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RESEARCH ARTICLE

MACHINE LEARNING BASED MODELLING OF TEMPORAL PATTERNS IN FINANCIAL MARKET DATA

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Abstract

Forecasting financial markets is a challenging problem due to their highly volatile, dynamic, and non-linear behavior. Accurate predictions are critical for investors, traders, and policymakers to mitigate risks and optimize decision-making. In this paper, We assess and contrast five machine learning algorithms for predicting the stock prices of Apple Inc. (AAPL): Random Forest, XGBoost, Support Vector Machines (SVM),Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU). Moving averages and momentum indicators were among the feature engineering techniques used to gather and pre-process historical stock data. Mean Squared Error (MSE), Mean Absolute Error (MAE), and prediction accuracy were used to train and assess each model.Exper imental results demonstrate that deep learning approaches, particularly GRU, achieve the highest accuracy (94.3%), effectively capturing long-term temporal dependencies. Conversely, ensemble learning techniques like XGBoost and Random Forest provide robust performance in handli ng non linear patterns,while SVM achieves competitive results with sm aller datasets.The findings highlight the advantages of integrating multi ple machine learning paradigms and suggest the potential of hybrid forecasting systems that combine traditional ensemble models with deep learning architectures for improved market prediction.

Introduction:-

Financial market forecasting is a critical task in computational finance, as accurate stock market predictions directly support investors, traders, and financial institutions in making data-driven decisions. The volatility, randomness, and non-linear behavior of stock prices make this problem especially challenging.For time series forecasting, traditional statistical models like GARCH and ARIMA have been widely employed, however they frequently can't manage the large dimensionality and stationary nature of financial data. These restrictions havespurred researchers to investigate more sophisticated techniques[1-4].Deep learning and machine learning have become extremely effective methods for financial forecasting in recent years. Complex non-linear patterns and interactions in financial data can be modelled by machine learning techniques like Random Forest, XGBoost, and Support Vector Machines (SVM). Additionally, they provide resilience against noise, which is a prevalent feature of time series from the stock market.

However, deep learning techniques like Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) networks are made specially to identify long-term dependencies in sequential data. These models are especially useful for stock price forecasting, where historical trends impact future movements, because they have proven to be exceptionally good at managing time-dependent patterns[5-8].This study combines five well-known models—Random Forest, XGBoost, SVM, LSTM, and GRU—to anticipate the stock prices of Apple Inc. (AAPL), a company that is highly volatile and traded on a large scale. Several performance indicators, such as accuracy, mean absolute error (MAE), and mean squared error (MSE), are used to assess the models. The goal is to highlight the advantages and disadvantages of deep learning techniques and classic machine learning algorithms in financial time series forecasting by comparing their predictive powers[8-12].

Literature Review:-

Several studies have demonstrated the effectiveness of machine learning in financial forecasting. Early works primarily relied on linear regression and statistical time series models, but these approaches struggled with the noisy and non-linear characteristics of financial markets. To overcome these limitations, researchers began incorporating advanced machine learning techniques.Patel et al. developed a hybrid framework that combined Support Vector Regression (SVR), Artificial Neural Networks (ANN), and Random Forest (RF) to predict stock indices. Their study showed that ensemble and hybrid approaches often outperform individual models due to their ability to capture multiple aspects of market behavior. Similarly, Wang et al. introduced convolutional neural network (CNN)-based architectures, leveraging their feature extraction capabilities to identify patterns within stock price data. This demonstrated that deep learning could extract complex features without extensive manual engineering.Trafalis et al. compared SVM with traditional neural networks for financial time series forecasting and found that SVM could achieve competitive accuracy, especially with small and medium-sized datasets. However, neural networks displayed better adaptability for larger and more dynamic datasets.

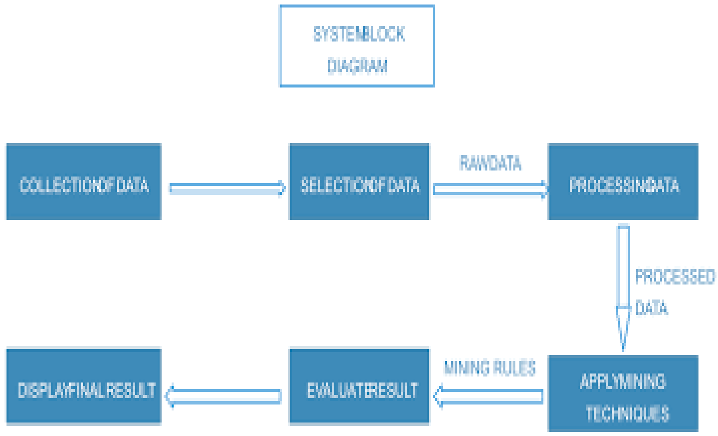
Recent developments demonstrate how effective recurrent neural networks (RNNs), especially Long Short-
models of Gated Recurrent Units (GRU) and Term Memory (LSTM). These designs are ideal for sequential tasks like stock price forecasting because they are made to solve the vanishing gradient problem and efficiently capture long-term temporal dependencies. When applied to extremely volatile financial time series, LSTM and GRU consistently outperform conventional machine learning models, according to multiple researches.In addition, research has begun exploring hybrid approaches that integrate deep learning models with ensemble methods, aiming to balance predictive accuracy with robustness. These results highlight how crucial it is to integrate several learning paradigms in order to create trustworthy and broadly applicable financial forecasting systems.

Existing System:-

The existing systems for financial market forecasting have largely relied on traditional statistical models and single-algorithm machine learning approaches. Stock price fluctuations and volatility have been widely modeled using traditional time series models like Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Autoregressive Integrated Moving Average (ARIMA). While these models provide interpretable results and are effective for short-term forecasting in stationary data, they are limited in handling the high volatility, non-linearity, and non-stationary nature of real-world financial markets.Support Vector Machines (SVM) and other machine learning approaches have also been used to predict the stock market. Some non-linear relationships in the data can be captured by SVMs using kernel functions. However, their effectiveness tends to decline with large datasets and highly complex time series due to their inability to employ sequential relationships efficiently. Similarly, single-algorithm models like decision trees or regression-based techniques do not generalize well in volatile environments where price fluctuations depend on a multitude of interdependent elements.

The incapacity of current systems to integrate various data viewpoints is another significant drawback. Conventional models usually ignore outside factors like news events, investor sentiment, and macroeconomic indicators—all of which have a big impact on financial markets—and instead only use past price and volume data. Furthermore, these models are less appropriate for long-term or real-time forecasting since they struggle to adjust to variables that change quickly.In summary, while statistical and single-model approaches have laid the foundation for financial forecasting, their restricted capacity to capture complex patterns and dynamic dependencies necessitates the development of more advanced solutions. This limitation serves as the motivation for exploring hybrid and deep learning-based systems, which are discussed in the proposed system.

Block Diagram of Proposed Forecasting System



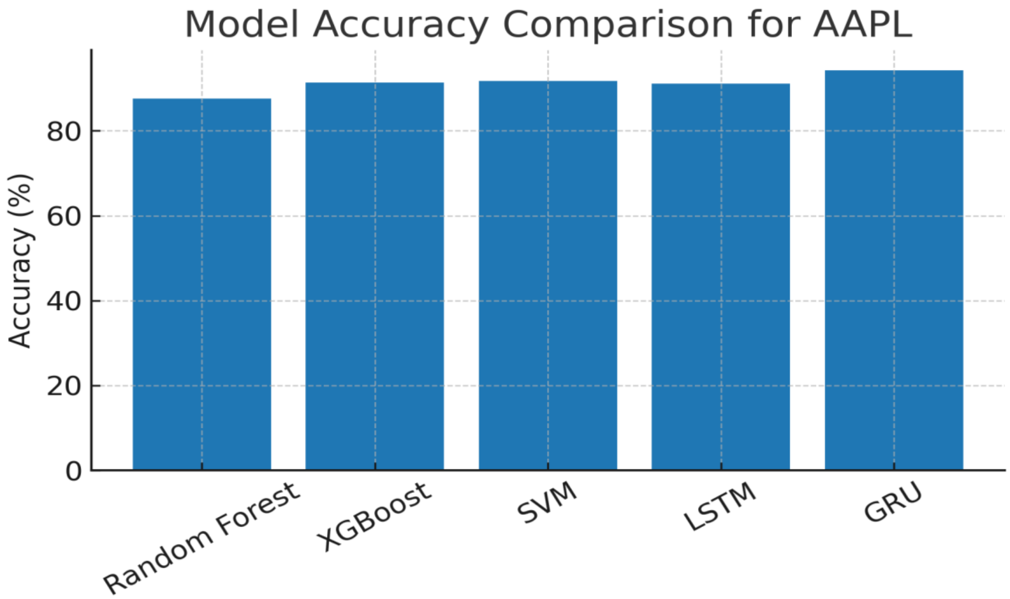
Results and Evaluation:-

The models were evaluated using both normalized metrics (MSE _scaled, MA _scaled) and dollar-based error metrics (MSE_$, MAE_$) to capture performance from two perspectives: relative error, which allows fair comparison across models, and absolute error in USD, which reflects real-world financial implications. Accuracy (%) was also computed to assess the reliability of each model's forecasts.The comparison shows that among the traditional machine learning models, SVM and XGBoost achieved competitive results with accuracies of 91.77% and 91.35%, respectively. Random Forest, although robust against overfitting, recorded the lowest performance at 87.56%, showing its limitations in capturing temporal dependencies in financial time series.The capacity of the deep learning models, LSTM and GRU, to represent sequential dependencies allowed them to perform better. While GRU was the best-performing model with the highest accuracy of 94.31%, the lowest mean absolute error of 5.36 USD, and the lowest mean squared error of 56.15 USD, LSTM reached an accuracy of 91.08% with balanced error metrics. This suggests that, in comparison to alternative methods, GRU is more effective at learning intricate temporal connections.

With a roughly 3% improvement over the next best model (SVM), the accuracy comparison graph highlights GRU's superiority over conventional machine learning methods. These results imply that recurrent neural architectures, especially GRU, are more appropriate for long-term sequential forecasting, even while ensemble techniques like Random Forest and XG Boost are good at identifying non-linear trends. This demonstrates how hybrid frameworks that integrate recurrent neural networks with ensemble learning can increase prediction robustness and accuracy.

Model Accuracy Comparison for AAPL

	MSE	MAE	MSE	MAE	Accuracy(%)
Random Forest	0.0255	0.1244	226.98	11.73	87.5%
XGBoost	0.0132	0.0865	117.74	8.156	91.3%
SVM	0.0112	0.0822	100.36	7.754	91.7%
LSTM	0.0144	0.0892	128.08	8.413	91.0%
GRU	0.0063	0.0569	56.151	5.367	94.3%



Accuracy Comparison of Forecasting Models

Conclusion:-

Five machine learning and deep learning models—Random Forest, XGBoost, SVM, LSTM, and GRU—were compared in this paper for financial market forecasting usingApple Inc. (AAPL) stock data. The models were assessed using a variety of error metrics, such as accuracy, mean absolute error (MAE), and scaled mean squared error (MSE).The findings demonstrate that deep learning techniques—in particular, GRU—performed noticeably better than conventional machine learning models, attaining the greatest accuracy of 94.3% and the lowest error values. Additionally, LSTM showed competitive performance, proving that recurrent architectures are superior for modelling sequential dependencies. Random Forest did the worst among the standard models, mostly because it was unable to identify temporal patterns in financial data, whereas SVM and XGBoost produced respectable results.

These results demonstrate how well recurrent neural network architectures perform tasks involving stock price prediction. The superiority of GRU suggests that it is a good fit for large-scale financial time series because of its straightforward gating mechanism, which offers both computing efficiency and forecast accuracy. Additionally, the comparative research indicates that deep learning approaches are more suited to manage the complexity and volatility of contemporary financial markets, even though machine learning methods are still helpful for capturing non-linear interactions.All things considered, this study supports the expanding use of deep learning in computational finance and establishes the foundation for hybrid strategies that combine the advantages of recurrent neural networks with ensemble learning. In financial applications, these models have a great deal of promise for enhancing forecast accuracy and facilitating better informed decision-making.

Future Work:-

Future research on financial market forecasting can be extended in several promising directions:-

1. **Frameworks for Hybrid Ensembles:**

The creation of hybrid systems that combine the advantages of deep learning and machine learning models is a crucial field of research. For instance, long-term temporal dependencies can be modeled using LSTM and GRU networks, whereas complicated non-linear feature interactions can be captured using ensemble techniques like Random Forest or XGBoost. Forecasting systems may achieve greater accuracy and robustness by combining or stacking several methods as opposed to relying only on one model.

2. **Integration of Sentiment and Alternative Data:**

Factors other than past price and volume data can influence market movements. Sentiment data from analyst reports, financial news, and social media sites (like Twitter, Reddit, and StockTwits) can be incorporated into future models.

Textual data can be converted into sentiment ratings and utilized as extra predictive features by using Natural Language Processing (NLP) methods like BERT or FinBERT. The forecasting models can be further enhanced by incorporating interest rates, global events, and macroeconomic data.

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3. **Reinforcement Learning for Trading Strategies:**

Reinforcement learning (RL) can be applied to design adaptive trading strategies. Unlike supervised learning models that predict prices, RL agents learn optimal actions—such as buy, sell, or hold—through interaction with a simulated trading environment. Algorithms such as Deep Q-Networks (DQN)**,** Actor–Critic methods, and Proximal Policy Optimization (PPO) have shown potential in developing intelligent trading systems that maximize long-term returns under uncertain conditions.

4. Multi-asset and cross-market forecasting:

More thorough analysis can be obtained by expanding predictions beyond a single stock (AAPL in this study) to include various assets, indexes, currency markets, and cryptocurrencies. To improve generalization and take advantage of market correlations, multi-task learning frameworks that share representations across various financial instruments can be created.

5. **Trust and Explainability:**

The use of AI-based forecasting models by financial institutions makes interpretability and transparency crucial. Explainable AI (XAI) methods like SHAP (Shapley Additive Explanations) and LIME may be used in future research to shed light on model choices. This will ensure widespread adoption by fostering confidence among regulators and investors.

6. **Scalability and Real-Time Forecasting:**

Finally, future research should focus on real-time forecasting systems capable of handling high-frequency trading data. Optimizations in computational efficiency, model compression, and deployment on cloud/edge environments will make advanced forecasting solutions feasible for real-world applications.

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