Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

A Hybrid Approach for Stock Price Prediction Using Support Vector Regression and Multi-View Learning

Umakant Singh[1], Ankur Khare[2], Punit Kumar Chaubey[3]

[1]*Research Scholar, Information Technology, Rabindranath Tagore University, Raisen, Madhya Pradesh, 464993,India,umakantsinghsrm@gmail.com*

[2]*Assistant Professor, Computer Science & Information Technology, Rabindranath Tagore University, Raisen, Madhya Pradesh, 464993,India, khareankur94@gmail.com*

[3]*Associate Professor, Computer Science & Engineering, Bansal Institute of Engineering and Technology, Lucknow, Uttar Pradesh,226021,India,pkcmar@gmail.com*

ARTICLE INFO

Received: 18 Oct 2024

Revised: 25 Nov 2024

Accepted: 12 Dec 2024

ABSTRACT

The stock market is an industry that is constantly changing and very complex. Such a situation is characterized in a new intra-day high and low by high volatility and low predictability. To make accurate forecasts regarding the stock prices is indeed vital for many shareholders, financial analysts, as well as financial organizations. The present study presents a combination of two machine learning algorithms, Multi-View Learning (MVL) and Support Vector Regression (SVR), to improve stock price forecasting. The model is applied to five major stocks like Apple (AAPL), Microsoft (MSFT), Google (GOOGL), TCS (TCS.NS), and Netflix (NFLX) uses technical indicators (14-day relative resistance index and 50-day simple moving average) as well as price-related data (Open, High, Low, Close, and Volume). The grid search method (GridSearchCV) is then employed to select the optimal combination of hyperparameters for SVR which is applied via structuring these features into two separate views, the algorithm allows the GridSearchCV model to tune hyperparameters and, to improve the SVR performance. The result of evaluation showcase model's capability, correctness and reliability by means of R-squared, MSE, and RMSE as performance metrics.

Keywords: Simple Moving Average (SMA), GridSearch, Support Vector Regression, Multi-view Learning, and Relative Strength Index (RSI).

1. Introduction:

Stock market prediction involves estimating future stock prices based on past and current data. It's an important tool in finance, helping investors, traders, and analysts make informed decisions, spot potential gains, and reduce risks [1], [2]. Traditionally, two main strategies are used: fundamental analysis, which analyzes a company's financial position, and technical analysis, which focuses on price trends and trading activity [3],[4]. While both methods provide useful information, they often fall short in capturing the complex and constantly changing behaviour of the market. Stock markets are highly unpredictable because they're affected by many factors like economic conditions, political events, investor emotions, and how well companies are performing [5], [6]. This makes it tough to accurately forecast stock prices. However, with the advent of ML and AI, advanced tools have emerged that can handle this complexity more effectively. Methods such as ANN (Artificial neural network), support vector machines (SVM) and long short-term memory (LSTM) often perform better than traditional methods. These ML models are great at spotting hidden trends in large sets of data, which helps make predictions more accurate and adaptable [7], [8].

One method in this field is Multi-View Learning (MVL). It works by looking at different sets of features—or "views"—from the same data. By learning from each view separately and then combining them, MVL can improve the model's capacity to simplify and make better forecasts.

1.1. Problem Statement:

Based on the above discussion, this paper objectives are:

RQ1: What types of machine learning algorithms are commonly used to predict the stock market?

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

RQ2: Have hybrid ML models been explored for forecasting stock prices?

1.3. The MVL-SVR Hybrid Model

This paper presents a mix model that combines MultiView Learning (MVL) and Support Vector Regression (SVR). This model processes two separate sets of features: (1) market-related Features, and (2) technical indicators.

Market-Based Features: Open, High, Low, and Volume, representing a price change and trading volume [3],[4].

Technical Indicators: SMA50 (50-day simple moving average) and RSI14 (14-day relative strength index) help analyze market trends and dynamics, as well as identify possible price fluctuations [11], [12].The final forecast is determined by averaging the results of the two SVR models. Each model is optimized using a radial basis function (RBF) kernel [5], [17].

We apply the MVL-SVR model above to historical stock price data of five large technology companies: Apple (AAPL), Microsoft (MSFT), Google (GOOGL), Tata Consultancy Services (TCS.NS), and Netflix (NFLX), using data obtained from Yahoo Finance. The main goal is to show how combining different feature perspectives and modelling techniques can improve stock price prediction, using common evaluation metrics to measure performance [1], [2], [3].

1.3.1. Advantages of MVL-SVR Hybrid Model

(i) Captures different aspects of stock movement [13][23].

(ii) Better generalization and the inclusion of additional views [16].

(iii) SVR is capable of dealing with nonlinear relationships in a competent way [7].

(iv) Instead of treating all features as a single input, the model avoids over fitting by evaluating features separately and then dividing them into significant categories by SVR [8].

2. Literature Review:

Subhadra Kompella et.al [1] - Paper forecast the stock bazaar by using stock value and the news heading as the input. They have performed a sentiment analysis which is the identification of the polarity of the article and then we also employ it in the detection of the article to figure out if it has any change in the stock. Sentiment scores are then used ascertain stock values and in adding these, we utilized the exponential moving average method to provide the complete set of inputs and saved it as the correct stock impact. After computation, the data is modernised and presented user in the form of graph. At last studied random forest algorithm performance and matched with logistic regression. Random forest much better than logistic regression variance. Random forest averaging outperforms absolute score logistic regression. Random forest is better than mean square logistic regression. RMSE from random forest is well than logistic regression. The results of trained model random forest are as expected, and the model also performs well in predicting stock prices for other words with similar sentiment.

Mehar Vijha et.al[2]-The fact that there are several parameters creating intricate patterns makes it impossible to estimate stock market returns because stock values fluctuate so much. The historical data set on the company website only includes the stock price high, low, open, close, adjacent closing prices, number of shares traded and other data. Not big enough for the ideal size. Using the current variables, new variables have been developed increase the correctness of price forecast. In addition using RF for a comparative study, ANN is used for forecast close price of a stock of next day. It evident from the comparison study based on MAPE,MBE and RMSE value that ANN performs well than RF stock price prediction. The ANN model yielded the best outcomes, according to the results (RMSE-0.42, MBE-0.013, and MPE-0.77). Future studies could develop deep learning model consider financial news items and attributes like close value, trade volume, loss and profit statement in order to potentially produce superior results.

Sanjeev Kumar Singh et.al [22] - We have suggested and tested an LSTM-centered stock value forecast model based on LSTM. The outcomes show that model forecast performance is fair and it can determine both the direction and the actual price of stock movements. The LSTM model was better than a baseline model and was able to adjust to parameter changes that is, few changes, which means that it is quite practical for stock market prediction. This study has found new evidence in the market of stock prediction. Using LSTM networks, we have shown that this is

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

possible even for difficult pattern and trends in commercial time series data. The model capacity to forecast stock value movements is important to investors and financial analysts when making investment decisions. Moreover, the idea of developing combined LSTM models or deep learning appertaining other architectures is another area of research. The typical way of approaching the market is by using different models or architectures in order to capture different aspects and, hence improve seeing the future with a higher precision. Otherwise, focus on understanding the right LSTM in case of the stock market as it can provide deeper insights. It is the reason that determines a model's prediction that can really help one to understand the reasons why stock prices moved and hence gaining trust and confidence in the model's predictions.

Warda M. Shaban et.al[29]- For this research, a newly proposed DL based system is described for the purpose of predicting close value of stock bazaar. Moreover, this article prepared a smart trading platform (STP) application that anyone could download to their phone. STP is a platform that offer people the opportunity to participate in the stock market. To start trading, all you really need is a phone, laptop, or computer with internet access. Investing in stocks is practically unrestricted and may be done from anywhere, even at home or at work. Furthermore efficiency of combining model BiGRU and LSTM was demonstrated in predicting stock market closing prices. Apple, Google, and IBM were used in the implementation of this study. To be clear, we made price predictions 10 and 30 minutes before the actual time. A dataset with 1-minute intervals was obtained from the historical data website, and before being sent to the LSTM network, the data was fed into BiGRU model to provide weighted value. Dense layer receives and accepts the updated weight values determined by the LSTM. The controller of complete model result sent to the output layer. The output layer's weight value changed and bring the system's loss function closer to the desired result. According to experimental results, the BiGRU-LSTM hybrid model performs noticeably better at predicting stock market closing prices than two conventional robust time series analysts, LSTM and GRU. Based on a DL model, the proposed application, has the following main benefits: (i) Real-time trading: Unlike calling your broker to request quotes, utilizing STP allows you to place trades and view the stock price in real-time via the online trading platform. This is one of the main advantages of using STP. You may examine stock prices, make an order, and finish the trade in a matter of seconds. (ii) Cost-effective: Compared to the traditional investment approach, our platform is extremely affordable because you will pay fewer brokerage fees and other costs. (iii) Instant access to market data:offers traders a wealth of research and analysis through technical charts and investment tools. Investors will be able to make wise decisions and boost returns in this way. In addition, it reduces the danger factor and saves time. Furthermore, (iv) Real-time alerts are an option offered by our platform.

E. Ismanto et al [31] – This paper helps in developing LSTM models for stock price predicting. The Optuna framework provided input to model and find best combination of hyperparameters. The optimal pair of hyperparameters minimizes loss and mean square error.

UK Lilhour et al. [32] – In this study, we explore the ML-based SVM, CART and XG-Boost model as well as proposed hybrid models for traditional neural networks. The accuracy levels achieved by

SVM, CART and XG-Boost are 84.21%, 72.69% and 90.81%.The model significantly performs better than traditional machine learning models.

Chen et al. [32]- Trained a long-term memory (LSTM) model with data from China Construction Bank by employing a genetic algorithm to enhance feature selection.The R-squared value served as the algorithm's fitness measure, with higher values indicating stronger predictive accuracy. Since LSTM is well-suited for time-series predicting, it was chosen analyse financial data. Their findings revealed that the combination of the genetic algorithm with the LSTM model resulted in lower mean squared error, reflecting more accurate predictions.

Ishwar Prasad Galla et al [28] – This study focuses on stock price forecasting using the Quantal Nifty-50 index dataset. Two ML algorithms were considered: support vector machine (SVM) and random forest (R-F). The R-F performed better than SVM (RMSE: 11.472, R^2: 98.9%) with RMSE 9.75 and R^2 99.2%.

Prachi Pathak[30]- Examine several machine learning techniques for stock price prediction such as support vector machines (SVMs), regression analysis, and time series models. The process involves key steps like cleaning and preparing the data, selecting and engineering useful features, and assessing model accuracy. Performance measures including mean absolute percentage error (MAPE), root mean square error (RMSE), and mean mean square error

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

(MSE) are used in the evaluation.The study also examines effectiveness of models like Support Vector Regression (SVR), linear regression and XGBoost to determine which provides the most reliable forecasts.

Guangya el.al [26]- To forecast stock values, the MS-SSA-LSTM model integrates sentiment analysis, deep learning, and data from many sources. The model's accuracy (R2) was 10.74% higher than that of the regular LSTM thanks to the combination of sentiment and transaction data from East Money Forum and the optimization of the LSTM hyperparameters using the sparrow search (SSA) technique. Good for short-term forecasting (5-10 time steps) and suitable for global markets. Future work will improve sentiment analysis and include a wider range of data sources.

Table1: Summary table of Literature review-

S.No.	Author and Paper	Techniques Used	Dataset Features	Key Findings	Limitations
1	Subhadra Kompella et al. [1]	Sentiment Analysis, Random Forest, Logistic Regression	Stock prices, news headlines, sentiment polarity scores, and exponential moving average	Random Forest provided more reliable stock impact predictions than Logistic Regression.	The approach relies only on basic sentiment analysis and does not explore deep learning methods.
2	Mehar Vijha et al. [2]	Artificial Neural Network (ANN), Random Forest (RF)	Stock bazaar historical data including open, close, high, low prices, and trade volume	ANN outperformed RF in predicting stock closing prices, achieving lower errors.	The study does not incorporate financial news or macroeconomic factors for better accuracy.
3	Sanjeev Kumar Singh et al. [22]	Long Short-Term Memory (LSTM) model	Historical stock value trends	LSTM model effectively predicts stock cost movements and adapts to parameter changes.	The model struggles with highly volatile markets and lacks external financial data integration.
4	Warda M. Shaban et al. [29]	BiGRU-LSTM Hybrid Model, Smart Trading Platform (STP)	High-frequency trading data (1-minute intervals) from Apple, Google, IBM	The BiGRU-LSTM model improves short-term price forecasting accuracy, and the STP app allows real-time stock trading.	The approach is limited to short-term forecasting and does not analyze fundamental company data.
5	E. Ismanto et al. [31]	LSTM with Optuna Hyperparameter Optimization	Stock price history	Optuna framework helps fine-tune LSTM hyperparameters, leading to better	The study focuses only on hyperparameter tuning without testing alternative

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

				model performance.	forecasting techniques.
6	U.K. Lilhore et al. [32]	Hybrid ML Model (Neural Networks, CART, SVM, XGBoost)	Technical indicators	XGBoost demonstrated the highest accuracy among tested models, outperforming traditional ML techniques.	The study does not incorporate external sentiment or economic indicators.
7	Chen et al. [32]	Genetic Algorithm (GA), LSTM	Financial data from China Construction Bank	GA enhances LSTM's feature selection, improving accuracy and reducing error rates.	The study is limited to one financial institution and lacks broader market validation.
8	Eswar Prasad Galla et al. [28]	Random Forest (RF), Support Vector Machine (SVM)	Nifty-50 stock index from Quandl	RF outperformed SVM in predicting stock prices, achieving an RMSE of 9.75 and R^2 of 99.2%.	The research focuses only on technical indicators and does not consider sentiment analysis.
9	Prachi Pathak [30]	Linear Regression, SVR, XGBoost	Stock price data with technical indicators	XGBoost provided better predictive performance compared to Linear Regression and SVR.	The study does not use advanced deep learning methods for better accuracy.
10	Guangyu et al. [26]	MS-SSA-LSTM (Multi-source data, Sentiment Analysis, SSA, LSTM)	Combining East Money forum trading data with investor sentiment	The model improved accuracy by 10.74% compared to standard LSTM, excelling in short-term forecasts.	The sentiment analysis considers only positive/negative sentiments, limiting emotional granularity.

3. Methodology:

In this work, we make use the MVL-SVR hybrid approach for stock market prediction .We combined Multi-view Learning (MVL) and Support Vector Regression (SVR) and emphasis on stock price forecast.

3.1. Multi-view Learning (MVL)

Multi view learning technique consider different view (or points of view) of the data to improve model performance. Each view provides different information that can complement each other. There are two opinions:

3.1.1. Price-related features (View 1):

- Open value
- High value
- Low value

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

- Volume

3.1.2. Technical indicators (View 2):

- Simple Moving Average (SMA50)
- Relative Strength Index (RSI14)

- Both views are treated separately and then combined to make a final prediction, leveraging the fact that each view provides complementary information about the stock's price.

3.2. Support vector regression (SVR)

- Support Vector Regression is a popular approach for regression and classification issues.
- This method uses SVR to model the relationship between input characteristics and target variable (stock price).
- SVR applied to each view (price characteristics and technical indicators) separately.

After training two separate models (one for each scene), their predictions are combined (averaged) to create a hybrid stock price forecast. Combining predictions from both views can produce better results than using a single view.

Working Steps:-

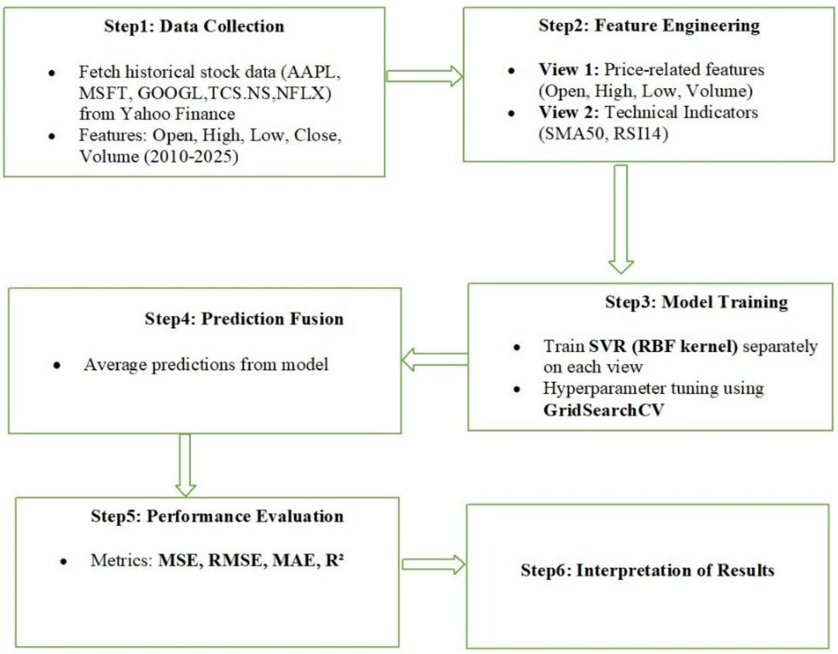

Fig1: Flowchart for Methodology

3.4 Data Collection:

The dataset for this study includes historical Yahoo Finance stock value data for five major companies:

- Apple (AAPL)
- Microsoft (MSFT)
- Google
- TCS(TCS.NS)
- Netflix (NFLX)

The target variable for the forecast is the stock's closing price. Each stock contains 3834 rows and 5 columns.

3.5 Feature Engineering- Feature Engineering: Creating new features technical indicators using raw stock price info (open, close, high, low and volume) to increase predictive capability of model. The purpose of these new features is extracted patterns and trends that may not be easily visible from the raw data. The technical indicators created are:

3.5.1. Simple moving average (SMA50)-50-day simple moving average (SMA50) is technical indicators use in stock market analysis and research, giving insights about the average closing price over the last 50 days. It is common to use SMA50 to find trends in stock price .The SMA50 is often used to identify short-term trends as well so if a current price is above the SMA50 that may indicate an upward trend, if below, that may indicate a downward trend. For each stock (AAPL, MSFT, GOOGL, TCS.NS, NFLX), a 50-day moving average is calculated based on the closing price, and the resulting price is stored as a new function in the dataset.

3.5.2. Relative strength index (RSI14)-The Relative Strength Index (RSI) is a momentum oscillator that measures the rate and size of price changes. It is often used to determine whether a stock is oversold or overbought. Range: 0–100. Overbought is defined as a reading above 70, and oversold is defined as a reading below 30.The RSI14 (14 day RSI) is capturing price movement momentum in the stock. It helps in spotting possible reversals in the price of the asset.

3.5.3. Additional Features-For each of the five stocks (AAPL, MSFT, GOOGL, TCS.NS, and NFLX), dataset contain raw stock data (low, high, open and volume). Together with technical indicators the model uses these unprocessed information as inputs (views).

3.5.3.1. Price-related features- The stock data's raw features are as follows

• Opening Price: The opening price of stock on a given day.

• High: The highest share value on a given day.

• Low: The lowest value of a stock on a given day.

• Volume: Volume of shares traded on a given day.

To assist the model in capturing unprocessed price movement patterns and trading activity, these characteristics are utilized as part of View 1 (price-related features).

3.6 Model training- For the model training us use SVR with RBF kernel in MVL framework for stock forecast. This step perform in two step:

(i) Divide the features into two view: price view and technical indicator view

(ii)Hyperparameter Tuning: This procedure is adopted to improve efficiency of the model system using Support Vector Regression (SVR). GridSearchCV technique of scikit-learn does this. It works by performing cross-validation to find hyperparameteres of model that may have the highest predictive power. There are three regulating parameters for SVR model which are:

3.6.1. C (Regularization parameter)- This parameter controls the level of error tolerance during training and smoothness of the decision function curve. If a value of C is set high, it will force fitting which will most likely case over fitting of the model. A lower value of C will make model more under fit, however, a smoother decision boundary will be achieved.

Range of Search: 'C': [1, 10, 100]

The search will try the values of C from the list [1, 10, 100].

The mathematical formula for C:

$$C=\frac{1}{\sigma 2} \tag{1}$$

where σ is the standard deviation of target variable.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

3.6.2. The gamma parameter- It is sometimes called as kernel coefficient. It defines how much weight does one training sample carry. When gamma is low, and the model tries to classify using all the points in the training set, then this will produce a smooth border decision. The effect of each point is more localized indicating overfitting decision boundary with higher gamma.

Range of Search: “gamma”: [0.001, 0.01, 0.1] (2)

The systematic search will evaluate gamma values from the following list: [0.001, 0.01, 0.1].

The mathematical formula for gamma:

$$\gamma = \frac{1}{2\sigma 2} \tag{3}$$

where σ is the standard deviation of input features.

3.6.3. epsilon (The Epsilon in the epsilon-SVR model)-The epsilon parameter sets a margin of error within which no penalties are imposed. A larger value of epsilon smoothes the model outputs thus making the model less sensitive to data errors. Smaller epsilon values allocate more sensitivity to errors, thus producing a model that attempts to fit the training data too closely.

Range of Search: "epsilon": [0.01, 0.1, 0.2] (4)

The search will evaluate the epsilon values provided in the list [0.01, 0.1, 0.2].

The mathematical formula of epsilon:

€=0.1*StdDev(y) (5)

3.7 Prediction Fusion:

In this step, we combine the both SVR model output and make the final prediction.

Final prediction= (Prediction from View1 + Prediction from View 2) / 2 (6)

3.8 Performance Evaluation:

Several metrics are used to measure model performance:

- **Mean Squared Error:** It calculates the mean squared discrepancy between the actual and expected values.

$$MSE = \frac{1}{n}\sum(y - y')^2 \tag{7}$$

Where:

n is total number of observation in the dataset.

y is observation’s true value.

y’is expected value of the i^{th} observation.

- **Root Mean Square Error (RMSE):** The square root of MSE is the standard deviation of the prediction error.

$$RMSE = \sqrt{MSE} \tag{8}$$

- **Mean Absolute Error (MAE):** represents mean absolute difference between predicted value and actual value.

$$MAE = \frac{1}{n}\sum|y - y'| \tag{9}$$

Where:

n is the number of observations in the dataset.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

y is the actual value of the observation.

y' is the predicted value of the i^{th} observation.

- **R^2:** This metric evaluates the extent to which the model accounts for variations in the target variable, representing the fraction of total variance explained by the model.

$$R^2 = 1 - \frac{MSE(model)}{MSE(Baseline)} \tag{10}$$

4. Algorithm for implement model-

BEGIN

// Step 1: Data Collection

Fetch the historical stock data (AAPL, MSFT, GOOGL, TCS.NS, NFLX) from Yahoo Finance

Extract the features: Open, High, Low, Close, Volume

Define the target variable: Closing Price

// Step 2: Feature Engineering

Compute View 1 (Price-related Features): Open, High, Low, Volume

Compute View 2 (Technical Indicators):

- Calculate SMA50 (50-day Simple Moving Average)

- Calculate RSI14 (14-day Relative Strength Index)

Normalize all features using MinMaxScaler

// Step 3: Model Training

Split data into Training (80%) and Testing (20%)

Initialize SVR with RBF kernel

// Train separate models for each view

Train SVR_Model_1 on View 1 (Price Features)

Train SVR_Model_2 on View 2 (Technical Indicators)

// Hyperparameter Tuning using GridSearchCV

Define parameter grid:

C = [1, 10, 100]

gamma = [0.001, 0.01, 0.1]

epsilon = [0.01, 0.1, 0.2]

Perform GridSearchCV on both SVR models

Select best hyperparameters

// Step 4: Prediction Fusion

Predict stock price using SVR_Model_1 → Prediction_1

Predict stock price using SVR_Model_2 → Prediction_2

Compute final prediction:

Final_Prediction = (Prediction_1 + Prediction_2) / 2

// Step 5: Performance Evaluation

Compute evaluation metrics:

MSE (Mean Squared Error)

RMSE (Root Mean Squared Error)

MAE (Mean Absolute Error)

R^2 Score

// Step 6: End & Interpretation

Analyze results

Compare individual SVR performance vs. hybrid model

Use best model for future predictions

END

5. Results-

The results for AAPL, MSFT, GOOGL, TCS and NFLX are shown in below table:

AAPL Hybrid Model (MVL-SVR) Stock Price Prediction –

Table2: AAPL Hybrid Model Performances Matrices

MSE	***RMSE***	***MAE***	***R^2***
3.7446	1.9351	1.0758	0.9992

Based on important valuation parameters, AAPL's hybrid stock price forecasting model (MVL-SVR) has shown excellent predicting ability. The mean squared error (MSE) of 3.7446 shows that the mean square difference between real price and forecast price is rather small. The root mean square error (RMSE), which was 1.9351, indicated average size of the prediction. Additionally, the model's mean absolute departure from the actual stock price is reflected in the mean absolute error (MAE), which is at 1.075. In particular, the model explains 99.92% of AAPL's stock price swings, according to its R2 score of 0.9992, which shows a high degree of accuracy and dependability. These outcomes demonstrate how well the MVL-SVR method predicts the price of Apple stock with a high degree of accuracy.

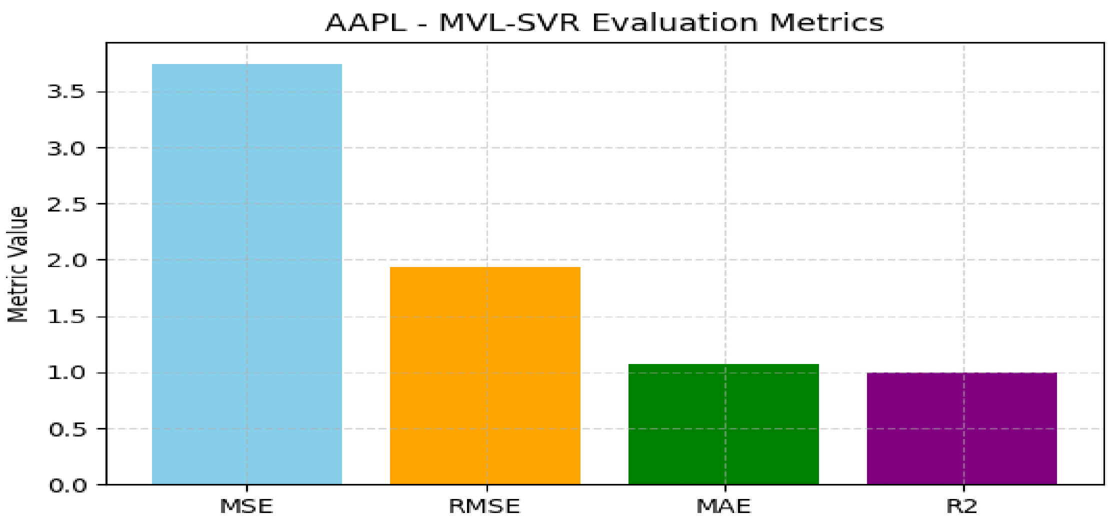

Fig 2:AAPL Performances Metrics

MSFT Hybrid Model (MVL-SVR) Stock Price Prediction –

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Table3: MSFT Hybrid Model Performances Matrices

MSE	***RMSE***	***MAE***	***R^2***
8.7125	2.9517	1.6035	0.9995

Based on important valuation parameters, the hybrid MSFT model for stock price forecasting (MVL-SVR) has shown excellent predicting ability. The mean square error (MSE) of 8.7125 indicates that the standard deviation between expected and real prices is relatively small. The root mean square error was 2.9517, indicating intensity of the prediction mistake. In addition, the mean absolute error (MAE) of the model's mean absolute deviation from real stock price is 1.6035. In particular, the model explains roughly 99.95% of the fluctuations in MSFT stock price, according to the R2 value of 0.9995, demonstrating good accuracy and dependability. These outcomes demonstrate how well the MVL-SVR method predicts changes in the price of Microsoft shares with a respectable degree of accuracy.

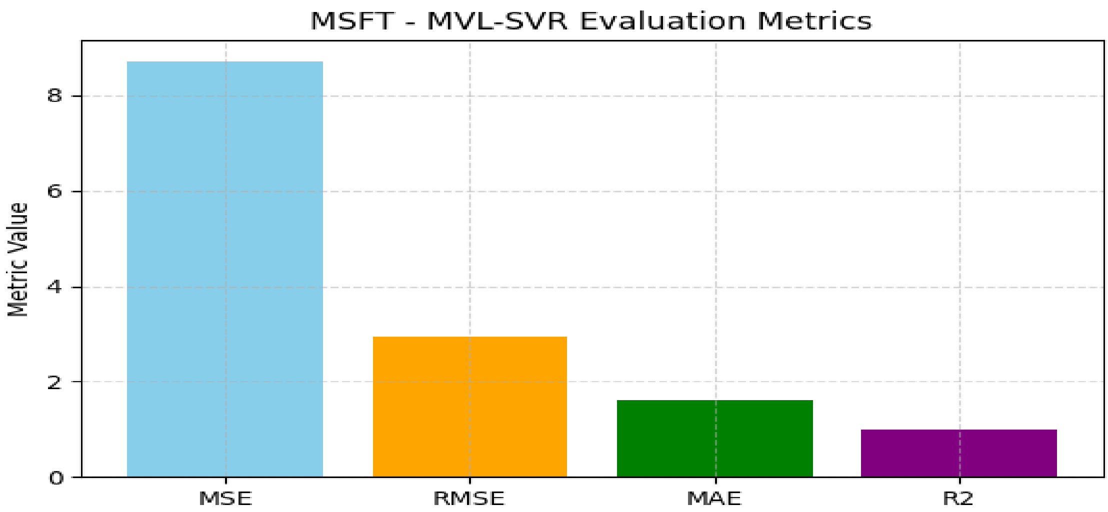

Fig 3: MSFT Performances Metrics

GOOGL Hybrid Model (MVL-SVR) Stock Price Prediction –

Table4: GOOGL Hybrid Model Performances Matrices

MSE	***RMSE***	***MAE***	***R^2***
2.0465	1.4305	0.8671	0.9991

On close examination of key evaluation metrics, GOOGL Hybrid Model (MVL-SVR) for Stock Price Prediction performed well. Mean Squared Error (MSE) – 2.0465 The RMSE reached 1.4305, illustrated the capability of the model avoid large forecast errors. Additionally, the model yielded a mean absolute error (MAE) of 0.8671, which represents average absolute divergence between actual price and predicted values. Model's R2 of 0.9991, forecast accuracy and reliability are good, which shows that it accounts for 99.91% of the variations in GOOGL's stock price. These findings support the efficacy of the MVL-SVR method in making very accurate stock price predictions.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

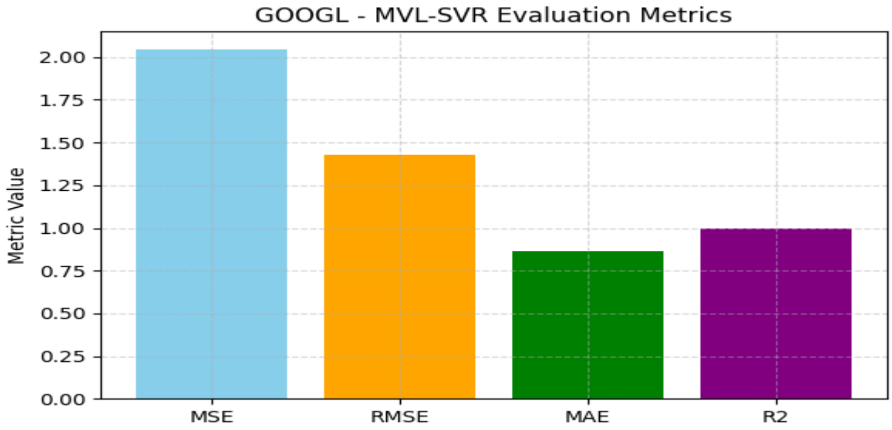

Fig 4: GOOGL Performances Metrics

TCS Hybrid Model (MVL-SVR) Stock Price Prediction –

Table5: TCS Hybrid Model Performances Matrices

MSE	***RMSE***	***MAE***	***R²***
17.7289	12.5644	7.8862	0.9987

17.7289 is MSE (mean squared error). This figure represents the average error and mean square difference between actual and forecasted prices. 12.5644 is the root mean square error (RMSE). This offers gauge forecast accurateness and in certain situations, entails significant variations. The model's average departure from the actual price is indicated by the mean absolute error (MAE), which is 7.8862. With an R2 value of 0.9987, the model can account for roughly 99.87% of stock price movements, which is predicted but performs worse than other equities (primarily AAPL and Google).

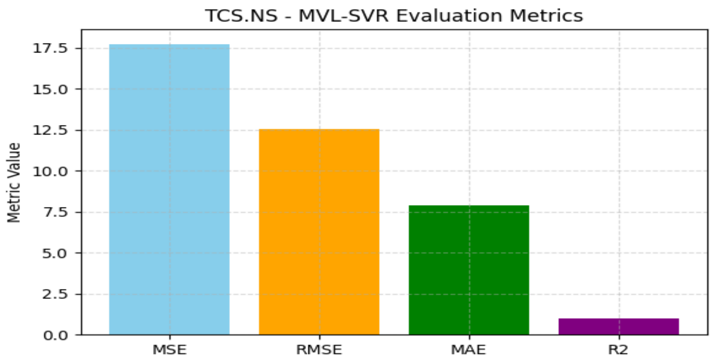

Fig 5: TCS Performances Metrics

NETFLIX Hybrid Model (MVL-SVR) Stock Price Prediction –

Table6: NFLX Hybrid Model Performances Matrices

MSE	***RMSE***	***MAE***	***R²***
10.3257	10.4559	5.7801	0.9977

The MVL-SVR model provides accurate forecasts for Netflix stock prices, as indicated by its evaluation metrics. The average squared difference between forecasts and real data represented by mean squared error (mse), which is 10.3257, relatively high due to Netflix's stock price volatility. The root mean squared error (RMSE) of 10.4559 suggests occasional large deviations, though overall trends are well captured. The mean absolute error (MAE) which displays average absolute difference between expected and actual prices at 5.7801, indicates accuracy of the model. The model explains 99.77% of stock price fluctuations, with an R2 value of 0.9977, suggesting a high degree of correlation between expected and actual movements.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

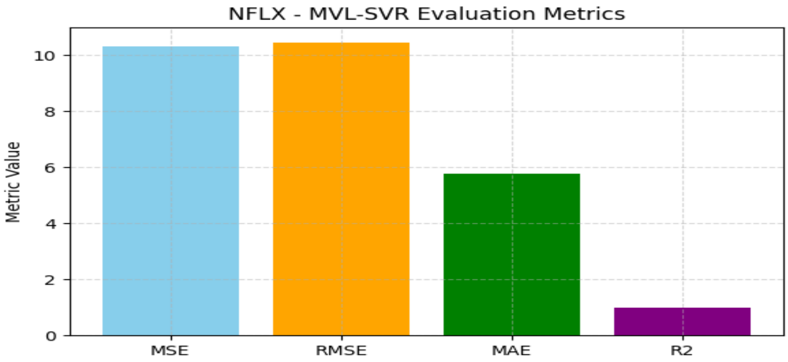

Fig 6: NFLX Performances Metrics

Performance Comparison of AAPL, MSFT, GOOGL, TCS and NETFLIX stock-

Table7: Summary table of Hybrid Model Performances Matrices

Stock	MSE	RMSE	MAE	R²
AAPL	3.7446	1.9351	1.0758	0.9992
MSFT	8.7125	2.9517	1.6035	0.9995
GOOGL	2.0465	1.4305	0.8671	0.9991
TCS	17.7289	12.5644	7.8862	0.9987
NFLX	10.3257	10.4559	5.7801	0.9977

Table 7 presents how combined view of hybrid MVL-SVR model performed across five major stocks—AAPL, MSFT, GOOGL, TCS, and NFLX. The performance is assessed using four important metrics: R-squared (R^2), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Squared Error (MSE).

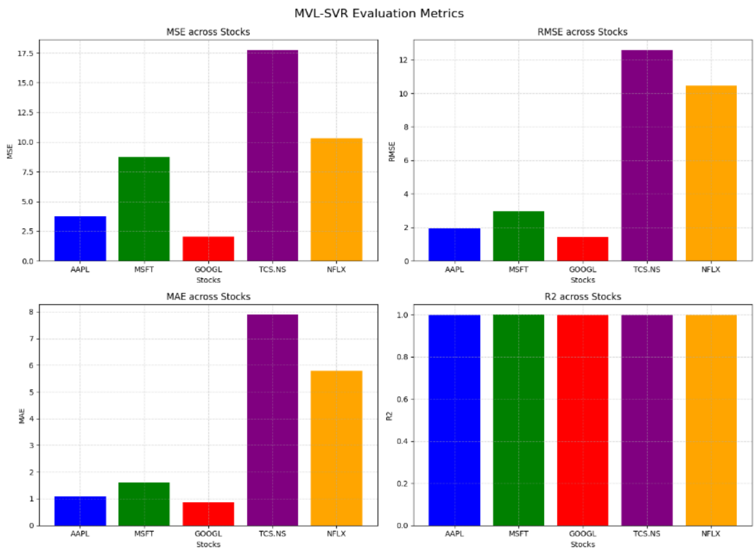

Fig2: Performance Comparison of AAPL, MSFT, GOOGL, TCS and NFLX Stock

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

The graph offers a side-by-side view of how well the MVL-SVR model predicted stock prices for AAPL, MSFT, GOOGL, TCS.NS, and NFLX. It highlights four key performance indicators: MSE, RMSE, MAE, and R^2.

6. Discussion-

The performance evaluation of the MVL-SVR hybrid model across five major technology stocks—AAPL, MSFT, GOOGL, TCS, and NFLX—demonstrates its strong predictive capabilities. The model consistently achieved high accuracy, with R^2 values above 0.99 for all companies, indicating it effectively captures the vast majority of stock price movements.

Among the stocks, Apple, Microsoft, and Google showed the most accurate results, with exceptionally low MSE, RMSE, and MAE values, reflecting the model's robustness when applied to relatively stable and high-volume stocks. While the performance for TCS and Netflix was slightly less precise—likely due to higher volatility or less predictable market behaviour—the model still maintained impressive accuracy, with R^2 values of 0.9987 and 0.9977, respectively.

These results confirm that the MVL-SVR framework, which integrates multiple feature views (market-based and technical indicators), enhances the model's ability to generalize and make accurate forecasts. This study highlights the potential of combining multi-view learning with advanced regression techniques for reliable stock price prediction in real-world financial markets.

7. Visualization-

The visual representation of all stock shows below that the predicted price closely matches the actual movement, demonstrating effectiveness of the model in tracking stock value movements.

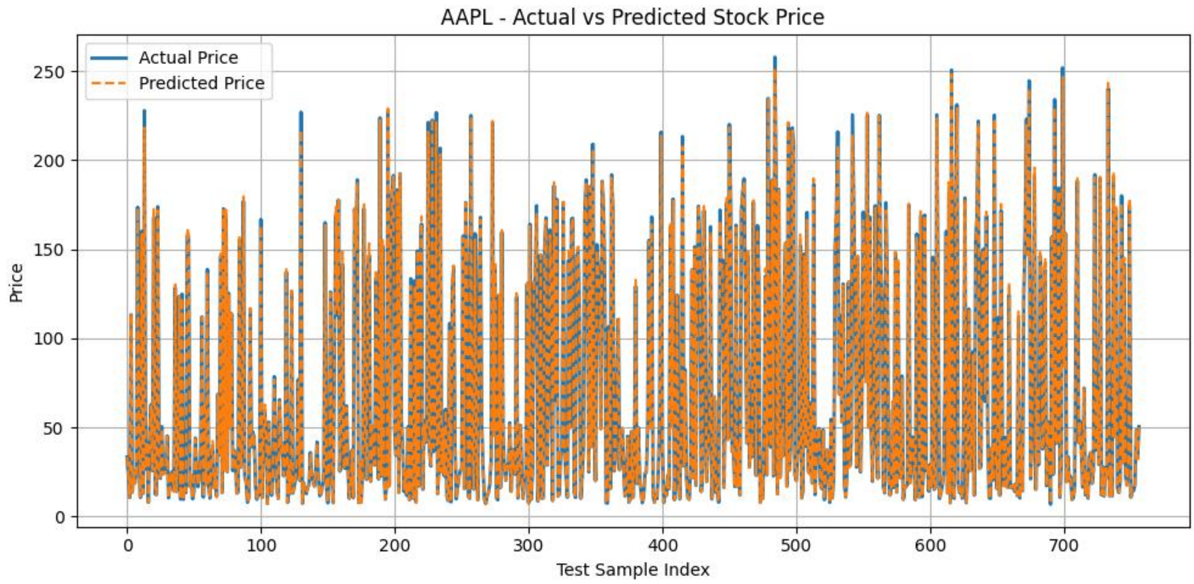

Fig3: AAPL Stock Price Prediction

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

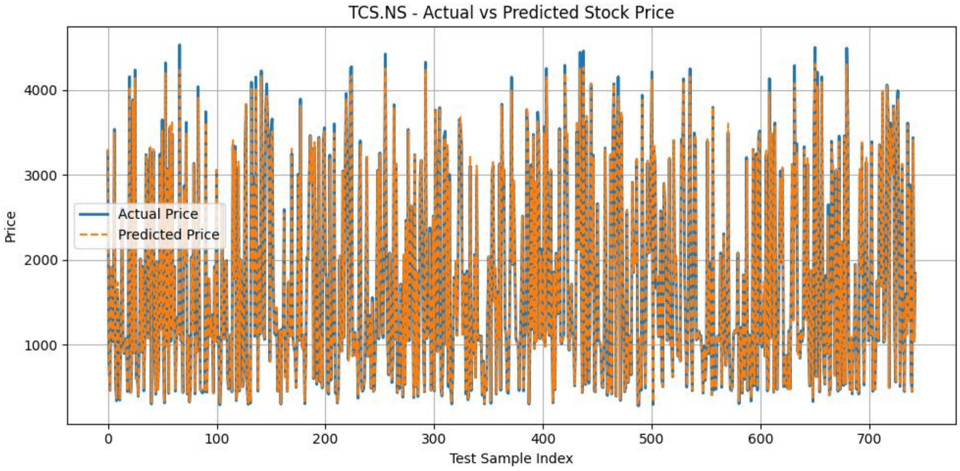

Fig4: TCS Stock Price Prediction

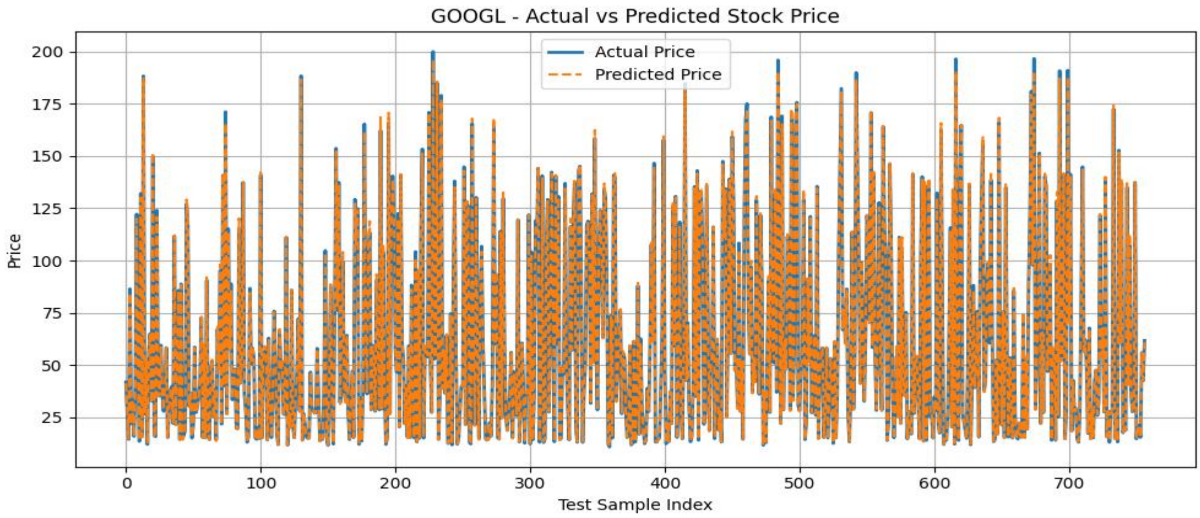

Fig5: GOOGL Stock Price Prediction

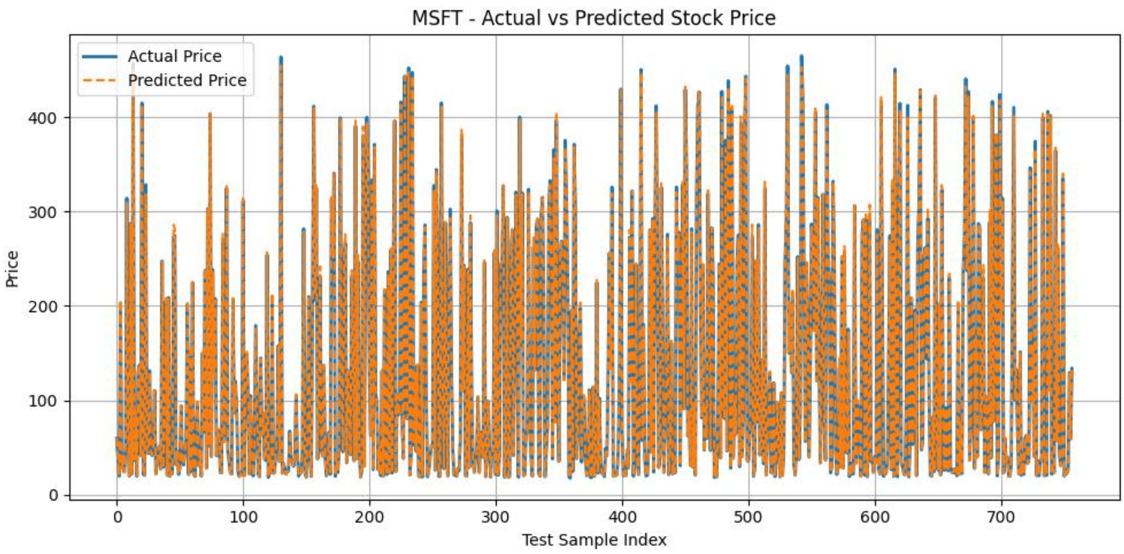

Fig6: MSFT Stock Price Prediction

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

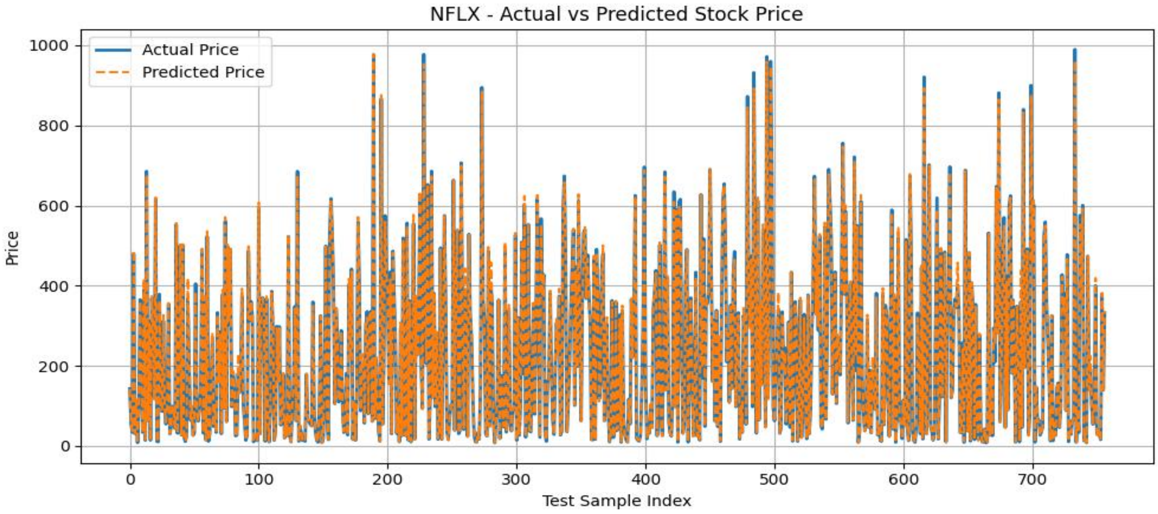

Fig7: NFLX Stock Price Prediction

Comparison of R-squared, and RMSE Value of previous model with proposed model:

Table7: Comparison of R-squared and RMSE Value

Model	R2	RMSE
Random Forest[28]	98.2	25.75
SVM[28]	98.9	17.472
Proposed Model	Close to 1 in all stock	Less than above

From the above table, it is clear that proposed model is good as compared to previous stock prediction market techniques because proposed model give the less value of RMSE and R2 value is close to one for all five stock. This shows the model's predictions are very close to the actual values. With improved feature separation (MVL), nonlinear learning function (SVR-RBF), hyper parametric tuning, and forecast fusion, the proposed model achieves low RMSE and R^2 close to 1, demonstrating higher accuracy and reliability than traditional stock forecasting models.

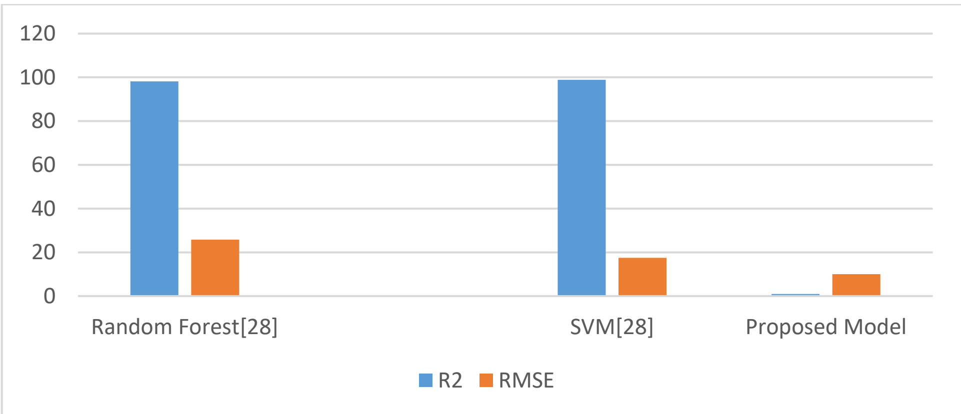

Fig 8: Comparison Visulization of R-squared and RMSE Value

Comparison of MSE, MAE, R-squared, and RMSE Value of previous model with proposed model:

Table8: Comparison of Performance Matrices Value of previous model with proposed model:

Model	MSE	MAE	RMSE	R^2
Linear Regression[30]	22979.04	127.31	151.58	.5777

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

Support Vector Regressor[30]	46084.09	122.82	214.67	.1532
XGBoost Regressor[30]	150.72	6.82	12.27	0.97
Proposed Model	Low MSE	Small MAE	Less than above value for all stock	Close to 1

From the above table value, proposed model produced low MSE and RMSE value and R2 value is close to 1 for all stock. So it show that model is reliable and accurate. Proposed model give small MAE value which shows that model fairly accurate predictions without significant deviations.Due to efficient feature separation, nonlinear pattern recognition, optimized hyper parameters, and prediction fusion, the model produces low MSE and RMSE, a small MAE indicates accurate prediction, and R^2 is close to 1, confirming its reliability.

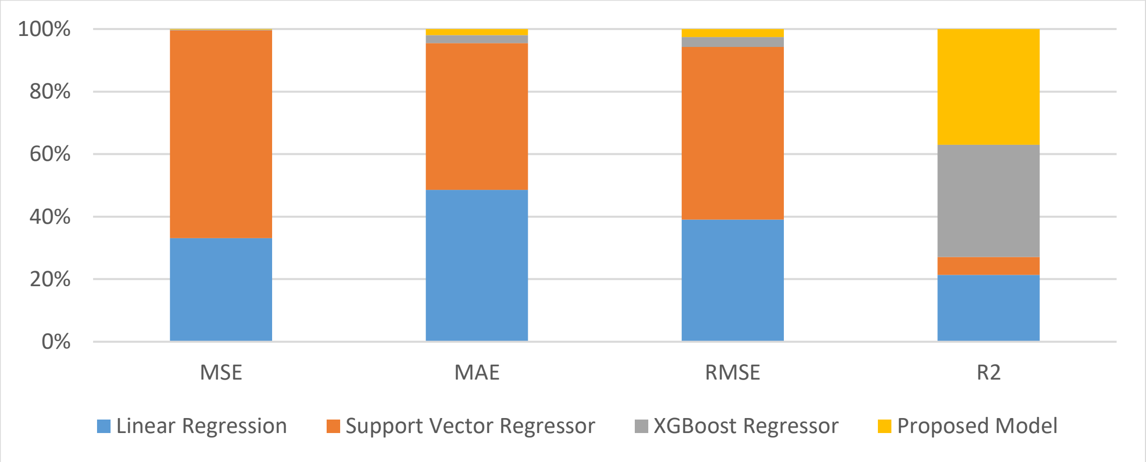

Fig 8: Comparison Visulization of Performance Matrices Value of previous model with proposed model:

Table9: **Comparison of Performance Matrices Value of previous model with proposed model:**

Metric	**ARIMA(12,1,12)** (34)	**Hybrid Model (For AAPL)**
MSE	6.4019	3.7446
RMSE	2.5302	1.9351
MAE	1.9184	1.0758

Table 9 highlights the performance difference between the ARIMA model and the proposed hybrid approach for AAPL stock. The hybrid model clearly performs better, showing lower error values across all metrics. This suggests it delivers more accurate and dependable predictions than the ARIMA method.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

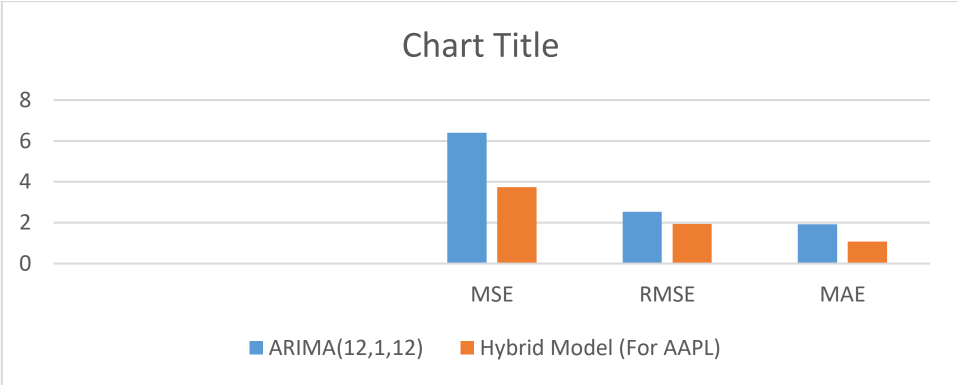

Fig 9: Comparison Visualization of Performance Matrices (MSE, RMSE, MAE) Value of AAPLE stock previous model with proposed model:

The hybrid model stands out by consistently delivering better results than the ARIMA model across all evaluation metrics. This is primarily due to two key reasons:

i. ARIMA is limited to linear assumptions, meaning it can only detect straight-line relationships in historical data. On the other hand, the hybrid model applies Support Vector Regression (SVR) with Radial Basis Function (RBF) kernels, which are well-suited for identifying the nonlinear and intricate movements commonly seen in stock price behaviour.

ii. While ARIMA focuses on a single data sequence, typically the closing price or returns, the hybrid model benefits from a multi-view learning approach. It draws insights from two different sets of features:

a. **Price-based indicators** like Open, High, Low, and Volume

b. **Technical analysis tools** such as the 50-day Simple Moving Average (SMA50) and the 14-day Relative Strength Index (RSI14)

8. Conclusion and Future Work-

This study investigates the performance of multi-view learning (MVL) using support vector regression (SVR) in stock price forecasting. Integrating price functions and technical indicators improves the accuracy of model forecasts. The hybrid approach offers the benefits of both approaches. One focuses on market price movements and the other on technical patterns, which together improve the model ability to capture trends and fluctuations in stock values. Support vector regression (SVR) proves to be a powerful stock price forecasting method when combined with hyperparameter optimization and multi-view learning. The model demonstrates flexibility when working with different stocks and remains accurate during market fluctuations. In addition, performance metrics such as MSE, RMSE, MAE, and R^2 can be used in conjunction with the visualization to provide valuable insight into forecast reliability. This research forms a solid basis for stock price forecasting and provides opportunities for further growth. Future developments may include the inclusion of macroeconomic indicators, financial sentiment analysis or alternative data sources to improve forecasts. In addition, deep learning models, convolution techniques or adaptive algorithm can be used to improve performance and adapt to dynamic market conditions. The hybrid MVL-SVR model represents a promising approach to financial forecasting and provides a framework that can be extended for more complex market analysis.

To provide a more complete view of market movements, the hybrid MVL-SVR can be improved by incorporating data from other sources, including fundamental measurements, sentiment analysis, and macroeconomic data. Advanced machine learning methods like Transformers, ensemble learning, and reinforcement learning can increase forecast accuracy by spotting intricate stock price patterns. By improving feature engineering and using technical indicators like MACD and Bollinger Bands alongside time series decomposition, trend detection may be reinforced. Out-of-sample testing and walk-forward validation should be used for more efficient performance evaluation in order to improve model reliability. Market forecasts can be further improved by adding economic and geopolitical data, and

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

the model's usefulness in dynamic trading situations can be expanded through automated trading systems and real-time data integration. The model's adaptability to diverse financial situations can be improved by tailoring it for different market sectors and taking market cycles into account. Furthermore, its applicability can be expanded beyond single-stock forecasting by using risk assessment metrics like Value at Risk (VaR) and the Sharpe ratio along with portfolio optimization techniques. Using feature significance techniques such as SHAP and LIME to increase model interpretability will give investors more insight into the decision-making process. Lastly, the model's predictive power for global financial markets can be enhanced by expanding it to international markets and examining cross-market linkages. These improvements will help the MVL-SVR model become a more accurate and dependable stock market forecasting tool.

References-

[1] Subhadra Kompella, Kalyana Chakravarthy Chilukuri, 2019, Stock Market Prediction Using Machine Learning Methods, International Journal of Computer Engineering & Technology (IJCET)
[2] Mehar Vijha , Deeksha Chandolab et al., 2019, Stock Closing Price Prediction using Machine Learning Techniques, International Conference on Computational Intelligence and Data Science.
[3] P.P. Singh Kohli, S.Zargar, S.Arora and P.Gupta,2019," Stock Prediction Using Machine Learning Algorithms", Applications of Artificial Intelligence Techniques in Engineering, Advances in Intelligent Systems and Computing 698 Springer Nature Singapore Pte Ltd.
[4] Vijh M, Chandola D, Tikkiwal VA, Kumar A ,2020, Stock closing price prediction using machine learning techniques. Procedia Comput Sci 167:599–606.
[5] Subba Rao Polamuri, K. Srinivas, A. Krishna Mohan,2019, Stock Market Prices Prediction using Random Forest and Extra Tree Regression, International Journal of Recent Technology and Engineering (IJRTE).
[6] Yadav A, Jha CK, Sharan A (2020) Optimizing LSTM for time series prediction in Indian stock market. Procedia Comput Sci 167:2091–2100. https://doi.org/10.1016/j.procs.2020.03.257.
[7] S. Bouktif, A. Fiaz and M. Awad, 2020,"Augmented Textual Features-Based Stock Market Prediction," in IEEE Access, vol. 8, pp. 40269-40282, doi: 10.1109/ACCESS.2020.2976725.
[8] Li-Pang Chen,2020, Using Machine Learning Algorithms on Prediction of Stock Price, Journal of Modeling and Optimization, https://doi.org/10.32732/jmo.2020.12.2.84.
[9] Vignesh CK, Applying Machine Learning Models In Stock Market Prediction, EPRA International Journal of Research and Development (IJRD).
[10] Thakkar A, Chaudhari K (2021) Fusion in stock market prediction: a decade survey on the necessity, recent developments, and potential future directions. Inf Fusion 65:95–107
[11] Manickamahesh N (2021) A study on technical indicators for prediction of select indices listed on NSE. Turkish J Comput Math Educ (TURCOMAT) 12(11):5730–5736
[12] Anushka Chaurasia, Mr. Rohit(2021)Kumar Tiwari, Stock Price Prediction using Various Machine Learning Algorithm, International Journal of Advances in Engineering and Management (IJAEM).
[13] Mehta, Yash, Atharva Malhar, and Radha Shankarmani, 2021,"Stock Price Prediction using Machine Learning and Sentiment Analysis." 2nd International Conference for Emerging Technology (INCET), IEEE, 2021.
[14] Kumbure MM, Lohrmann C, Luukka P, Porras J (2022) Machine learning techniques and data for stock market forecasting: a literature review. Expert Syst Applic 197:116659. https://doi.org/ 10.1016/j.eswa.2022.116659
[15] Soni P, Tewari Y, Krishnan D (2022) Machine Learning approaches in stock price prediction: a systematic review. In: Journal of Physics: Conference Series (Vol 2161, No. 1, p. 012065). IOP Publishing.
[16] Srivinay MBC, Kabadi MG, Naik N (2022) A hybrid stock price prediction model based on PRE and deep neural network. Data 7(5):51
[17] R S Abirami, K.Varalakshmi, Maddika Jaswanth Reddy, et al.,2022, Stock Market Price Prediction Using Random Forest And Support Vector Machine on International Journal of Creative Research Thoughts (IJCRT) www.ijcrt.org.
[18] Mr D.B Khadse, Ashutosh Ambule2 , Tuba Khan et al.,2022 , Stock Price Prediction Using Random Forest Method and Twitter Sentiment Analysis on International Journal of Advanced Research in Science, Communication and Technology (IJARSCT).

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

[19] R. Parekh et al., "DL-GuesS,2022, Deep Learning and Sentiment Analysis-Based Cryptocurrency Price Prediction," in IEEE Access, vol. 10, pp. 35398-35409,doi: 10.1109/ACCESS.2022.3163305.
[20] R.Dileep Kumar, K.Sivadeep.et.al, 2022, Stock Market Prediction Using Machine Learning, Journal of Engineering Science (ISSN NO: 0377-9254).
[21] T. Kabbani and E. Duman,2022, "Deep Reinforcement Learning Approach for Trading Automation in the Stock Market," in IEEE Access, vol. 10, pp. 93564-93574, doi: 10.1109/ACCESS.2022.3203697.
[22] Dr. Sanjeev Kumar Singh, Raunak Sulekh et al., 2023, Stock Price Prediction Using LSTM on Indian Share Market, International Journal of Novel Research and Development (www.ijnrd.org)
[23] Sahu AK, Gupta PK, Dohare AK, Singh AK, Mishra A, Rao A, Jha S (2023). Stock market prediction using machine learning. In: 2023 International Conference on Computational Intelligence, Communication Technology and Networking (CICTN) (pp. 512-515). IEEE. https://doi.org/10.1109/CICTN57981.2023.10140750.
[24] Krishnapriya CA, James A (2023) A survey on stock market prediction techniques. In: 2023 International Conference on Power, Instrumentation, Control and Computing (PICC) (pp 1-6). IEEE.
[25] Zaheer S, Anjum N, Hussain S et al (2023) A multi parameter forecasting for stock time series data using LSTM and deep learning model mathematics. Multidiscip Digit Publish Inst (MDPI) 11(3):1–24.
[26] G. Mu, N. Gao, Y. Wang and L. Dai, 2023,"A Stock Price Prediction Model Based on Investor Sentiment and Optimized Deep Learning," in IEEE Access, vol. 11, pp. 51353-51367, doi: 10.1109/ACCESS.2023.3278790.
[27] Mr. H. P. Khandagale, Rajvardhan Patil, Shreyas Patil, Dhanashri Bhosale,2023, International Journal of Engineering Applied Sciences and Technology(http://www.ijeast.com).
[28] Eswar Prasad Galla, Hemanth Kumar Gollangi , Venkata Nagesh Boddapati ,2023, Prediction of Financial Stock Market Based on Machine Learning Technique,in Journal of Contemporary Education Theory & Artificial Intelligence.
[29] Prachi Pathak,2024, Stock Market Prediction Using Machine Learning, International Journal for Multidisciplinary Research (IJFMR).
[30] Vikas Deswal , Dharminder Kumar ,2024,Hyperparameter Tuning of the LSTM model for Stock Price Prediction, International Journal of Intelligent Systems And Applications In Engineering(www.ijisae.org).
[31] E. Ismanto, "LSTM Network Hyperparameter Optimization for Stock Price Prediction Using the Optuna Framework," Jurnal Ilmiah Teknik Elektro Komputer dan Informatika (JITEKI), vol. 9, no. 1, pp. 22–35, 2023, doi: 10.26555/jiteki.v9i1.24944.
[32] U. K. Lilhore et al., "Hybrid CNN-LSTM model with efficient hyperparameter tuning for prediction of Parkinson's disease," Sci Rep, vol. 13, no. 1, Dec. 2023, doi: 10.1038/s41598-023-41314-y.
[33] S. Chen and C. Zhou, "Stock Prediction Based on Genetic Algorithm Feature Selection and Long Short-Term Memory Neural Network," in IEEE Access, vol. 9, pp. 9066-9072, 2021, doi: 10.1109/ACCESS.2020.3047109.
[34] Che Liu,"Prediction of the Technology Stock Market in American: Based on Apple, Microsoft and Netflix", CONF-MPCS 2024, DOI: 10.54254/2753-8818/51/2024CH0148.