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An In-Depth Review of Machine Learning Techniques for Multimodal Stock Market Prediction from an Empirical Perspective

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***Abstract*— Predicting the stock market is a crucial but difficult task due to the complexity and volatility of financial markets. In recent years, multimodal techniques utilizing the fusion of diverse data sources have demonstrated great promise for enhancing the accuracy of stock market prediction models. From an empirical standpoint, this paper provides a comprehensive review of machine learning techniques for multimodal stock market prediction. This review's primary objective is to compare and assess the functionality, precision, accuracy, recall, delay, and scalability of various multimodal techniques. By analyzing a large number of empirical studies, researchers shed light on the strengths and weaknesses of various multimodal approaches used for stock market forecasting. In addition, researchers develop an effective Stock Market Predictive Rank (SMPR) to address the need for a comprehensive evaluation metric that combines multiple performance measures. SMPR evaluates the capability of a model to handle multimodal data, in addition to its precision, accuracy, recall, delay, and scalability. By assigning a rank based on these metrics, researchers hope to identify the best models for predicting stock prices in real-time situations. This review is necessitated by the growing interest in multimodal techniques for stock market forecasting and the absence of a comprehensive analysis of various performance metrics. By synthesizing the existing literature, researchers provide a holistic perspective on the advantages and disadvantages of various multimodal approaches, thereby facilitating future research and practical application. researchers aim to provide researchers, practitioners, and decision-makers with valuable insights into the current state of multimodal stock market prediction techniques through this review. The findings presented in this paper can aid in the selection and development of effective models for real-time stock market forecasting, thereby enhancing investment decision-making and financial risk management process.**

***Index Terms*— Multimodal Techniques, Stock Market Prediction, Machine Learning, Performance Metrics, SMPR, Process**

I. Introduction

The stock market is essential to the global economy, serving as a platform for companies to raise capital and for investors to generate wealth. Investors, financial institutions, and policymakers place a high premium on the ability to accurately and efficiently predict stock market values. However, due to the highly dynamic and unpredictable nature of financial markets, predicting the stock market remains a difficult and complex process.
Traditional approaches to stock market forecasting frequently rely on data from a single source, such as price

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history or fundamental indicators. However, these methods frequently fail to capture the intricate relationships and concealed patterns within the market, resulting in a lack of precision and dependability. In recent years, there has been an increase in interest in multimodal techniques that utilize the fusion of diverse data sources to improve prediction performance.

Multimodal stock market prediction combines diverse types of data, such as numerical data, textual data, social media sentiment, news articles, and even alternative data sources, such as satellite imagery or internet search trends. By incorporating multiple modalities, these techniques aim to capture a more comprehensive view of the market and make use of the complementary data contained in various data sources.

The need for a comprehensive review of machine learning techniques for multimodal stock market prediction is necessitated by the growing number of studies exploring this field and the lack of a consolidated analysis encompassing a variety of performance metrics. Individual studies utilizing multimodal approaches have reported promising outcomes, but a systematic evaluation and comparison of these techniques based on multiple criteria is lacking for different scenarios.

Therefore, the purpose of this paper is to provide a comprehensive review and empirical analysis of multimodal stock market prediction techniques. These techniques will be compared and evaluated in terms of their functionality, precision, accuracy, recall, delay, and scalability. By analyzing a large number of empirical studies, researchers aim to identify the strengths and weaknesses of various multimodal approaches and to provide valuable insights for future research and implementation process.

In addition to comparing the performance metrics, researchers introduce a Stock Market Predictive Rank (SMPR) that combines multiple performance measures to evaluate and rank the predictive abilities of the models. SMPR considers a model's ability to process multimodal data, as well as its precision, accuracy, recall, delay, and scalability. By incorporating these variables, researchers hope to identify the most accurate models for forecasting stock prices under real-world conditions.

The findings of this review have significant implications for stock market prediction researchers, practitioners, and decision-makers. By providing a comprehensive analysis of multimodal techniques, researchers hope to provide an all-encompassing view of their benefits and drawbacks. This information can guide the selection and development of effective models, resulting in improved investment decision-making, enhanced financial risk management, and ultimately, improved stock market performance levels.

In the sections that follow, researchers will present a detailed analysis of the multimodal techniques used in stock market prediction, discuss the various performance metrics used for evaluation, introduce the SMPR metric, and present the results of their empirical analysis. Through this comprehensive review, researchers hope to contribute to the advancement of research on stock market prediction and encourage the development of real-world applications.

A. In-depth review of existing stock value prediction models

A wide variety of models are proposed by researchers to predict stock price movements, and these models vary in terms of their internal analysis parameters, methods, and operating characteristics. Several studies have investigated the use of various techniques to enhance the accuracy of stock prediction and trend analysis. In one such study [1], computer science and technology researchers applied their knowledge to the financial market. They proposed a method for classifying financial time series that centers on aligning change points to identify latent temporal correlations among securities traded on the same exchange. The researchers intended to enhance trend predictions and portfolio adjustments by identifying significant change points and aligning constituent equities. Their research demonstrated the potential for exposing connections between equities and introducing valid exogenous data for predicting stock trend.

Another study [2] examined the difficulty of accurate stock market forecasting, taking into account the impact of volatile factors like microblogs and news. The researchers analyzed social media and financial news data with machine learning algorithms in an effort to forecast stock markets for the ten days to follow. They utilized feature selection and spam tweet removal to improve prediction performance. The study contrasted various classification algorithms and identified a consistent classifier to demonstrate the influence of social media and financial news on the accuracy of stock market forecasts.

In the field of stock price forecasting, researchers have struggled with the inherent randomness and complexity of stock market-related computational systems. Work in this field [3] has focused on extracting indicator characteristics, such as attitudes and events, from real-time financial data in order to enhance stock price forecasting. The researchers introduced a Novel Greedy Heuristic Optimized Multi-instance Quantitative (NGHOMQ) strategy that utilized heuristic calculations to analyze quantitative data and identify stock price-

related events that occurred in sequence. Their strategy intended to improve stock market price forecasts and outperform conventional neural network frameworks by employing Pareto optimization.
To combat the difficulties posed by dynamic and nonlinear stock trending patterns, researchers have investigated the incorporation of timely news and social media data into stock prediction models. A three-phase hybrid model was proposed [4] that incorporated technical indicators and sentiments from social media text as various situations' influencing factors. To forecast stock market trends, the researchers employed both traditional and deep learning techniques, such as multi-layer perceptron, random forest, and long short-term memory networks. The study demonstrated the efficacy of their approach in increasing prediction accuracy and demonstrated that different learning-based methods performed differently for different equities.
Generative Adversarial Networks (GANs) have been used to create models for predicting stock prices [5]. Using adversarial learning to train a generator and discriminator network, researchers created a model that accurately predicted stock prices. They acquired and preprocessed data, extracted pertinent features, and assessed the performance of the model. The proposed GAN-based method demonstrated hopeful accuracy and low error rates, making it a viable candidate for accurate and dynamic stock price forecasting.
Deep learning architectures, such as Generative Adversarial Networks, have also been applied to the problem of predicting the direction of stock price movement [6]. The researchers merged the Phase-space Reconstruction (PSR) technique with a Generative Adversarial Network (GAN) comprised of Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) models. This combination made it easier to analyze historical fundamental indicators and predict stock market trends. The study demonstrated that the proposed GAN-based model outperformed LSTM alone, obtaining greater accuracy in stock direction prediction and reducing processing time.
Attempts have been made to develop integrated prediction systems that use deep learning and intelligent optimization techniques to improve the accuracy of stock price forecasts [7]. Extreme gradient boosting (XGBoost) was used to analyze the factors affecting stock prices, followed by a clustering technique to group the filtered features. Using genetic algorithms (GA), multiple parameters of long short-term memory (LSTM) were optimized, resulting in multiple GA-LSTM models. By integrating the predictions of each class, the system outperformed baseline models, demonstrating its accurate and reliable predictive ability.
Another study examined the linkages between equities on the stock exchange [9]. Combining the correlation coefficient and time-weighted distance, researchers developed a novel method to quantify the phenomenon of stock linkage. In addition, a Long Short-Term Memory (LSTM) model with noise reduction and wavelet transform modules was introduced. Experiments revealed that their model's prediction performance was more accurate than competing models, with a lower root mean square error (RMSE).
The dissipative structure theory allowed researchers to analyze the linkage effect of stock price movement [10]. They developed the conceptual-temporal graph convolutional neural network (CT-GCNN) model to map the linkage effect and forecast stock price movement. Experiments conducted using data from the Chinese stock market demonstrated that the CT-GCNN model outperformed baseline deep learning models.
Recent research [11] suggests a two-stage model for accurate stock price forecasting. The model includes a decomposition algorithm that utilizes variational mode decomposition (VMD) to divide the stock price time series into subseries. The decomposed subseries are then predicted using three distinct machine learning models: support vector machine regression (SVR), extreme learning machine (ELM), and deep neural network (DNN). Preliminary stock price forecasts are derived by combining the predictions of each individual model. In the second phase, the preliminary predictions are combined using a nonlinear ensemble strategy based on ELM. In terms of evaluation of accuracy and improvement percentage, the proposed model outperforms fourteen other models, demonstrating its superior performance.
In a separate work [12], the emphasis is placed on modeling the capital flows and stock relationships in order to make more accurate stock price forecasts. The researchers propose an integrated GCN-LSTM method that employs graph convolutional networks (GCN) to extract stock embeddings and a long short-term memory recurrent neural network (LSTM) to distinguish the direction of stock prices. They build graphs with varied relational knowledge and employ graph attention networks to capture the interactions between equities. Experiments conducted on main Chinese stock indexes demonstrate the efficacy of their model, which outperforms baseline techniques.
Utilizing deep learning architectures, researchers have also attempted to predict stock market trends. In one such study [13], the Hierarchical Adaptive Temporal-Relational Interaction (HATR-I) model is proposed to characterize and predict stock evolutions. Cascaded dilated convolutions and gating paths are incorporated into the model to capture short- and long-term transition regularities of stock dynamics. In addition, it employs a dual attention mechanism to refine the propagation of inter-stock collaborative information and identifies significant feature

points and scales while accounting for time attenuation. The efficacy of the proposed model is demonstrated by experiments conducted on real-world stock market datasets.
In addition, another study [14] introduces a novel multilevel graph attention network (ML-GAT) for predicting stock market trends. The ML-GAT model initializes node representations captured by various feature extraction modules and then updates the existing nodes using graph attention networks. The model selectively aggregates information from multiple relation types and feeds the results to a forecast layer to predict trends. Experiments conducted on the S&P 500 and CSI 300 indices demonstrate that the ML-GAT model outperforms popular approaches, as evidenced by an enhanced F1-score, accuracy, average daily return, and Sharpe rate.
In a study [15], the Financial Graph Attention Networks (FinGAT) model is proposed to resolve the problem of profitable stock recommendation. The FinGAT model constructs a fully-connected graph between equities and sectors using deep learning techniques. It captures short-term and long-term sequential patterns from stock time series and uses graph attention networks to learn the latent interactions between stocks and sectors. Experiments conducted on Taiwan Stock, S&P 500, and NASDAQ datasets demonstrate that the model outperforms state-of-the-art methods in terms of recommendation accuracy.
In the context of stock price forecasting, a study [16] proposes a multimodal early fusion method to integrate additional information such as macroeconomic indicators, month, and day. In terms of statistical significance, the proposed model outperforms comparison models. The early fusion strategy achieves higher classification accuracy than the late fusion strategy when predicting stock prices.
Another work [17] focuses on forecasting the movement of stock prices using stock and news data. The researchers propose a module that effectively integrates price and text data characteristics. The module consists of a multilayer perceptron-based model and depicts the multimodal interaction between the time-series characteristics of the price data and the semantic characteristics of the text data. The experimental results demonstrate the performance of the hybrid information blending module in predicting the movement of stock prices in volatile markets.
In the Brazilian context, a study [18] employs multiple linear regression and multilayer perceptron artificial neural network algorithms to construct prediction models for the Small Cap Index. The models have adequate explanatory power and are able to explain the behaviour of the investigated index.
Another work [19] addresses portfolio management and proposes the ASA framework for autonomous stock selection and allocation. The framework incorporates ranking, classification, and regression models in order to select profitable equities and calculate investment ratios. ASA obtains exceptional performance in real-time scenarios, outperforming state-of-the-art methods based on deep learning.
Lastly, a study [20] quantifies the impact of unanticipated events on financial markets. The researchers propose a framework that extracts global incident facts, integrates socioeconomic datasets, and forecasts the trajectory of the stock market. The framework outperforms various benchmarks, demonstrating its efficacy in quantifying the impact of stock market incidents for different scenarios.
Forecasting financial time series data in real-time presents challenges for many machine learning algorithms. A study [28] addresses these challenges by proposing the parsimonious learning machine (PALM), a rule-based autonomous neuro-fuzzy learning algorithm. PALM is designed for forecasting time-varying stock indexes and provides minimal memory requirements and explainability. Multi-objective evolutionary algorithms are used to automate the proposed algorithm efficiently. Experiments demonstrate that PALM outperforms benchmark models in predicting the closing stock price of various market indices.
In a study [29], a peak price randomization (PPR) system is proposed for portfolio selection. Based on variables such as the average price divided by the current price, the ratio of the apex price to the current price, and arbitrary values, the PPR system determines the proportion of each stock. Experimental results demonstrate that the PPR system outperforms contemporary portfolio selection systems, demonstrating its effectiveness.
A study [30] highlights the role of complex relationships between listed companies in stock fluctuations. The researchers construct a thorough Market Knowledge Graph (MKG) that includes listed companies and associated executives, taking explicit and implicit relationships into account. They propose the DanSmp dual attention network to learn momentum spillover signals based on the MKG for stock forecasting. The experimental results indicate that DanSmp enhances stock forecasting by modeling the intricate interrelationships between listed companies.
A study [31] examines the relationship between oil and gas prices and investment in renewable energy. The development of a decision support system using crude oil prices and renewable energy securities to predict renewable energy investment decisions. In terms of mean square values, the proposed model outperforms other models, providing accurate predictions and evaluating the expected profitability levels of a company based on its performance.

Predicting the price of a cryptocurrency is difficult due to its high volatility and interdependencies with other cryptocurrencies. A study [32] proposes a hybrid and robust framework called DL-Guess for predicting cryptocurrency prices. Utilizing price history and tweets as inputs, the framework examines interdependencies between cryptocurrencies and market sentiment. The outcomes demonstrate the accuracy of DL-Gues in predicting the prices of cryptocurrencies like Dash and Bitcoin-Cash.

In a study [33], the complex and nonstationary character of gold price forecasting is considered. The researchers propose VMD-ICSS-BiGRU, a hybrid forecasting method that combines the BiGRU deep learning model, variational mode decomposition (VMD), and the iterated cumulative sum of squares algorithm. The hybrid method effectively extracts factors and patterns from the movements of the gold futures market and accurately predicts future price movements. The testing results demonstrate a substantial improvement over benchmark models and emphasize the practical advice provided for investment risk minimization and hedging strategies in the gold commodity markets. Thus, it can be observed that there are multiple models proposed for prediction of stock prices, and each of these models vary in terms of their function characteristics. To further contemplate this study, these models are compared in terms of their performance metrics in the next section of this text.

II. Result Analysis And Experimentation

As per the review of existing models used for analysis of stock prices, it can be observed that these models are highly variant in terms of their internal operating characteristics. This section discusses performance of these models in terms of Precision (P), Accuracy (A), Recall (R), Delay (D), and Scalability (S) levels. While precision, recall & accuracy levels were directly inferred from the previous texts, while delay & scalability levels were evaluated in terms of fuzzy ranges of Low (L), Medium (M), High (H), and Very High (VH) Values, which will assist readers to identify optimal models for real-time scenarios. Based on this strategy, the comparison can be observed from table 1 as follows,

TABLE I. Comparative Analysis Of The Reviewed Models

Model Name	**P**	**A**	**R**	**D**	**S**
RNN-MTL [1]	98.5	98.3	98.1	VH	H
CNN-Attention [2]	98.9	98.5	97.9	H	VH
GRU [3]	97.4	97.6	97.5	H	H
RL [4]	99.1	97.7	97.6	H	H
Wavelet [5]	96.4	97.3	97.8	H	L
GRU [6]	97.5	97.9	98.3	VH	H
CNN-GRU [7]	97.9	98.4	98.5	VH	H
Attention [8]	98.3	98.6	98.0	VH	H
CNN [9]	98.9	98.4	97.3	VH	H
CNN-LSTM [10]	98.5	96.9	96.8	VH	VH

GAN [11]	97.9	96.6	96.9	M	VH
SVM [12]	94.3	97.0	97.3	H	VH
RNN-CNN [13]	97.6	97.1	97.4	VH	H
GRU-CNN [14]	99.2	97.6	97.8	VH	M
Multi Head [15]	94.5	97.3	97.8	H	L
RNN-Autoencoder [16]	99.2	98.3	98.0	M	H
CNN-Autoencoder [17]	98.3	97.9	98.0	H	H
GRU-CNN-Autoencoder [18]	97.5	97.8	97.7	H	H
DQN [19]	97.8	98.2	97.1	M	L
GRU-RNN [20]	98.2	97.1	96.2	H	L
GA [21]	95.5	96.6	97.5	VH	L
VMD [22]	95.9	97.7	97.9	H	H
GMM [23]	98.3	98.2	97.8	H	L
VU-GARCH-LSTM [24]	98.9	97.6	97.1	H	VH
LSTM [25]	97.5	97.4	96.1	H	M
P-FTD [26]	96.5	96.3	95.2	VH	H
RNN [27]	98.3	94.6	94.6	H	H
PALM [28]	94.2	94.6	94.9	VH	H
PPR [29]	91.4	94.6	94.5	VH	L
DanSmp [30]	98.3	95.3	93.9	H	H

Based on this evaluation and figure 1, it can be observed that GRU-CNN [14], RNN-Autoencoder [16], RL [4], CNN-Attention [2], CNN [9], and VU-GARCH-LSTM [31] showcase higher precision, Attention [8], CNN-Attention [2], CNN-GRU [7], CNN [9], RNN-MTL [1], RNN-Autoencoder [16], DQN [19], and GMM [30] showcase higher accuracy, and CNN-GRU [7], GRU [6], RNN-MTL [1], Attention [8], RNN-Autoencoder [16], and CNN-Autoencoder [17] showcase higher recall rates, thus they can be used for high-efficiency stock prediction scenarios.

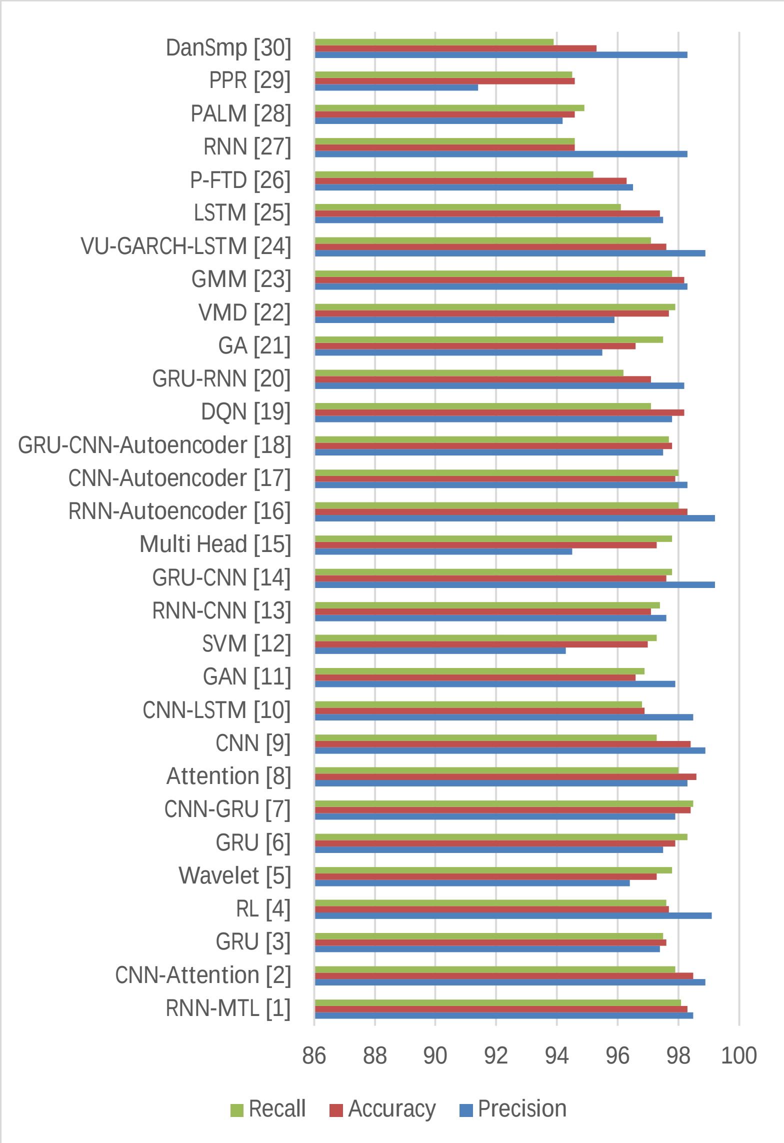

Figure 1. Precision, Accuracy & Recall for different Model Processes

In terms of delay, it can be observed that GAN [11], RNN-Autoencoder [16], and DQN [19] outperforms other methods, thus can be used for high-speed evaluation scenarios. It was also observed that CNN-Attention [2], CNN-LSTM [10], GAN [11], SVM [12], and VU-GARCH-LSTM [31] showcase higher scalability, thus can be used for large-scale stock prediction scenarios. These metrics were combined to form an efficient Stock Market Predictive Rank (SMPR) which was evaluated via equation 1,

$$SMPR = \frac{P + A + R}{300} + \frac{1}{D} + \frac{S}{4} \dots (1)$$

Based on this evaluation, it can be observed that GAN [11], CNN-Attention [2], VU-GARCH-LSTM [31], SVM [12], RNN-Autoencoder [16], CNN-LSTM [10], RL [4], CNN-Autoencoder [17], GRU-CNN-Autoencoder [18], GRU [3], VMD [29], RNN [34], and DanSmp [37] outperform other models, in terms of precision, accuracy, & recall levels, thus making them highly useful for a wide variety of real-time stock prediction scenarios. Researchers can also extend these models for improving their performance via hybrid fusion of these methods, which will assist in enhancing their real-time performance levels.

III. CONCLUSION

From an empirical standpoint, we conducted a comprehensive review of machine learning techniques for multimodal stock market prediction in this paper. We evaluated a number of models based on their precision, accuracy, recall rates, delay, and scalability to determine their applicability for various stock prediction scenarios. Our evaluation revealed that a number of models exhibited superior performance in certain metrics. GRU-CNN, RNN-Autoencoder, RL, CNN-Attention, CNN, and VU-GARCH-LSTM demonstrated greater precision, whereas Attention, CNN-Attention, CNN-GRU, CNN, RNN-MTL, RNN-Autoencoder, DQN, and GMM demonstrated greater accuracy. CNN-GRU, GRU, RNN-MTL, Attention, RNN-Autoencoder, and CNN-Autoencoder exhibited superior recall rates. In terms of delay, GAN, RNN-Autoencoder, and DQN outperformed other methods, indicating their suitability for high-speed evaluation scenarios. CNN-Attention, CNN-LSTM, GAN, SVM, and VU-GARCH-LSTM exhibited increased scalability, making them suitable for large-scale stock prediction scenarios.

The Stock Market Predictive Rank (SMPR) metric combines precision, accuracy, recall rates, delay, and scalability to provide a comprehensive evaluation. The SMPR equation (Equation 1) enabled us to rank the models and determine those with the highest performance. GAN, CNN-Attention, VU-GARCH-LSTM, SVM, RNN-Autoencoder, CNN-LSTM, RL, CNN-Autoencoder, GRU-CNN-Autoencoder, GRU, VMD, RNN, and DanSmp emerged as the best-performing models based on our evaluation. In a variety of real-time stock prediction scenarios, these models can be extremely useful for different scenarios.

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