on statistical and economic methods; however, these models struggle to effectively forecast stock market behavior in dynamic and complex environments. As a result of technological progressions in information technology, ML predicts stock prices and their fluctuations, which helps investors decide on investment strategies to mitigate risk and increase returns [6-7].

Random Forest (RF) combines multiple decision trees and determines final output relying on individual tree that reduce the variance of the model. As noise in stock market is usually high, that causes trees to grow differently, leading to forecasting errors [8]. Artificial Neural Network (ANN) identifies fundamental trends from data and generalizes from it. It is proficient of analyzing complex patterns in unstructured data. However, training ANN requires computational time for complex networks [9]. Convolutional Neural Network (CNN) extracts potential characteristics of stock market at a corresponding period from feature graphs. Nevertheless, if the data is not sufficient, it affects the efficiency of the models [10]. Hybrid RNN-GRU model is proposed for predicting stock exchanges.

2025 8th International Conference on Circuit, Power & Computing Technologies (ICCPCT) | 979-8-3315-4317-4/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICCPCT65132.2025.11176673

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RNN considers the context of data suitable for stocks at the time of training, as fluctuations at a particular time contain some relation to previous trends. GRU merges forget and input gates into a single update gate. GRU is a simpler model than any other conventional method. Thus, RNN with GRU is applied for predicting stock price movements. The performance of the prediction model is further enhanced optimization technique. There are various optimization algorithms.

Particle Swarm Optimization (PSO) efficiently evolves initial weights in neural networks, enhancing convergence. However, its performance degrades in large-scale problems with deep architectures. Artificial Rabbits Optimization (ARO) offers a balance between global exploration and local exploitation, helping avoid local optima, but it is computationally intensive, especially with large datasets [11-12]. To address these limitations, a Golden Eagle Optimization algorithm is proposed for optimizing hyperparameters in a hybrid RNN-GRU model, improving prediction accuracy for complex tasks like stock market forecasting.

Research Gaps

Integrating hybrid RNN-GRU models with optimization techniques like Golden Eagle for stock price prediction. While RNN and GRU are used individually, their combined application with advanced optimization remains underexplored. Existing models often lack the ability to scale efficiently, generalize across markets, and provide real-time accuracy. Additionally, there is a need for more data-driven approaches that incorporate diverse market data to enhance predictive performance.

The contributions of the proposed work are:

- To ensure clean and structured data, data preprocessing technique is employed to handle missing values and removing outliers.
- To efficiently predict stock prices, a DL based hybrid RNN-GRU model in integrated to enhance prediction accuracy and for better stock price forecast.
- To improve efficiency of stock price prediction model, GEO is utilized to fine tune the model hyperparameters.

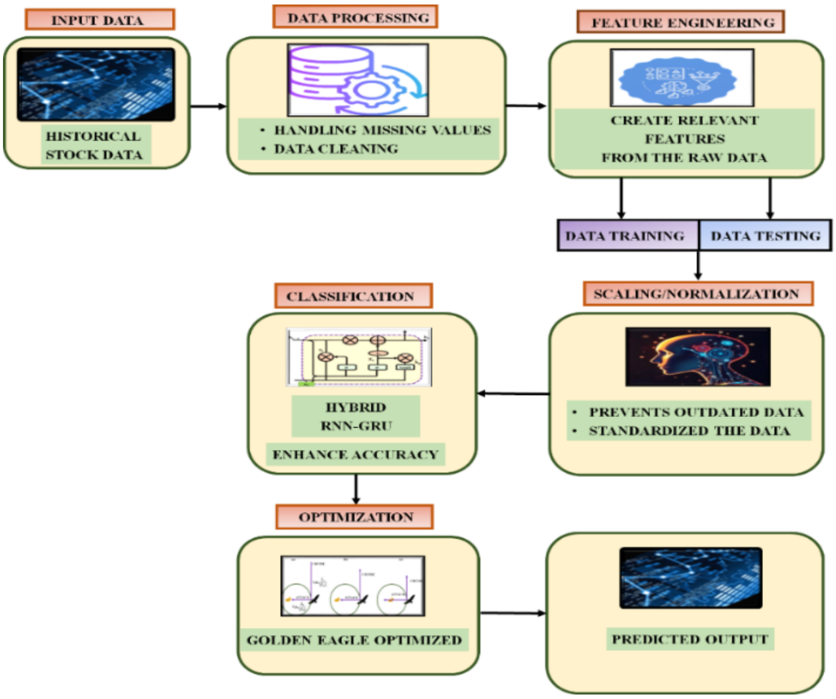

Fig. 1. Block diagram configuration of proposed model.

Fig. 1 depicts a block diagram, it outlines stock price prediction using golden eagle-optimized hybrid RNN-GRU model. The model is initialized by collecting historical stock data that is fed into DL model for prediction purposes. Stock data comprises information about price fluctuations and trading volume over a specific period. Raw stock data is preprocessed by using data cleaning, which remove duplicates, handle outliers and handles missing values. From preprocessed data, prominent features are captured to enhance model's predictive power by feature engineering technique. Features extracted comprises of essential patterns or trends in the stock market. In the next step, data is split into training and testing sets. Scaling/Normalization is applied to transform features to similar scale. The standardized data are classified by hybrid RNN-GRU method. RNN are appropriate for sequential data such as stock prices, whereas GRUs solve vanishing gradient problem, allowing model to capture long-term dependencies. GEO algorithm fine-tunes model parameters to improve their accuracy and efficiency. Finally, trained model predicts future stock prices. Predicted outcomes provides vital insights to investors and traders, allowing them to make informed decisions.

II. Proposed System. Modelling

A. Data Preprocessing

Data preprocessing stage includes operations for data cleaning that handles noise and inconsistent data. Data preprocessing is crucial as DL models require structured and manageable data for enhancing accuracy and effectiveness in predictions operations.

a) Data Cleaning

Data cleaning includes operations that correct irrelevant data, remove incorrect data out of the dataset and reduces unnecessary detail of data. This process detects discrepancies and unwanted data.

b) Handling Missing Values

Missing values are addressed to main data integrity and efficiency, thus ensures the stock prediction accuracy.

B. Feature Engineering

Feature engineering reduces the dataset by eliminating redundant or irrelevant features (or dimensions). The aim of feature engineering is to identify a minimal set of attributes that preserve the original probability distribution of the data output attributes (or classes) as closely as possible. This process enhances the clarity of extracted patterns and boosts interpretability.

C. Train Test Split

The dataset is split into two subsets: training and testing. Training allows the model to learn patterns, when testing assesses its performance and generalization ability.

D. Scaling/Normalization

DL models are sensitive to unnormalized data, so the data is normalized into a range of $[0, 1]$ by MinMax Scaler which is then fed to the prediction model.

$$X_{std} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

$$X_{scaled} = X_{std} * (max - min) + min \tag{2}$$

Where $min = 0$ and$max = 1$. Normalization rescales data to a uniform range, preventing attributes with large max-min differences from disproportionately affecting distance calculations and skewing the learning process. This technique also accelerates learning in DL models by aiding faster weight convergence.

E. Hybrid RNN-GRU classification

RNN is a supervised ML algorithm comprises of neurons and feedback loops which perform recurrent cycles over time or sequence.

RNN input vector x to the output vector y at current time-step and make predictions at the subsequent step. Hidden state (h) and update function is given as,

$$h_t = g_1(W_{hh}h_{t-1} + W_{hx}x_t + b_h) \tag{3}$$

$$y_t = g_2\left(W_{yh}h_t + b_y\right) \tag{4}$$

Distinct matrix layer weight parameters are W_{hh}, W_{hx}, W_{yh}, bias parameters of the node are b_h and b_y, activation functions are $g_1$and g_2, RNN network output layer is y_t.

Architecture of GRU-RNN is depicted in Fig.2 Hidden state h_t is not directly generated from previous hidden state h_{t-1} in GRU-RNN. Instead, it is formed by two gates (reset gate and update gate). Update gate z_t determines number of past information passed along the future state and reset gate r_t decides number of informations needs to be discarded.

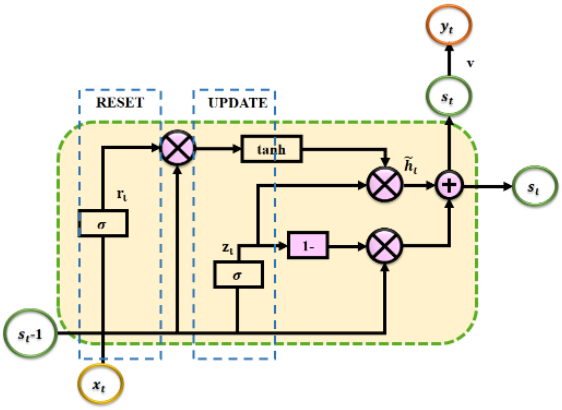

Fig. 2. Architecture of hybrid RNN-GRU.

$$\sigma(X) = \frac{1}{1+e^{-x}} \tag{5}$$

$$tanh = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{6}$$

σ and $tanh$ function is used to calculate gate and state activation function respectively,

F. Golden Eagle Optimization.

GOA approach is a population-based heuristic that mimics the swarming behavior of golden eagles in nature. It is inspired by the ability of golden eagles to fine-tune their speed during the hunting process. GOA optimally tunes the parameters of the hybrid RNN-GRU approach. The mathematical formulation of the proposed optimization algorithm to mimic the golden eagles that search for prey is described as follows:

1) *Golden eagle's spiral motion:* In every iteration, each golden eagle selects prey of another golden eagle f and encircles the best location visited so far by. Golden eagle i circle its own memory, $f \in \{1,2, \dots, PopSize\}$.

2) *Prey Selection:* It randomly selects target prey from the memory of whole flock. Attack and cruise vectors are computed. If a new position is better than previous position, then memory is updated.

3) *Exploitation:* Attack is modelled by vector starting from current position to the ending position of the prey in eagle's memory. Attack vector $\vec{A}_i$ for golden eagle i is calculated by the eqn (5).

$$\vec{A}_i = \vec{X}_f^* - \vec{X}_i \tag{7}$$

Best location of prey is $\vec{X}_f^*$ and eagle current position is$\vec{X}_i$.

4) Exploration: Cruise vector is computed from attack vector and it is a linear speed of golden eagle relative to prey. In n −dimensions, cruise vector is inside a tangent hyper plane to the circle and expressed in eqn (8).

$$h_1x_1 + h_2x_2 + \cdots + h_nx_n = d \Rightarrow \sum_{j=1}^{n} h_jx_j = d \tag{8}$$

Normal vector $\vec{H} = [h_1, h_2, \dots, h_n]$, variable vector $X = [x_1, x_2, \dots, x_n]$, arbitrary point on the hyper plane is $\vec{P} = [p_1, p_2, \dots, p_n]$ and $d = \vec{H} \cdot \vec{P} = \sum_{i=1}^{n} h_jp_j$. Destination point of cruise hyper plane is,

$$\vec{C}_i = \left(c_1 = random, c_2 = random, \dots, c_k = \frac{d = \sum_{i,j \neq k} a_j}{a_k}, \dots, c_n = random\right) \tag{9}$$

5) Moving to a new position

Displacement between attack and cruise vector of golden eagle is defined as,

$$\Delta x_i = \vec{r}_1 p_a \frac{\vec{A}_i}{\|\vec{A}_i\|} + \vec{r}_2 p_c \frac{\vec{C}_i}{\|\vec{C}_i\|} \tag{10}$$

Random vectors are $\vec{r}_1$ and $\vec{r}_2$, Euclidean attack and cruise vectors are $\|\vec{A}_i\|$ and $\|\vec{C}_i\|$ are computed by using eqn (9)

$$\|\vec{A}_i\| = \sqrt{\sum_{j=}^{n} a_j^2}, \quad \|\vec{C}_i\| = \sqrt{\sum_{j=}^{n} c_j^2} \tag{11}$$

Golden Eagle's position in $t+1$ iteration is evaluated by combining step vector in t iteration to position in t iteration.

$$x^{t+1} = x^t + \Delta x_i^t \tag{12}$$

Algorithm gets terminated if any of the criteria are satisfied.

6) Transition from exploration to exploitation:

Changes in attack and cruise are shown in Fig. 3

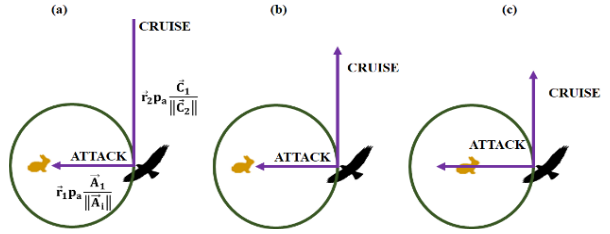

Fig. 3. Transition behavior of golden eagle.

GEO uses p_a and p_c for shifting from exploration to exploitation. Initially, GEO starts with low p_a and high p_c after a few iterations, p_a gradually increased and p_c slowly decreased. Linear transition is displayed in eqn (11),

$$\begin{cases} p_a = p_a^0 + \frac{t}{T}\left|p_a^T - p_a^0\right| \\ p_c = p_c^0 + \frac{t}{T}\left|p_c^T - p_c^0\right| \end{cases} \tag{13}$$

Flowchart of GEO algorithm is visualized in Fig. 4

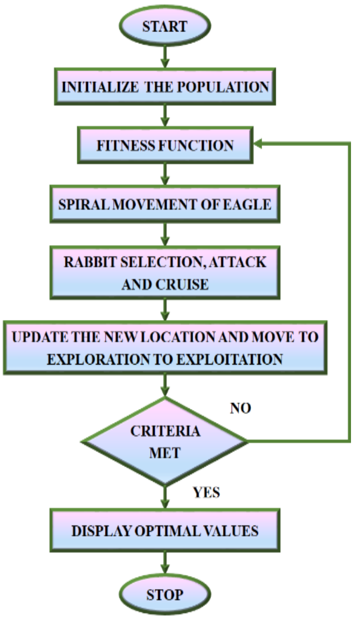

Fig. 4. Flowchart of GEO

Falcon optimization stands out compared to models like PSO, ARO because of its ability to mimic golden eagle hunting behavior, enabling an effective balance between exploration and exploitation during optimization. This leads to faster convergence and enhanced local and global search efficiency, significantly improving the accuracy of the BiLSTM model. Additionally, its flexibility in handling complex, high-dimensional problems makes it particularly suitable for precision demanding applications, such as stock price prediction.

III. RESULT AND DISCUSSION

The proposed work utilizes the "World Stock price (Daily Updates)" dataset to evaluate the effectiveness of the proposed methodology, which is implemented using Python software. The discussion below explores the outcomes of research, comparing with existing techniques.

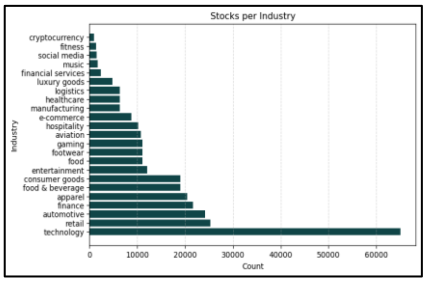

Fig. 5. Stocks per Industry.

Fig. 5 visualizes the distribution of stocks across various industries. From the bar chart it shows that "technology" leads with highest count followed by retail, automotive and finance reflecting robust activity in these sectors. In contrast, industries such as cryptocurrency, fitness, social media, and music have fewer stocks. This distribution emphasize the trends in forecasting stock prices through DL based hybrid RNN-GRU model.

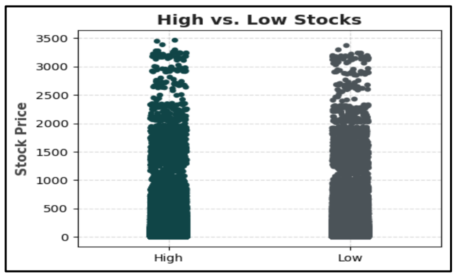

Fig. 6. High Vs Low Stocks.

Fig. 6 presents the distribution of high and low stock prices. Each point shows stock price observation. "High" stock category reaches up to 3500 with a dense cluster from 2000 to 3000. "Low" stock category has a narrow range with most prices are below 2000 and only fewer observations at higher values. These visualization are integral for stock price prediction models.

Fig. 7 represents the distribution of stock prices during open and close market, which is a crucial factor in stock price prediction models. X-axis shows stock prices. Y-axis shows opening and closing prices. Both opening and closing prices share a similar distribution, concentrated at lower values, with lengthened tails extending to higher prices, indicating occasional significant price shifts.

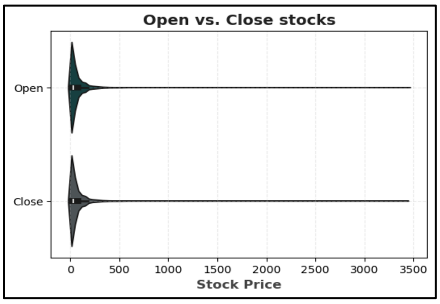

Fig. 7. Open Vs Close Stocks.

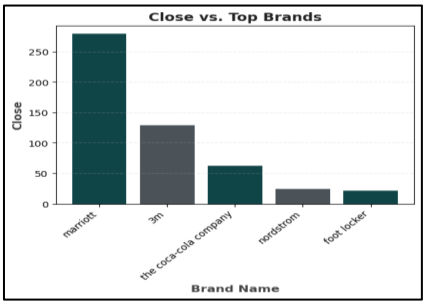

Fig. 8. Close Vs Top Brands.

Fig. 8 displays the closing stock prices of top brands such as Marriot, 3M, the coca-cola company, Nordstrom and foot locker. Marriott stands out with the highest closing price, vastly surpassing others, while Foot Locker has the lowest. This disproportion reflects significant differences in market valuation among these companies.

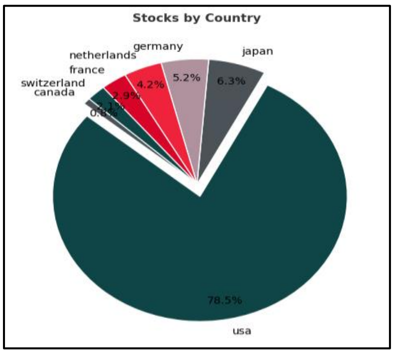

Fig. 9. Stocks by Country.

Fig. 9 illustrates a pie chart with the distribution of stock by countries. It shows the dominance of USA, accounts for78.5%. Other countries such as Japan(6.3%), Germany(5.2%), Netherlands(4.2%), France(2.9%), Switzerland (2.1%) and Canada (0.8%) holding smaller shares. This distribution highlights the substantial influence of the US stock market compared to others.

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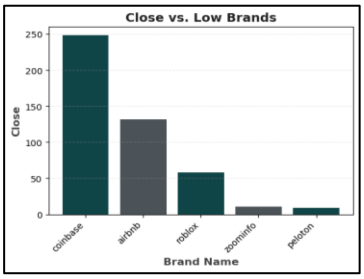

Fig. 10. Close Vs Low Brands.

Fig. 10 demonstrates the closing values of various brands, highlight on their stock performance by deploying golden eagle optimized hybrid RNN-GRU model in stock price prediction. Coinbase stands out with a notably higher closing value compared to other brands such as Airbnb, Roblox, Zoominfo, and Peloton. The chart emphasizes the potential for market volatility and the critical role of precise predictive models under dynamic market environment.

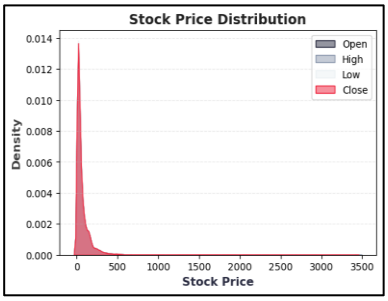

Fig. 11. Stock Price Prediction.

Fig. 11 depicts the density of open, high, low and close stock prices with a major concentration near the lower end of the price spectrum. "Close" price data, marked in red, reveals the most prominent peak in the lower range, highlighting that most closing prices are clustered around this level. This distribution provides insights into the typical range and variability of stock prices by golden eagle optimized hybrid RNN-GRU model.

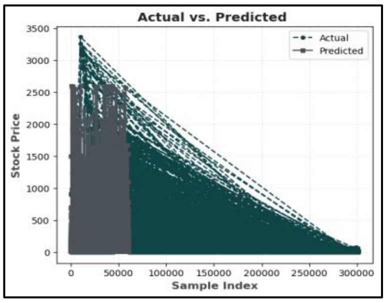

Fig. 12. Actual Vs Predicted

Fig. 12 visualize actual and predicted indicates the performance of golden eagle optimized hybrid RNN-GRU model for stock price prediction. X-axis indicates sample index and Y-axis denotes stock prices. Model's predictions align closely with actual stock prices, particularly in latter portion of the sample range, reflecting its strong predictive capability.

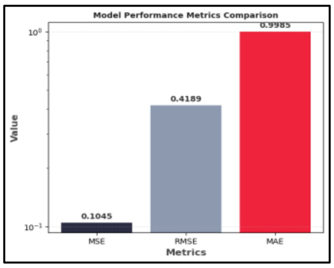

Fig. 13. Model performance metrics comparison.

Fig. 13 compares the models' performance metrics with MSE at 0.1045, Root Mean Square Error (RMSE) at 0.4189, and

Mean Absolute Error (MAE) at 0.9985 revealing smaller average deviations, highlighting the model's accuracy and error distribution for stock price prediction.

TABLE I. PERFORMANCE METRICS.

Performance Metrics	
MSE	0.1045
RMSE	0.4189
MAE	0.9985
R^2	0.9980

Table I presents the model's performance is evaluated using metrics such as MSE of 170.501, RMSE of 13.057, MAE of 6.479, and an R^2value of 0.9980, indicating a strong fit to the data.

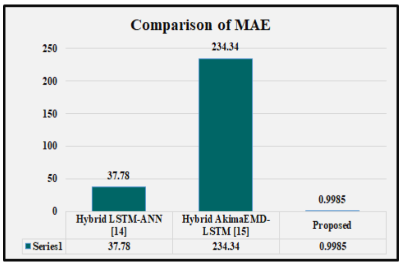

Fig. 14. Comparative Analysis of MAE.

Fig. 14 represents an MAE comparison chart that demonstrates the predictive performance of various models for stock price forecasting. The Hybrid Long Short-Term Memory (LSTM)-ANN model records an MAE of 37.78, whereas the Hybrid Akima Empirical Mode Decomposition (EMD). (EMD)-LSTM model exhibits a much higher MAE of 234.34. In contrast, the proposed model achieves a significantly lower MAE of 0.9985, showcasing its superior accuracy. This comparison underscores the proposed model's effectiveness in reducing prediction errors and its reliability for stock price forecasting using a data-driven deep learning method.

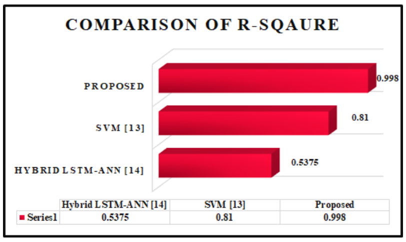

Fig. 15. Comparison of R^2 value.

Fig. 15 showcases R-squared values for various stock price prediction models. The Proposed model, a Golden Eagle optimized Hybrid RNN-GRU, achieves an impressive R-squared of 0.998, reflecting an excellent fit to the data. In comparison, Support Vector Machine (SVM) model and the Hybrid LSTM-ANN model records an R-squared of 0.81, 0.5375 respectively. The superior R-squared of proposed model highlights its effectiveness and reliability, emphasizing the benefits of Golden Eagle optimization and the Hybrid RNN-GRU design in stock price forecasting.

IV. CONCLUSION

This paper proposes novel golden eagle optimized DL based hybrid RNN-GRU approach for stock market prediction. Data is cleaned and hissing values are handled by preprocessing techniques, ensures high quality data. Relevant features are extracted by feature engineering, thus prediction accuracy is enhanced. The hybrid RNN-GRU model, improves classification performance by capturing both temporal and spatial dependencies in medical images. Optimal stock price prediction performance is attained by GEO algorithm, that optimally fine tunes model parameters. The proposed model is implemented in python software and demonstrates an effectiveness of the proposed approach, attaining with MSE of 170.50, RMSE of13.06, MAE of 6.48 and R^2score value of 0.9908 correspondingly. Experimental result shows the proposed method is utilized as more useful indicator for stock prediction.

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