**Abstract**

**INTRODUCTION**

Today, the stock market has become an inseparable part of the global economy. Any fluctuations in this market can affect the economic conditions of companies as well as the financial lives of individuals and organizations. Due to its high returns, the stock market is always considered one of the most popular investment sectors. However, certain factors influencing the market have made its behavior unpredictable. The market trend refers to the meaningful movement of prices within a specific time frame. Trends can be upward, downward, or neutral. In an upward trend, prices tend to strengthen and rise rather than weaken. In a downward trend, prices are more likely to weaken and decrease rather than strengthen. A neutral trend indicates equal power between buyers and sellers at a particular time. Numerous models have been presented so far using various tools and techniques to predict market trends.

The unpredictability of the factors influencing price changes in financial markets, especially the stock market, has always been a reason for turning to currency price predictions. For this reason, capital market experts and forex market specialists have devoted years to studying the market and identifying various patterns for prediction, employing a combination of pattern recognition and experience based on observing causal relationships. Additionally, numerous software programs exist that aid in this decision-making process and serve as prediction engines.

Deep learning is one of the methods based on machine learning and falls under the broader category of artificial intelligence techniques. Deep learning models are categorized based on the machine learning algorithms they employ. More specifically, these models are classified according to how training data are utilized. Commonly, these methods are divided into supervised, semi-supervised, and unsupervised learning approaches.

In supervised learning, the neural network uses labeled training data. In unsupervised learning, the network is trained based on unlabeled data **(Gosh and colleagues, 2024)**. In other words, the database used in this method does not have labels. Semi-supervised learning utilizes a mix of both labeled and unlabeled data available in the database for training the network. Simple forms of this type of learning involve networks with many hidden layers. In these networks, an MLP (Multi-Layer Perceptron) includes one input layer, several hidden layers, and one output layer. Another type of supervised learning is recurrent neural networks (RNNs), which offer advantages such as precise prediction capabilities for time series, high convergence speed, and high adaptability. Each neuron in the output layer receives feedback through a buffer layer.

Although a traditional recurrent neural network (RNN), if large enough, should theoretically be capable of generating sequences of any complexity, in practice, this does not occur. Recurrent neural networks struggle with storing information related to past inputs over long periods. Additionally, this limitation weakens the ability of these networks to model long-term structures, and this “forgetting” makes them unstable during sequence generation. Having a longer memory is stabilizing because even if the network cannot form an accurate understanding of its most recent history, it can still complete its prediction by looking further back in time.

In contrast to traditional RNNs, where content is rewritten at each time step, Long Short-Term Memory (LSTM) networks are capable of preserving memory through gates that enable decision-making. Intuitively, LSTMs can identify significant features in early input steps and maintain these features over long sequences. This ability allows LSTMs to capture long-term dependencies more effectively than traditional RNNs, making them well-suited for sequence prediction tasks where long-range dependencies are important.

An enhanced version of Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, makes it easier to store past data in memory. The issue of vanishing gradients, which affects traditional RNNs, is resolved in LSTMs, particularly for tasks such as classification, processing, and time series forecasting. This network is suitable for modeling time series data in the presence of unspecified temporal delays. It trains the model using backpropagation, making it effective for capturing long-term dependencies in sequential data.

The performance of machine learning models primarily depends on data representation **(Dian & Brijlal, 2024)**. Recurrent Neural Networks (RNNs) are superior when it comes to storing sequential information in tasks involving Natural Language Processing (NLP).

In recent years, the use of artificial intelligence for stock price prediction has become one of the key research areas. Various studies have shown that machine learning-based methods, particularly in predicting financial markets, have been highly effective. These methods, such as Artificial Neural Networks (ANN), are capable of identifying complex, nonlinear patterns in financial data, allowing analysts to make more accurate predictions. At the same time, the use of Support Vector Machines (SVM), an emerging approach, has also demonstrated good performance in stock market prediction. These kernel methods can effectively separate complex data and provide more accurate predictions. However, SVM is still in the developmental stages and has the potential for further improvement.

On the other hand, Long Short-Term Memory (LSTM) networks, specifically designed for time-series data analysis, perform well when the input data is large and voluminous. However, the need for large datasets for the effective functioning of these models, such as LSTM and SVM, could be considered a drawback. Overall, the integration of these two approaches—LSTM and SVM—has significant potential as a new strategy for prediction. This combination also performs well in time-series analysis with large datasets. This section presents the theoretical background and research review.

**Literature review**

In (**Bai et al. 2024**), researchers explored the use of generative artificial intelligence in managing and predicting financial market data. By integrating multiple data sources and feature extraction techniques such as fundamental analysis, technical indicators, global economic data, and sentiment analysis, generative AI creates a comprehensive deep learning framework that significantly improves the performance of financial data management and prediction accuracy. Particularly, technologies like Generative Adversarial Networks (GANs) and Variational Autoencoders (VAE) show great potential in augmenting data and optimizing models. The practical value of this model is further enhanced through reinforcement learning techniques for real-time market prediction and optimization of trading strategies.

In **(Che et al. 2024)**, the authors utilized Conditional Generative Adversarial Networks (cGAN) for simulating and predicting temporal dynamics in financial markets. The results demonstrate that the model effectively understands the complexity of financial market data. The study shows that the deviation between predicted outcomes and actual market performance is minimal, indicating a high level of accuracy in predictions.

The goal of the study by **(Bahoo et al. 2024)** is to provide a comprehensive overview of existing research in this field and identify research directions that require further investigation. To achieve this, a large number of articles published between 1992 and March 2021 were analyzed using bibliometric and content analysis tools. The results show that the literature on this topic has significantly expanded since the beginning of the 21st century, covering various countries and applications of artificial intelligence in financial affairs. Among these, predictive systems, early warning detection systems, and data mining (Big Data Analytics/Text Mining) have been highlighted more than other areas.

In **(Rahmani et al. 2023)**, a comprehensive classification of artificial intelligence applications in various economic domains is provided. This classification helps researchers and economic practitioners identify different applications of AI in various fields and improve the performance of financial and economic systems. On the other hand, various AI techniques, including deep learning, neural networks, and data mining, are widely used in this field. These techniques, by analyzing historical and real-time data from financial markets, provide more accurate predictions and help improve economic decision-making.

**Methodology**

A common architecture for recurrent neural networks (RNNs) to overcome the problem of vanishing gradients is the Long Short-Term Memory (LSTM). LSTMs are designed to remember information for a longer period of time and are considered an improved version of neural network architecture for time series data. This default behavior of the model is under examination. **(Khoa, Huynh, 2022)**

Extracted features may come from fundamental data, macroeconomic data, technical data, or a combination thereof. After aggregation, the data are normalized using the min-max normalization technique, and other normalization methods will be evaluated in the subsequent section for the LSTM model. The input sequence for the model is then created using a specific time step. Hyperparameters such as the number of neurons, number of epochs, learning rate, batch size, and time step are selected for the model. Once the hyperparameters are adjusted, the input data are fed into the model to predict the final price of the stock market index. The quality of the proposed LSTM model is assessed using metrics such as RMSE, MAPE.

LSTM is used for predicting time series data. For example, RNN, a popular deep learning technique, is employed in LSTM for classification and regression tasks, as well as for predicting stock market trends.

As mentioned, LSTM uses memory cells to overcome the problem of vanishing gradients and consists of an input layer, a hidden layer, a cell state, and an output layer. A key component of the LSTM architecture is the cell state, which runs through chains and maintains the information flow unchanged. The LSTM modifies or deletes information from the cell state and provides a mechanism for selective information passage. This mechanism includes a sigmoid layer, a hyperbolic tangent layer, and point-to-point multiplication operations.

Figure.1 shows the structure of the LSTM, which is designed for modeling sequential inputs.



**Fig.1. LSTM cell architecture**

Here's the translation:

Support Vector Machine (SVM) is a powerful and widely used supervised machine learning algorithm, particularly suitable for solving binary classification problems. SVM is also used for classification and regression tasks, aiming to separate data points into two distinct classes based on their features. The primary objective of SVM is to find the optimal hyperplane that maximizes the margin between data points of different classes, thus creating a clear distinction between them **(Lin et al., 2013)**.

The execution steps of the SVM are as follows:

**Input Data**: Collection of training data with class labels.

**Data Preprocessing**: If necessary, the data should be preprocessed to address missing values, scaling, normalization, and any issues related to the data quality.

**Feature Selection**: Select relevant features that significantly impact the classification process to reduce noise and irrelevant information.

**SVM Training**: Find the optimal hyperplane for the preprocessed data by the model, which maximizes the margin of separation between data points of different classes.

**Kernel Trick (if needed)**: If the data is not linearly separable in the feature space, the kernel trick can be used to transform the data into a higher-dimensional space, where linear separation becomes possible.

**Model Evaluation**: The model performance is evaluated using appropriate metrics such as accuracy, precision, recall, etc., through cross-validation. This helps in assessing the generalization ability of the model and its effectiveness in classifying new, unseen data.

**SVM Parameter Tuning**: Fine-tuning the model's parameters to improve its performance.

**Model Execution**: Executing the model on validation data to predict new and unknown events with the desired performance.

**Prediction**: Using the model to predict class labels for new data points.

**Model Interpretation**: By examining the support vectors and decision boundaries, we gain an understanding of how the model makes predictions.

**Random Forest** is a powerful ensemble learning method that uses multiple decision trees to enhance prediction accuracy and robustness. During training, each tree is constructed using a random subset of data (both features and samples), and these trees are built through a non-overlapping random sampling process. This helps to prevent overfitting, which is common in individual decision trees. During prediction, the model aggregates the outputs of the individual trees using either averaging or majority voting to determine the final output. By combining predictions from different trees, Random Forest effectively reduces variance and minimizes overfitting, making it capable of handling high-dimensional datasets.

In Random Forest, the Bootstrap Aggregation (Bagging) method is used, where multiple decision trees are trained in parallel using random samples of data. Each tree is trained independently. After training all the trees, the model uses averaging for regression tasks and majority voting for classification tasks to make the final prediction. This method is suitable for both classification and regression tasks, and it performs well even when dealing with missing data or datasets with a large number of features (Breiman, 2001).



**Fig.2. Bagging architecture**

**Results**

**Future Works**

**Conclusion**

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