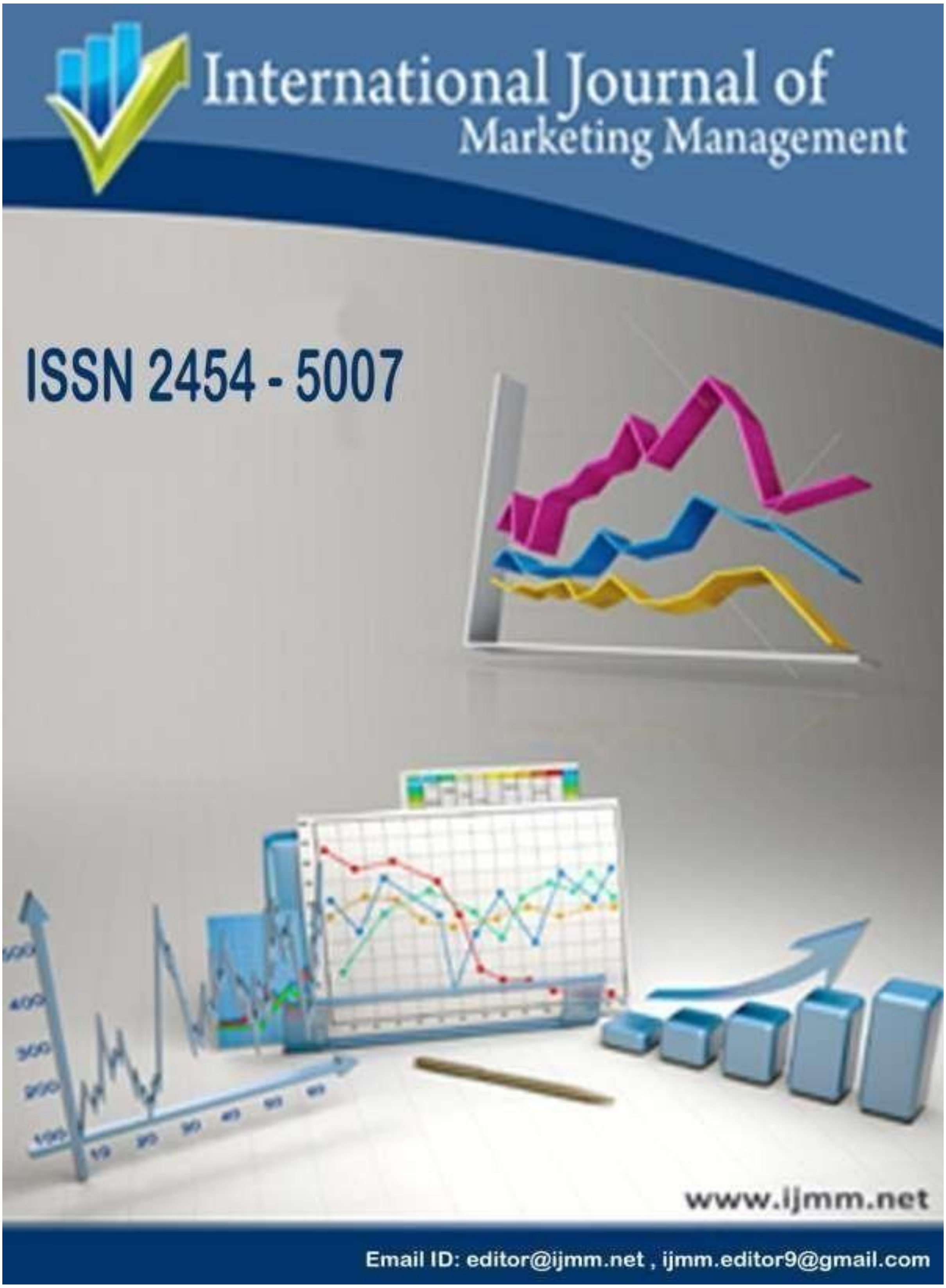
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Implementing a Hybrid Bilst-GRU Model for Stock Price Prediction

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Abstract- ***Predicting stock prices with any degree of accuracy has always fascinated and encouraged scholarly curiosity in the financial industry. To make educated decisions regarding purchasing, selling, or holding stocks, investors, traders, and financial institutions greatly value accurate stock price forecasts. Traditional stock prediction relies on a number of factors that are susceptible to changes in economic data, investor sentiment, market trends, company fundamentals, and the emotional tone of news reports. To circumvent these issues, this research recommends a hybrid BiLSTM-GRU model for stock price forecasting. Data preparation is the first step and include dealing with missing values and using robust data cleaning procedures to ensure the information is correct and dependable. The next stage, feature engineering, aims to enhance the model's ability to identify intricate stock market trends and patterns by the extraction of valuable features from the raw data.When assessing the model's efficacy, the train-test split plays a significant role. We use normalization techniques to standardize the data so that all characteristics scale uniformly and the model performs as well as it can. Finally, two classification models, BILSTM and GRU, will be used to model sequential data using deep learning. By feeding these models the characteristics that have already been analyzed and developed, we can anticipate how the stock price will move. To carry out this project, the programming language Python is used.***

1.INTRODUCTION

1.1 STOCK PRICE

The stock market is a fascinating area where investors try to understand trends and patterns in order to make smart judgments, thanks to the complex dance of supply and demand. Numerous variables, including economic data, geopolitical events, investor attitude, and corporate performance, impact stock prices, which are the beating heart of this market.

Figure 1 Stock Price Prediction

International Journal of Marketing Management

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Vol. 11, Issue. 3, 2019

Traders, analysts, and investors all face the constant difficulty of trying to understand and forecast these movements. Machine learning algorithms and other cutting-edge computer methods have changed the game when it comes to predicting stock prices in recent years. Of these advancements, hybrid models like the Bidirectional Long Short-Term Memory (BiLSTM) and the Gated Recurrent Unit (GRU) stand out as powerful resources that might lead to better accuracy and prediction. The need for reliable models that can deftly and precisely negotiate the stock market's intricacies has never been greater than in this age of data-driven decision-making. Research into hybrid BiLSTM-GRU models for stock price prediction is therefore cutting edge in the field of finance, with the ability to provide novel insights and approaches to the ever-changing investing landscape.

1.2 STOCK PRICE METHODS

The term "stock price prediction methods" refers to a wide range of strategies for gauging the direction of stock values in the future. Some approaches that are often used include:

Statistical Models

To project what prices will be in the future, statistical models look at past data and use mathematical methods. Arrima, Holt-Winters, and other exponential smoothing models are examples, as are Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models.

Machine Learning Algorithms

The capacity of machine learning algorithms to detect intricate patterns in data has led to their increased use in the field of stock price prediction. The field often makes use of algorithms like GBM, Linear Regression, Support Vector Machines (SVM), Random Forests, and Neural Networks (including LSTM, GRU, and hybrid architectures).

Technical Analysis

Looking at price and volume data from the past might help in technical analysis by revealing trends and patterns that could happen again. This strategy for making forecasts is based on trend analysis, chart patterns, and technical indicators like Moving Averages and the Relative Strength Index.

Fundamental Analysis

To find the true worth and future prospects of a firm, fundamental analysis looks at its financial standing and performance indicators. Income, expenditure, profit margins, debt, and other macroeconomic variables are all part of this strategy.

Sentiment Analysis

To determine how investors feel about certain companies or the market as a whole, sentiment analysis looks at textual data like as news stories, social media messages, and more. The extraction of sentiment and attributes related to sentiment is a common use of natural language processing (NLP) methods.

Hybrid Approaches

Predictions may often be improved by combining several approaches or models. For example, a hybrid method may combine technical and fundamental research, use sentiment analysis in prediction models, or combine statistical models with machine learning techniques.

Deep Learning

A number of deep learning algorithms have shown potential for accurately predicting stock prices over longer time horizons and for understanding sequential relationships in the data. Two such RNNs are LSTM and GRU.

Ensemble Methods

By combining the predictions of several models, ensemble approaches enhance the overall accuracy and resilience of the system. It is possible to merge the predictions of several models using methods like bagging, boosting, and stacking.

Market Microstructure Models

To foretell how stock prices will change in the near future, these models analyze the interplay between order flow, market liquidity, and price effect. Models like this often make use of high-frequency trade data together with characteristics of the market's microstructure.

Event Studies

Regulatory changes, mergers and acquisitions, earnings releases, and other particular events are examined in event studies to determine their effect on stock prices. These analyses are useful for gauging the immediate and distant consequences of news on stock values.Analysts and researchers may create reliable

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Vol. 11, Issue. 3, 2019

models for forecasting stock prices and making educated investment choices by integrating and customizing these methodologies to particular market circumstances and investment goals.

2.LITERATURE SURVEY

XuanJi *et al* [2021] introduced a novel deep learning-based prediction approach that incorporates both conventional stock financial index variables and text data from social media into the prediction model. In order to achieve dimensionality parity between text feature variables and stock financial index variables, this study used Doc2Vec to construct lengthy text feature vectors from social media. The vectors are then reduced in size using stacked auto-encoder. Meanwhile, to remove the random noise induced by stock market swings, the time series data of stock prices is decomposed using the wavelet transform. The stock price is predicted in this study using a long-term memory model. When it comes to predicting stock values, our technique outperforms the three benchmark models across the board. Most stock price time-series data is also nonstationary since the stock price is sensitive to a wide variety of unpredictable variables. Hence, among the most difficult topics in prediction research generally, stock price prediction stands out. Researchers have looked at stock price prediction from a variety of angles over the last few decades, with the two most prominent being the development of better prediction models and the selection of more appropriate model characteristics. The autoregressive integrated moving average and other econometric models were the most often utilized in the first research. Doc2Vec produces a vector dimension that is very high and noisy, leading to major over-fitting issues.

Saud S *et al* [2021are the new stock market prediction model's three main stages: prediction, feature extraction, and optimum feature selection. We start by extracting statistical variables such as variance, skewness, kurtosis, standard deviation, and mean from the stock market data that has been gathered. Rate of change (ROC), relative strength index (RSI), average true range (ATR), and exponential moving average (EMA) are some of the typical indicators used in the computation of the indexed data. Choosing the most relevant characteristics is more important to get the best-predicted outcomes. The Red Deer Adopted Wolf Algorithm is a novel hybrid model that uses the extracted features (statistical features, features based on technical indications) to determine the ideal features. In addition, in order to forecast the stock's movement, the chosen attributes are put via the ensemble approach. Classes such as Support Vector Machine (SVM), Optimized Neural Network (NN), Random Forest 2 (RF2), and Random Forest 1 (RF1) are all part of the ensemble approach. This research use the ensemble technique to enhance the precision of the Saudi stock market forecast. Unfortunately, the interpretability is not apparent since the features of a crucial function go unnoticed.

Suman Saha *et al* [2021have implemented a bedding approach (such as Node2Vec) for stock ranking prediction and provided assessment metrics. We found three main things in our investigation. One thing to note is that while using the same embedding strategy, list-wise loss improves NRBO@10 in three of the four examples. Utilizing the list-wise loss for NASDAQ with the Wikidata graph outperforms the combined point-wise and pair-wise loss by 2.65 percent. In the case of the NASDAQ, this gain is 6.7 percent, whereas in the case of the NYSE, it is 1.4 percent. Training time for graph-based methods to predict stock rankings may be drastically cut using node embedding algorithms like Node2Vec. This exemplifies a major benefit of the list-wise loss in predicting stock rankings. With list-wise loss, training time for sparse graphs like the Wikidata graph can be reduced while performance in NRBO@10 and MRRT can be enhanced. Nevertheless, it will not be possible to determine which approach is superior since their accuracy will be same. When the stock correlation graph is dense, as the NYSE with Industry graph, Node2Vec's performance is somewhat worse than the baseline model.

Yi-Ling Hsu *et al* [2023] have created a new model using deep learning called Financial Graph Attention Networks (FinGAT) to deal with the problem when there are no preset stock associations. The concept of FinGAT is three-pronged. In order to learn both the short-term and long-term sequential patterns from stock time series, you must first create a hierarchical learning component. Second, in order to understand the latent interactions across stocks and sectors, graph attention networks are used in conjunction with fully linked stock and sector graphs to develop a learning model. As a third step, a multi-task goal is developed to forecast stock movement and jointly propose profitable stocks. We found that our FinGAT outperformed state-of-the-art algorithms in recommendations on the Taiwan Stock, S&P 500, and NASDAQ datasets. Investors may benefit from the information on stock impact and correlation provided by the FinGAT model. On the other hand, not all stock exchanges make sector data readily available. But, investing in stocks often has a very high degree of risk, making the development of an appropriate investment strategy an essential undertaking. **Jooweon Choi *et al***

International Journal of Marketing Management

ISSN 2454-5007, www.ijmm.net

Vol. 11, Issue. 3, 2019

[2023] have proposed a strategy for using stock and news data to forecast future stock price movements. Predicting the movement of stock prices requires taking market volatility into account, as the stock market is influenced by several factors. Stock prices swiftly reflect all types of information due to the efficiency of the stock market. It proposes a hybrid information mixing module that combines price and text data features, and it uses two map blocks to effectively interact between the two features, creating a new fusion mix. This method successfully extracts the multimodal interaction between the statistical aspects of the text data and the time-series feature of the period. When it comes to forecasting the movement of stock prices, the hybrid information mixing module outperforms the other models. To test how well the hybrid information mixing module works, we look at the accuracy, Matthews' correlation coefficient (MCC), and F1 score of the stock price movement forecast. Only the direction of the predicted change in stock price—upward or downward—is classified by the binary classifier.

Nagaraj Naik *et al* [2021] to eliminate stocks' superfluous financial parameter aspects, they put out the HFS algorithm. Naive Bayes is the second, and it is thought to be able to categorize solid fundamental stocks. The third case is when a stock price bubble was identified using the Relative Strength Index (RSI) technique. The fourth is that the stock price crisis point has been identified using moving average data. Predicting a stock market disaster using XGBoost and DNN regression is the aim of the fifth section. These three metrics—root mean square error (RMSE), mean absolute error (MAE), and mean squared error (MSE)—are used to assess the model's performance. When it came to forecasting the stock crises, the XGBoost technique based on HFS outperformed the DNN method based on HFS. When compared to BP, reasoning neural networks have a faster learning rate and fewer hidden nodes, which is a benefit. Eliminating superfluous features from stock financial parameters is done using the Hybrid Feature Selection (HFS) method. The problem is that the error term changes with time due to the nonlinear nature of stock price data.

Xianghui Yuanl *et al* [2020] using time-sliding window cross-validation to establish the parameters of machine learning-based stock price trend prediction models using 8-year data from the Chinese A-share market. Feature selection methods are employed in this process. The model outperforms competing integrated models when feature selection and stock price trend prediction are handled by the random forest method. A long-short portfolio is built using the random forest technique to assess the efficacy of the best model. Using the kernel function, SVMs are able to overcome the linear indivisibility issue of data, which is an advantage over LR models. It is possible to make nonlinear data that is in a low-dimensional space linear by mapping it to a high-dimensional space. To achieve the mapping from low-dimensional to high-dimensional space and to decrease complexity, the kernel function maps to the function of high-dimensional space by calculating the inner product of two vectors in low-dimensional space.

Teema Leangarun *et al* [2021] have characterized the process of identifying stock price manipulation as a game of cat and mouse. Manipulators are always coming up with new ways to evade capture. The bulk of the relevant research relied on supervised learning methods, which required pre-existing instances of manipulation patterns to train their models. Utilized unsupervised learning to train deep neural networks for stock price manipulation detection, allowing for the detection of unknown and unobserved manipulation. Normal trading behaviors were taught into the models using order book limits. We defined manipulated anonymous trading activities as those that did not adhere to the learning patterns. Our method's strength is that it doesn't need knowing its manipulation properties in advance. Consequently, it excels at identifying manipulations that have not been seen before. There were two model architectures that were tested: generative adversarial networks (GANs) and autoencoders (AE).

Baqar A Rizvi *et al* [2020] have suggested an unsupervised learning-based detection approach that makes use of Kernel Principal Component Analysis (KPCA) and applies more variance to some latent characteristics in higher dimensions. In order to detect anomalous manipulation patterns in the data, the chosen components are subjected to a multidimensional kernel density estimation (MKDE) clustering algorithm. By lowering the high dimensions acquired by traditional KPCA and eliminating the ambiguity of assuming values for several parameters, this study outperforms the current techniques in terms of computing complexity. Variations in the dataset window length and the occurrence of two or more manipulative acts in close proximity to one another have also been used to assess the detection model's resilience. Without disclosing the precise site of the alteration, we validated the model on several datasets and evaluated its performance thoroughly.

Agus Tri Haryono *et al* [2023] have proposed ways to measure public opinion on news stories by looking at their chronological order. Quotations of news sentiment are based on the categorization model's daily confidence score. Sentiment indicators are the end product of the active learning model's categorization model

International Journal of Marketing Management

ISSN 2454-5007, www.ijmm.net

Vol. 11, Issue. 3, 2019

that takes time sequence data into account. The suggested Transformer Encoder Gated Recurrent Unit (TEGRU) design then makes use of the sentiment indicators for stock price predictions. The TEGRU incorporates a transformer encoder that uses multi-head attention to learn pattern time series data, which is then passed on to the GRU layer for stock price determination. In order to assess forecasting models that are vulnerable to the misclassification of stock price movements, the AcMAPE is used. Using an active learning model, the feature extraction approach creates a sentiment indicator that takes into account time sequence data and several aspects in order to represent the stock market in depth. Nonetheless, it seems that predicting stock prices still resolves the bare minimum of financial risk.

Jiahong Yuan *et al* [2020] analyzes the connections between currency rates and the Chinese stock index, proposing a road map based on the stock-oriented and flow-oriented models. In order to account for the daily data variations and minimize the impact of the central bank on the exchange rate, two fuzzy approaches are used. Specifically, the integral-based measure and the centroid-based measure are used for data processing. Examine the stock index's link to the exchange rate using the Granger causality test and Pearson's correlation coefficient. Additionally, we can better assess their connection and provide a reference for a broader application of the suggested fuzzy methods by comparing the findings and their differences using the standard crisp approach and our two fuzzy techniques rather than just one. Two fuzzy methods—the centroid-based and the integral-based approaches—have been identified; these two have certain benefits over the crisp approach that relies on the closing price. These may condense the information while still capturing the daily ebb and flow of the financial markets. The optimism level is an additional element in the integral-based technique that may improve the accuracy and completeness of the study outcomes.

Kazi Ekramul Hoque *et al* [2021] have shown how optimization of hyperparameters affects ML models used for stock price prediction. The scientific and financial sectors have acknowledged that predicting stock prices is a difficult endeavor since stock prices are dynamic and nonlinear. Machine learning models have the potential to be useful tools for predicting stock prices because of their capacity to deal with nonlinear data. For the purpose of making stock price predictions for eleven businesses listed on the Saudi Stock Exchange, this research empirically evaluates eight traditional machine learning models. Additionally, for every machine learning model, the best hyperparameter configuration is found. Two popular error measures, root mean square error (RMSE) and mean absolute percentage error (MAPE), are used to assess the effectiveness of forecasting. By comparing the predicting performance of tuned and un-tuned machine learning models, the effect size is used to quantify the influence of hyperparameter tweaking. Tuning the hyperparameters of machine learning models for stock price forecasts has different effects, according to the empirical data. After hyperparameter adjustment, support vector regression significantly beats competing forecasting models. The key benefit is that, being non-parametric, it does not need a distribution in the data. Also, it doesn't care about the value's magnitude, therefore it's fair when dealing with outlier data.

Kun Huang *et al* [2022] provided details on an Attention Model for Multilevel Graphs Used in Stock Prediction. Academics and businesses have been studying stock market volatility for a long time, and predicting stock trends is difficult. While previous studies have explored ways to incorporate past pricing data into graph networks, they have mostly disregarded the impact that other types of information, including news and current events, might have on projections. Despite the intricacy of stock linkages, the majority of current graph-based learning approaches still rely on manually creating stock relationships to generate stock graphs. In order to forecast stock market movements, we suggest a new multilevel graph attention network (ML-GAT) that is based on these. But much of the previous research hasn't looked at which connection data is better for forecasting market changes. Hence, use the graph attention neural network to choose collect data from various relation kinds. While LSTM is the most accurate model when it comes to modeling stock connections, GCN is just somewhat less accurate.

Mojtaba Nabipour *et al* [2020] have evolved to greatly lessen the danger of trend forecasting using ML and DL algorithms. We choose four classes of stocks from the Tehran Stock Exchange for our experimental evaluations: diversified financials, petroleum, non-metallic minerals, and basic metals. The following machine learning models and two strong deep learning techniques are compared in this study: Decision Tree, Random Forest, Adaptive Boosting (Adaboost), Extreme Gradient Boosting (XGBoost), Support Vector Classifier (SVC), Naïve Bayes, K-Nearest Neighbors (KNN), Logistic Regression, and Artificial Neural Network (ANN). We have 10 technical indicators derived from a decade's worth of data as inputs, and there are two methods to put them to use. First, we use stock trading values as continuous data to calculate the indicators. Then, before we use them, we convert them to binary data. The inputs are used to assess each prediction model using three

International Journal of Marketing Management

ISSN 2454-5007, www.ijmm.net

Vol. 11, Issue. 3, 2019

measures. When it comes to continuous data, the assessment findings show that RNN and LSTM perform much better than other prediction models. Noting that each of them has its own set of restrictions is, however, critical. Neither the input data representation nor the prediction mechanism is independent of the outcome of the predictions. If we find the most important characteristics and use them as input data instead of all information, we can significantly enhance the prediction models' accuracy.

Binghui Wu *et al* [2020] are discussing the effects of risk contagion on investor behavior and the creation of an artificial stock market model. Since investors base their trades on newly available market data, any new data, whether it's from the macro or micro sector, has the potential to affect investor behavior and the spread of risk. We construct a fictitious stock market model in which the introduction of new information is the only variable that may cause stock values to rise and fall. Several factors impact investor mood, including how sensitive investors are to new information, the investment choices made by nearby investors, and investors' preferences for interpreting new information. The following are some findings that may be taken from simulation experiments: For starters, when the fundamental contagion coefficient is minimal or when investor neighbors are very sensitive to fresh information, stock price volatility spikes. Secondly, when investors are more sensitive to news from their neighbors, stock price volatility decreases, assuming either a smaller fundamental contagion coefficient or lower investor sensitivity to news. The available literature on artificial stock market models is filled with constant revisions based on the SFI-ASM model. Typically, investors in these models are assumed to be either rational traders or noise traders, or technical analysts or fundamental analysts.

Salah Bouktif *et al* [2020] have suggested making a positive contribution to this discussion by doing empirical research on the directionality predictability of stock market movements using an improved sentiment analysis approach. To be more specific, try out different combinations of past stock prices, polarity of sentiment, subjectivity, N-grams, and features delays for finer-grained analysis combined with bespoke text-based features. In order to solve problems related to predicting stock market movements using sentiment analysis, five research topics were examined. It has compiled the NASDAQ stock prices of 10 major firms from various industries. Advanced causality analysis, algorithmic feature selection, and other machine learning approaches, such as regularized model stacking, augment the analytical approach. It is already difficult to anticipate market movements due to the complicated interplay of political and economic variables. Gathering relevant data to understand stock movement patterns and trading habits is crucial to developing a successful market trading strategy. The lack of a system to handle words that rely on their context is a big problem with this method.

Qian Chen *et al* [2020] have created an innovative deep learning model that combines a bidirectional long-short-term memory neural network, attention mechanisms, and multilayer perceptrons. It all starts with reducing the dimensionality of the raw data using principal component analysis. This includes four kinds of datasets: historical stock prices, technical indications of stock closing prices, natural resource prices, and data from the Google index. Next, a multi-layer perceptron is employed to quickly transform the feature space and perform gradient descent. A bidirectional long-short-term memory neural network is then employed to extract temporal features from stock time series data. Finally, an attention mechanism is employed to ensure that the neural network places higher weights on crucial temporal information. In order to overcome these drawbacks, the suggested model draws on a knowledge base that includes the extensive correlations between stock prices, natural resource prices, and other data. It also makes use of several neural networks to handle different kinds of data. Nevertheless, stock forecasting is one of the most challenging time series issues due to the multi-noise, nonlinearity, high frequency, and chaos of stock. **Thendo Sidogi *et al* [2023]** have shown using rough route theory to condense LOB data for use in training ML models by extracting characteristic path features. In terms of model prediction error, it shows that our strategy outperforms conventional auto-regression techniques. To further evaluate the suggested method's efficacy in comparison to conventional methods using raw LOB data, we used deep neural networks (DNN) and random forests (RF). According to the results, Sig-DNN (a DNN with signature features) beats DNN (a regular neural network) with raw LOB data in both prediction error and efficiency, but Sig-RF (a regular neural network) with signature features falls short in prediction but makes up for it in efficiency. Experts in the field are working hard to find a solution to this problem so they can stay ahead of the competition. Nevertheless, deciphering the fundamental dynamics and market events that influence this data might prove to be quite a challenge. As a solution, quantitative analysts working on the buy side are looking for ways to compress high-frequency data streams while preserving other important information.

Daehyeon Park *et al* [2021] with a concentration on real estate bubbles, have put out theories on the connection between the property and stock markets. The relationship between the stock market and changes in home prices is often stronger than the reverse. Changes in home prices may foretell the turbulence in the stock

International Journal of Marketing Management

ISSN 2454-5007, www.ijmm.net

Vol. 11, Issue. 3, 2019

market, thanks to the data supplied by the housing market. It followed suit and used LSTM neural networks to construct a home market early warning system (EWS) based on machine learning. Also, since building houses often takes more than a few years, the supply of homes on the market is not very responsive. So, housing market bubbles are likely to occur as a consequence of the oversupply of homes on the market. Nevertheless, real estate policies and other external factors contribute to the volatility of home values, making it challenging to directly apply traditional time-series models to the housing market.

Xingqi Wang *et al* [2021] put forth a clustering approach that integrates kmeans clustering with morphological similarity distance (MSD) for the purpose of mining comparable stocks. Then, C-HTM, an online learning model based on Hierarchical Temporal Memory (HTM), is used to learn patterns from comparable stocks and provide forecasts. In terms of price prediction trials, 1) C-HTM outperforms HTM, which has not learnt comparable stock patterns, in terms of forecast accuracy; 2) C-HTM outperforms all baseline models in terms of short-term prediction. As an added bonus, individuals and businesses alike have reaped substantial advantages from a stock prediction algorithm that shows promise. Due to the nonlinearity, high noise, and real-time nature of market data, the stock price prediction job remains a difficult issue despite its attractiveness to academics. So, a lot of academics are trying different things to get better results. On the other hand, RNN and LSTM are ineffective or even harmful.

3.HYBRID BILSTM-GRU

3.1 INTRODUCTION

The stock prediction has been the subject of study for decades because of its tremendous importance in maximizing the return from stock investments. It is believed that news stories have an effect on stock prices, according to the Efficient Market Hypothesis (EMH). Listed companies often have many pieces of significant news every day, each with the potential to impact the market in a different way. But current approaches don't take into account how various occurrences can affect the stock price. Although this is not always the case, all techniques are predicated on the assumption that all news has the same impact. As the sportswear maker was mocked on social media, the stock price of the business fell roughly 1% on the second trading day. The stock market was swayed by this negative news, regardless of any other favorable news about Nike. The majority of social media material is news-related, and public news is one of the main sources for stock market predictions. Twitter guarantees extensive coverage of key news stories in the United States and speeds up the dissemination of information generally. According to this view, Twitter is a reliable tool for predicting stock prices. Our goal is to forecast changes in the value of U.S. stocks by analyzing news and tweets together. We can learn about everything that occurred during a trade day from the news, and we can receive people-focused commentary on those events via Twitter. Recently trending news items often influence the stock market. Tweets about the announcement show how passionate people were about the incident and how investors felt about it. Therefore, to cover important information for prediction, it is required to mix news and tweets. Furthermore, our primary focus is investigating the many factors that impact the forecasting of stock market movements. Our technique essentially involves redistributing the weight of events by having the model reassign the weight of text information. News and social media are the primary sources of event information for the stock market. The stock price data includes both event-related and non-event-related information, such as the capitals' trading operations, in its analysis. The second piece of information is not available in the media or on social media. We can't verify the many impacts of events if we include stock price data, and that goes against our study aim. Background data, however, is mostly used to study how events affect the stock market via text. For the sake of objectivity, we avoid using price data or other indications and instead rely on text data to validate our model.

3.2 BLOCK DIAGRAM OF PROPOSED SYSTEM

International Journal of Marketing Management

ISSN 2454-5007, www.ijmm.net

Vol. 11, Issue. 3, 2019

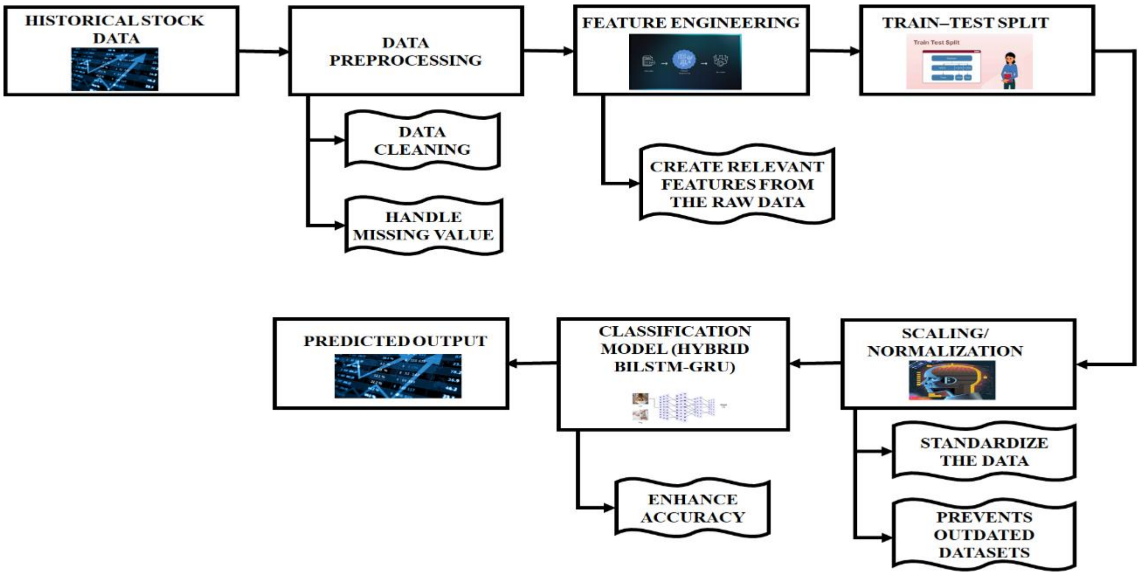

Figure 2 Block Diagram of proposed System

Data cleansing and missing value management are two of the first steps in data preparation that make use of robust approaches. The security and trustworthiness of the dataset are maintained by these procedures. The focus shifts to extracting relevant features from the raw data during the feature engineering phase. The objective of this stage is to improve the model's ability to detect complex trends and patterns in the stock market's dynamics. The train-test split data is a crucial part of the process since it allows for a trustworthy evaluation of the model's performance. The data is normalized using these approaches so that the model can scale consistently across features, which leads to better performance. To use deep learning's strengths in modeling sequential data, the hybrid BILSTM-GRU classification models are integrated in the last step. In order to predict changes in stock process, these models are trained utilizing the preprocessed and designed characteristics.The Python programming language is used to execute this project.

4.PREDICTION OF STOCK PRICE MODEL

4.1 INTRODUCTION

Investors, traders, and financial analysts have long sought, in the ever-changing and sometimes unexpected financial markets, an advantage via the correct prediction of stock prices. Due to their reliance on past data and human intuition, traditional approaches of predicting stock prices, such fundamental and technical analysis, have severe limits. A more data-driven approach has emerged, however, thanks to advancements in machine learning and deep learning. This method makes use of AI to sift through mountains of data in search of patterns that people would miss.

A method that has recently attracted a lot of interest is the use of hybrid deep learning models. These models integrate several types of neural networks to make predictions more accurate and resilient. When it comes to predicting stock prices, one hybrid architecture that has shown promise is the Bidirectional Long Short-Term Memory (BiLSTM) and Gated Recurrent Unit (GRU) model. This hybrid design seeks to overcome some of the shortcomings of both LSTM and GRU models while simultaneously capturing intricate patterns and temporal relationships in stock price data.

For time series forecasting applications, such as stock price prediction, the LSTM architecture has shown to be very effective because to its capacity to maintain long-term dependencies and manage data sequences with varied time intervals. Long short-term memory (LSTM) models may not be able to adequately capture short-term changes in stock values and may be computationally costly to train, especially on big datasets. However, GRU architecture is more suitable to applications dealing with massive volumes of data because to its computational efficiency and quicker training durations. It is comparable to LSTM but has fewer parameters and simpler gating mechanisms.

International Journal of Marketing Management

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Vol. 11, Issue. 3, 2019

By combining the best features of the two architectures—a bidirectional connection network and gated mechanisms—the hybrid BiLSTM-GRU model is able to process data from both the past and the future. The model's ability to analyze the input sequence in both forward and backward orientations allows it to better grasp the data's underlying trends and patterns by capturing both short-term variations in stock prices and long-term interdependence. The GRU architecture's gated mechanisms also let the model learn and modify its forecasts over time in response to changing market circumstances.

Researchers and practitioners have been experimenting with alternative network topologies, hyperparameters, and training procedures to maximize performance in recent years while using the hybrid BiLSTM-GRU model for stock price prediction. Using stock price data from the past as input features and training the model to anticipate price movements based on patterns and trends from the past is a typical strategy. To further improve the model's forecasting capabilities, researchers have also investigated the possibility of including characteristics like sentiment analysis, technical indicators, and macroeconomic considerations. There are still obstacles and limits that must be overcome, even if the hybrid BiLSTM-GRU model has shown encouraging outcomes in both empirical research and practical applications. For instance, under very uncertain or volatile market situations, the model may not be able to generalize well or perform as expected. Another issue with deep learning models is their interpretability. It might be difficult to figure out what exactly is causing the model to make certain predictions and where the bias or inaccuracy is coming from.

To sum up, the use of BiLSTM-GRU architecture and other hybrid deep learning models shows potential for more accurate and dependable stock price prediction. This hybrid model has the ability to surpass conventional techniques and single-model approaches by integrating the best features of LSTM and GRU architectures to provide a robust framework for detecting intricate patterns and temporal relationships in stock price data. Investors and stakeholders will be able to make better decisions in the dynamic financial landscape with the help of hybrid architectures like BiLSTM-GRU, which will be more important as deep learning models for stock price prediction are studied and improved.

Figure 3: Stock Price Model

5. RESULT AND DISCUSSION

International Journal of Marketing Management

ISSN 2454-5007, www.ijmm.net

Vol. 11, Issue. 3, 2019

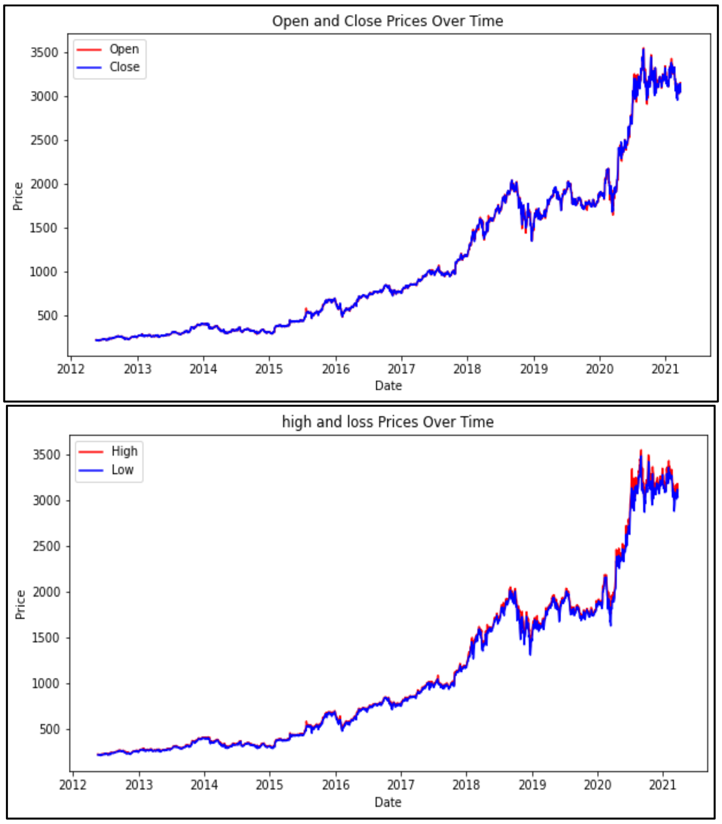
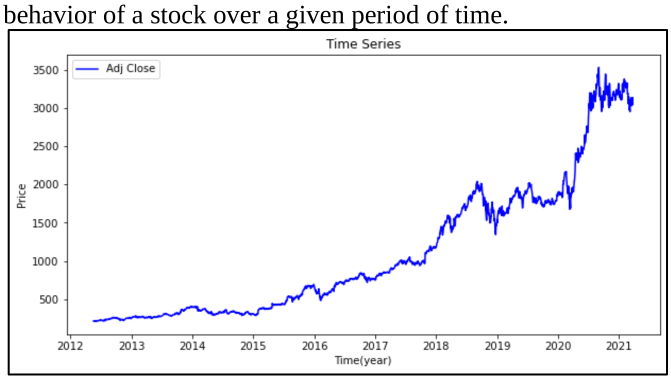


Figure 4 Open Close and High Loss prices over time

Figure 4 represents that the terms "open,""close,""high," and "low" prices refer to key data points that are crucial for analyzing the behavior of a stock over a given period of time.



International Journal of Marketing Management

ISSN 2454-5007, www.ijmm.net

Vol. 11, Issue. 3, 2019

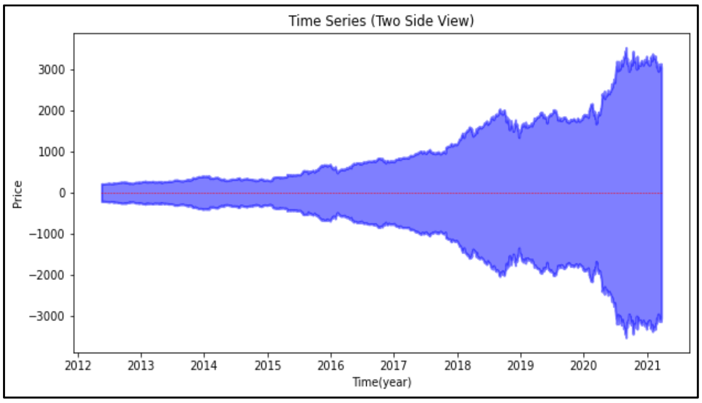


Figure 5: Time Series

Figure 5 demonstrates that time series. A time series in the context of stock prediction refers to a sequence of data points representing the historical prices of a stock or financial asset over a specific period of time.

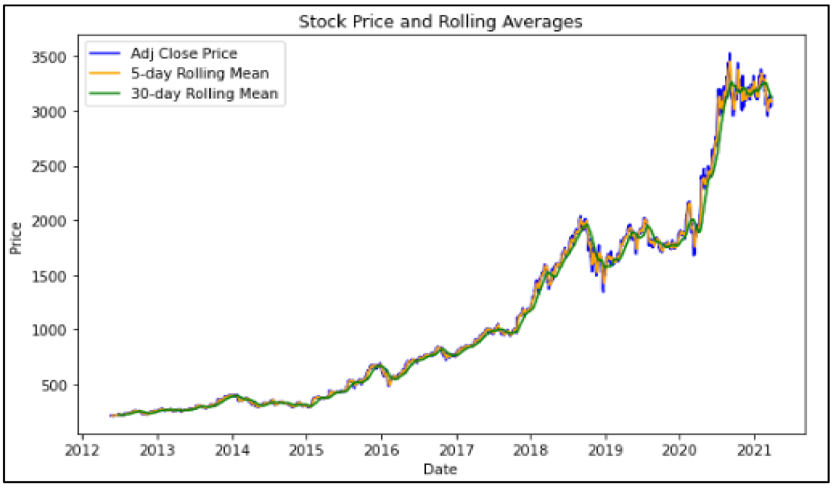


Figure 6 Stock Price and Rolling Averages

Figure 6 shows that Stock Price and Rolling Averages. To find prices and calculate rolling averages for stock prediction, start by accessing historical price data for the stock of interest.

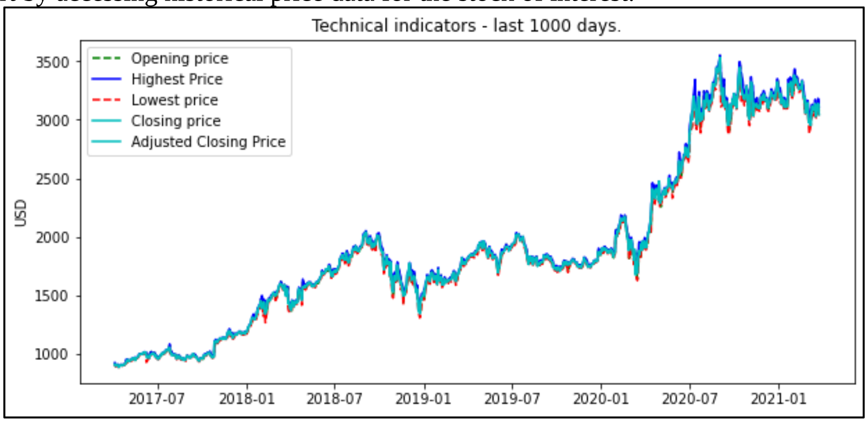


Figure 7 Technical Indicators

Figure 7 establishes that Technical Indicators for stock prediction are mathematical calculations or statistical tools used by traders and analysts to interpret historical price data and identify potential trends or patterns in the stock market.

International Journal of Marketing Management

ISSN 2454-5007, www.ijmm.net

Vol. 11, Issue. 3, 2019

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 bidirectional (Bidirectiona  (None, 60, 320)          220160
 l)

 dropout (Dropout)           (None, 60, 320)           0

 bidirectional_1 (Bidirectio  (None, 60, 160)          256640
 nal)

 dropout_1 (Dropout)         (None, 60, 160)           0

 gru (GRU)                   (None, 40)                24240

 dropout_2 (Dropout)         (None, 40)                0

 dense (Dense)               (None, 30)                1230

 dropout_3 (Dropout)         (None, 30)                0

 dense_1 (Dense)             (None, 1)                 31

=================================================================
Total params: 502,301
Trainable params: 502,301
Non-trainable params: 0
```

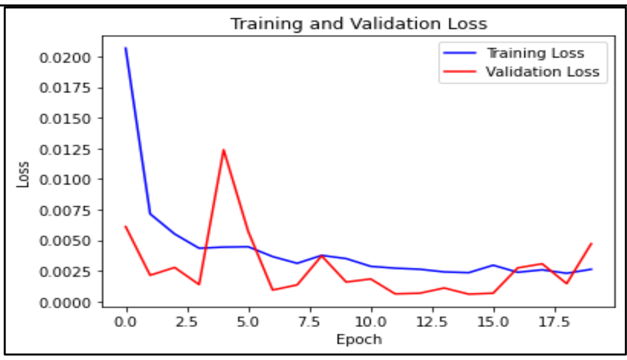


Figure 8 Hybrid BILSTM-GRU

Figure 8 represents that different states of brain activity and are commonly categorized into specific frequency bands, such as delta, theta, alpha, beta, and gamma waves.

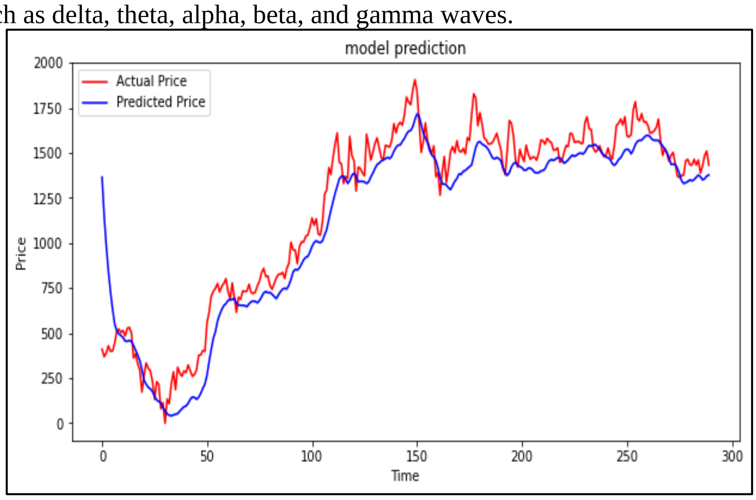


Figure 9 Model Prediction

Figure 9 displays the model's forecast. When discussing stock predictions, "model prediction" is making use of mathematical or computer models to foretell how financial assets' or stocks' prices will change in the future by analyzing past data and other pertinent aspects.

CONCLUSION

Preliminary results from a stock price prediction model that combines a Bidirectional Long Short-Term Memory (BiLSTM) and a Gated Recurrent Unit (GRU) with careful procedures like data preprocessing, feature

International Journal of Marketing Management

ISSN 2454-5007, www.ijmm.net

Vol. 11, Issue. 3, 2019

engineering, a train-test split, normalization, and classification are encouraging. By using this all-encompassing strategy, we were able to create a strong predictive framework that could accurately anticipate stock price movements. Combining BiLSTM and GRU architectures has improved the model's ability to detect both short-term relationships and long-term patterns in the data, which helps it make accurate predictions. The forecasts produced by this complex model provide financial experts and investors with useful information for navigating the ever-changing world of stock market investing. Improvements in stock price forecasting might be possible in the future when this hybrid model is fine-tuned and optimized to release even more predictive power.

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