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A Detailed Review of Machine Learning Algorithms for Accurate and Robust Stock Price Prediction

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Abstract. *The prediction of stock market trends has long been a central focus of financial analytics and computational research. With the exponential growth of financial data and the increasing complexity of market dynamics, traditional statistical models often fall short in accurately forecasting price fluctuations. This paper explores the application of Machine Learning (ML) algorithms in stock price prediction, emphasizing their ability to identify patterns and extract insights from vast, noisy, and non-linear datasets. The study begins with a discussion on the need for accurate stock forecasting, highlighting its importance in informed investment decisions and risk mitigation. Various machine learning techniques, including Random Forest, Support Vector Machines, K-Nearest Neighbors, Decision Trees, Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks, are examined for their predictive capabilities. The literature review synthesizes findings from recent research, showcasing the effectiveness of ML and Deep Learning approaches in achieving high accuracy and robustness across diverse financial datasets. Furthermore, a generalized architecture of ML-based stock prediction is presented, detailing the end-to-end workflow encompassing data collection, preprocessing, feature selection, model training, validation, and prediction. The study also discusses critical challenges and limitations, such as market volatility, non-stationarity of data, overfitting, and the interpretability issues inherent in complex models. By integrating insights from empirical studies and theoretical frameworks, this work underscores the transformative potential of machine learning in enhancing market analysis, supporting real-time decision-making, and guiding future research toward more adaptive, transparent, and interpretable financial prediction models.*

Keywords: Stock Market Prediction, Machine Learning, Random Forest, LSTM, SVM, Neural Networks, Financial Forecasting, Time-Series Analysis, Data Preprocessing.

Introduction

The stock market is a dynamic and intricate system where shares of publicly listed companies are traded, enabling investors to grow their wealth while providing firms with access to capital [1]. However, stock prices are inherently volatile, influenced by numerous factors such as political developments, global economic conditions, company performance, investor sentiment, and unforeseen events like natural disasters or pandemics. For instance, during the COVID-19 pandemic, pharmaceutical companies experienced significant growth in their stock values due to increased demand for healthcare services [2]. These market fluctuations not only affect individual investors but also impact national and global economies, underscoring the importance of accurate stock price prediction. Understanding the causes of these price oscillations—ranging from macroeconomic policies and corporate performance to public sentiment—is essential, yet traditional forecasting methods struggle to adapt to the dynamic and nonlinear nature of financial markets. Historically, two principal methodologies—fundamental analysis and technical analysis—have dominated stock prediction. Fundamental analysis evaluates a company's intrinsic value by examining key financial indicators such as revenue, earnings, market share, and growth potential. In contrast, technical analysis focuses on historical price and volume data to identify patterns and trends through statistical and graphical techniques. While these traditional methods, including the Dow Theory, have provided valuable insights, they are often limited in capturing sudden shifts driven by social, psychological, or global factors. As a result, researchers have increasingly turned to advanced computational models and artificial intelligence (AI) to enhance forecasting precision [3].

In recent years, Machine Learning (ML) has emerged as a transformative approach for stock price prediction. ML algorithms can process vast amounts of historical and real-time financial data, uncover hidden patterns, and adapt to evolving market conditions without explicit programming. These models integrate diverse data sources—such as historical stock prices, trading volumes, macroeconomic indicators, financial news, and even social media sentiment—to produce more reliable forecasts [4]. By leveraging both structured and unstructured data, ML provides a significant improvement over conventional methods, supporting investors in making informed, data-driven decisions and mitigating risks associated with market uncertainty. Several ML techniques have proven effective in financial forecasting. Artificial Neural Networks (ANNs), inspired by the human brain's structure, excel in modeling nonlinear relationships between variables, making them ideal for volatile markets [5]. Support Vector Machines (SVMs) perform well in regression and classification tasks by identifying optimal boundaries between data points. Bayesian Networks offer probabilistic modeling for handling uncertainty, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are particularly suited for time series data, as they capture temporal dependencies and long-term trends. Additionally, Multi-Layer Perceptrons (MLPs) effectively model interactions among multiple input features [6]. The adaptability and predictive accuracy of these algorithms have made them central to modern financial analytics. The complexity of financial data—often characterized by its five key attributes (5Vs): volume, variety, velocity, veracity, and value—necessitates automated ML-driven systems for real-time analysis. Such systems synthesize numerical indicators with textual sentiment from financial reports, news, and social media to generate holistic forecasts. Empirical studies demonstrate that hybrid models, combining quantitative and qualitative data, outperform traditional single-source approaches. Beyond individual investments, accurate stock prediction holds macroeconomic significance, as stock markets serve as vital indicators of economic stability and growth. In India, exchanges such as the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE) play pivotal roles in reflecting economic health through market indices and trading activities [7]. Given the complexity and volatility of these markets, the development of robust ML-based predictive frameworks is essential for informed decision-making.

This paper presents a detailed survey of various machine learning algorithms applied to stock price prediction, highlighting their methodologies, data requirements, strengths, and limitations. By analyzing these approaches, the study aims to provide insights into the most effective strategies for leveraging ML in financial forecasting and to guide future research in this evolving field.

Need For Stock Price Prediction

The stock market is a dynamic platform where investors aim to generate profits by strategically trading company shares. With the rapid advancement of computational technologies, the accuracy of stock price forecasting has significantly improved, enabling investors to make data-driven decisions and manage financial risks effectively [8]. Predicting stock price movements plays a crucial role in optimizing investment strategies, and machine learning (ML) techniques have emerged as powerful tools for this purpose. ML models can analyze large volumes of historical and real-time financial data, detect hidden patterns, and forecast market trends with greater precision than traditional analytical methods [9].

The ML-based stock prediction process typically involves multiple stages as shown in figure 1. Initially, historical and live market data are collected from stock exchanges and databases such as NASDAQ. The collected data undergo preprocessing to eliminate noise, handle missing values, and standardize attributes for analysis. Feature selection techniques are then applied to extract the most relevant variables, reducing dimensionality and improving model efficiency. The refined dataset is divided into training and testing subsets, which are used to develop and evaluate predictive models capable of forecasting stock prices and trends [10].
Once the predictions are generated, actionable insights are communicated to investors through alerts, helping them to capitalize on profitable opportunities or mitigate potential losses. This structured and data-driven workflow enables investors to make informed trading decisions in a highly volatile market. The following sections of this paper present a comprehensive review of machine learning algorithms used for stock price prediction, examining their methodologies, advantages, and limitations in practical financial applications.

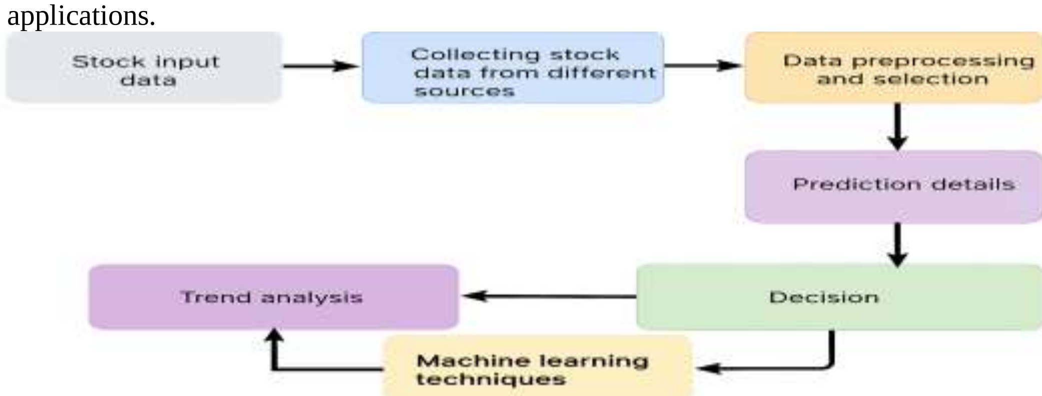

Figure 1: Stock market prediction process.

In summary, the integration of machine learning into stock market prediction involves data collection, pre-processing, feature selection, model training, and result dissemination. This structured process allows investors to leverage historical trends and real-time market data to anticipate future stock movements effectively. The subsequent sections of this paper present a detailed survey of the various ML algorithms applied in stock price prediction, analyzing their methodologies, strengths, limitations, and applications in both academic research and practical investment scenarios.

Existing ML Algorithms Methods Used For Stock Price Prediction

Predicting stock prices has long been a critical challenge due to the volatile and dynamic nature of financial markets, where investor decisions are influenced by global events, company performance, policies, and market sentiment. Traditional methods such as fundamental and technical analysis offer insights but are often limited in capturing nonlinear relationships and long-term dependencies in financial data [11]. In recent years, machine learning (ML) algorithms have emerged as powerful tools for stock price prediction, enabling computers to learn from historical data, identify complex patterns, and make predictions without explicit programming. Various ML approaches have been applied to this domain, ranging from classical methods like Linear Regression, which is simple but better suited for linear relationships, to more advanced techniques such as Decision Tree Regression, K-Nearest Neighbors (K-NN), Support Vector Regression (SVR), Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM) networks, and ensemble methods like Adaptive Boosting (AdaBoost) [12]. ANNs, with input, hidden, and output layers, are highly effective in modeling nonlinear and volatile data, using backpropagation to iteratively refine weights and improve prediction accuracy. K-NN classifies data based on proximity to known instances, while SVR identifies optimal hyperplanes to capture trends in time series data. Decision Tree Regression offers interpretable hierarchical models, and LSTM networks overcome the limitations of traditional recurrent neural networks by maintaining long-term dependencies in sequential data through memory cells and gating mechanisms. Ensemble techniques like AdaBoost [13] further enhance prediction performance by combining multiple weak learners into a robust model. In this section, the paper explores these ML algorithms in detail, analyzing their methodologies, strengths, limitations, and practical applications in stock market prediction, providing insights into the most effective approaches for accurate forecasting and informed investment decision-making.

Artificial Neural Network (ANN)- In the simplest of words, Artificial Neural Networks are a mesh of numerical equations. One or more input variables are taken and then processed by a sequence of equations resulting in one or multiple outputs. Any network generally has three layers — An input layer, Hidden layer, and Output layer. The layer containing all the feature variables shown as x1, x2, x3 up to xn is the input layer. The hidden layer comprises one or more nodes (hidden units). The circles in the diagrams below represent a node. Then comes the output, which can be one or more than one. The more nodes and layers, the more complex calculations can be solved through the network [26]. An artificial neural network structure containing four neurons in the first layer and a single neuron in the second layer is an example of a generic structure shown in Figure 2.

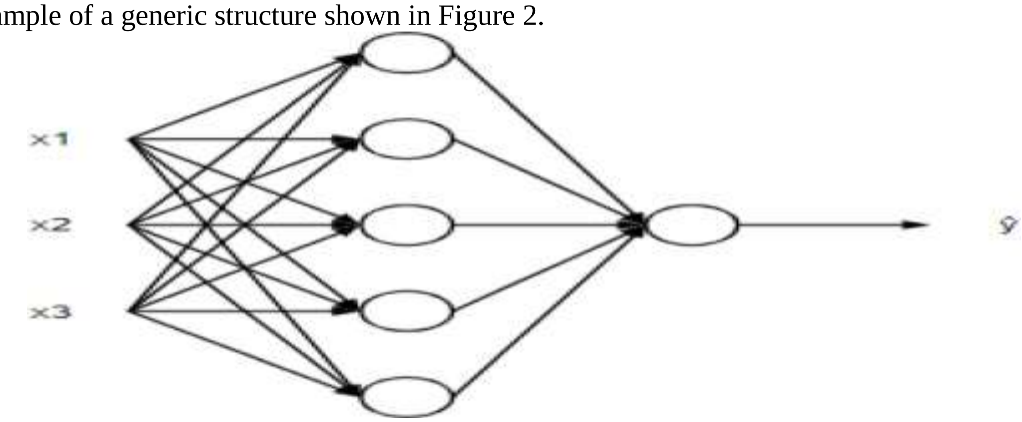

Figure 2: Generic structure of ANN.

The hidden layer is considered the most crucial layer of the algorithm; it acts as a distillation layer that only forwards important data and patterns from the input to the next layer. It makes the network significantly faster and efficient [14].

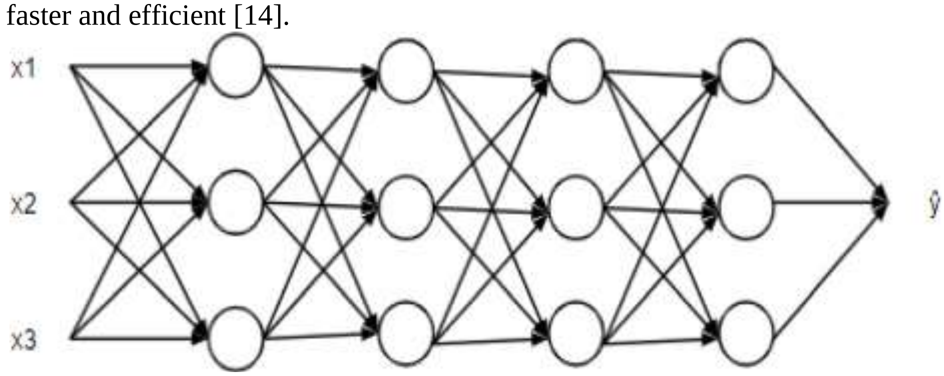

Figure 3: Layers of a neural network.

Figure 3 represents the neural network layers of three types of layers: input layer, hidden layer, and output layer. The key to getting a good model is the accurate prediction of the Weights. The Back Propagation

Algorithm achieves this task; this algorithm is what makes ANN a learning model. It learns from the mistakes and adjusts itself accordingly. ANN can model better data with high volatility and non-constant variance. ANN has also come out as the most efficient in predicting financial time series as the Data is also highly volatile [15].

ANN proves to be the best modeling technique for datasets. These have a non-linear relationship like data fitting and prediction for which it is applied. It is a Multi-layer perceptron (MLP) and a self-organizing map; the MLP uses supervised learning, while the Kohonen network uses unsupervised learning.

Linear Regression Algorithm- The linear regression algorithm falls under the category of supervised learning in ML. This algorithm makes predictions of values that are well within the range rather than predicting categories. It establishes a linear relationship between the dependent and the independent variable and does not work very well with the non-linear type of data sets due to the presence of outliers as shown in figure 4. Researchers used this algorithm for stock market predictions and came to the conclusion that this algorithm when used for predicting daily stock values, offered serious challenges that must be taken care of. [16] Using this algorithm's prediction, investors cannot reliably invest money.

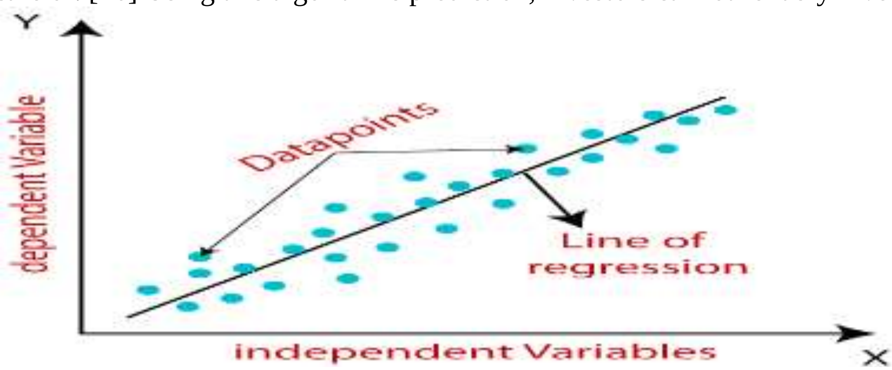

Figure 4: Linear Regression.

K-Nearest Neighbours Algorithm- K-nearest-neighbor (K-NN) being one of the most essential and effective algorithms for data segregation is capable of becoming the primary choice for implementation especially when the given data is quite ambiguous. The K-NN algorithm is positioned under the supervised type learning technique and although it is suited for classifying as well as regressing both, it is predominantly utilized for classifying objects. K-NN can also be referred to as the lazy learner algorithm, as the data set is only stored initially, but the learning process of the training data set does not take place until there is a demand for classification or prediction of the new data set. It is also non-parametric in nature, i.e., in K-NN there does not exist any predetermined method between the input and output as shown in figure 5 [17].

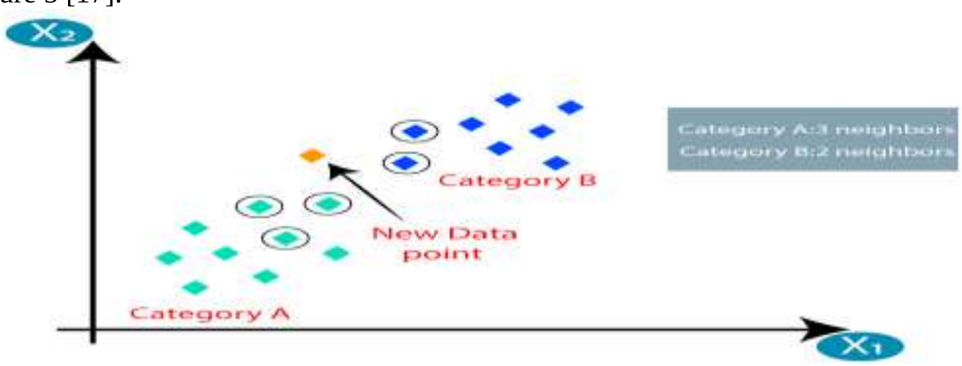

Figure 5: K-Nearest Neighbour Algorithm.

Support Vector Regression- Among one of the highly prevalent supervised type learning algorithms, the Support Vector Regression algorithm is intended for regression and classification problems. For support vector machine regression or SVR, a hyperplane is identified with maximum margin such that the maximum number of data points are within those margins. In SVR, the best fit line is the hyperplane that has the maximum number of points. In SVR algorithm, extreme vector points called Support Vectors are chosen which help in creating an appropriate hyperplane. It is similar to the Support Vector Machine (SVM) algorithm when it comes to the working principle. It is used for working with time series data. [18]. The best binary classifiers are none other than Support Vector Machines; it creates a boundary so that the points are segregated as their category and divided by the boundary as shown in figure 6. SVM model's results are one-tenth of a point better than just guessing during prediction. The machine learning model's accuracy is most impacted by Feature Selection.

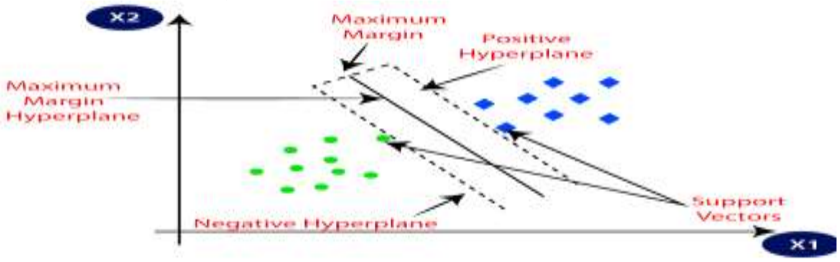

Figure 6: Support Vector Regression Algorithm.

Decision Tree Regression Algorithm- Decision Tree Regression algorithm, belonging to the supervised learning class of algorithms is mostly preferred for solving classification problems but either way, it may be used in classifying as well as in regressing cases. It consists of inner nodes representing the structures of the branches, dataset, representing the verdict given by the algorithm, and each leaf node representing an outcome. There are two nodes, first is the decision node, that is used to make a decision and has various branches; and second is the leaf node, which is the output of decision nodes and has no further branches as shown in figure 7. The root node is a starting point that further expands to various branches making it a tree-like structure. Decision tree simply forks the tree into sub-trees on the basis of answer to question i.e., whether a yes or a no.

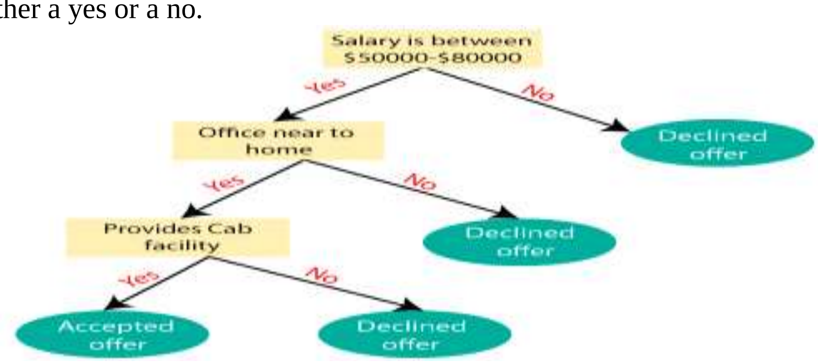

Figure 7: Decision Tree Regression Algorithm.

Long Short-Term Memory- Algorithm Due to back-propagation with real-time recurrent learning or time, the error-incorporated signals running rearward in time are likely to disappear or blow up; the temporal shifts of the error incorporated signal to a great extent relies on the weight sizes. In case of blowing up, the weights are quite likely to start oscillating and in case of disappearance, either the time consumed to learn bridging longer time lags is out of bounds, or in the worst case it does not work. The primary version of this Long short-term memory algorithm only consisted of cells, input, and output

gates. This algorithm is capable of bridging time breaks in excess of steps even when the sequences being used for input are incompressible or noisy in nature while preventing losses of short time break abilities as shown in figure 8. In LSTM algorithm, the input of a current step is the output of the previous step, thereby solving the issues of long-term dependencies of RNN where the RNN give precise predictions on recent information but are incapable of predicting data stored in long term memory. Some of the major applications of LSTM are captioning images, generation of handwriting chatbots answering questions, and various others.
LSTMs are a critical part of machine learning; most RNN cannot overcome short-term memory. Hence, it becomes tough to carry information from past steps to steps taken in the future. For example, if processing a dataset or some numbers is predicted, Recurring Neural Networks could leave some data from the past.

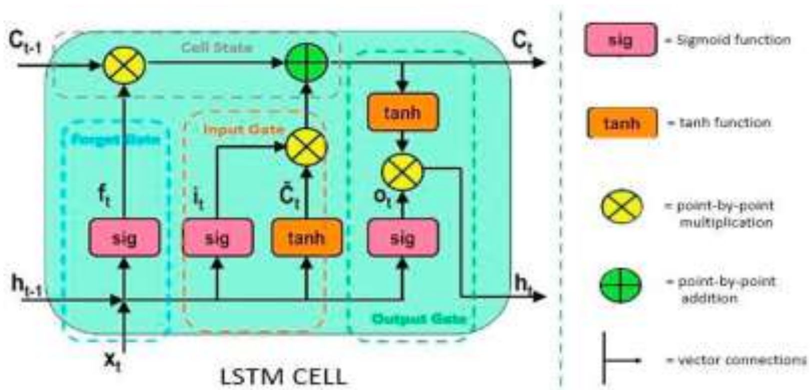

Figure 8: Long Short-Term Memory Algorithm.

Adaptive Boosting (AdaBoost)- Boosting method is an ensemble method which is mostly used for predictions. This method is a group of algorithms which converts weak learners to a powerful learner. By using boosting weak learners are trained sequentially to correct its past performance. AdaBoost was the initial boosting algorithm which was successfully being used to meet the requirements of binary classification. AdaBoost algorithm is used to raise the performance of any machine learning algorithm, and it is mostly used with weak learners.

Literature Review

Bharat Kumar Meher et al. [1] formulated stock forecasting models for top three Fintech companies in India, including Policy Bazar, One 97 Communications Paytm Ltd., and Niyogin Ltd., using a Random Forest model with high-frequency data. Their study, conducted over a period from October 1, 2022, to September 30, 2023, used data from 293,280 data points and achieved a coefficient of determination greater than 95% for all companies. In contrast, Md. Mobin Akhtar et al. [2] assessed a machine learning-based model to predict stock movements with an accuracy of 80.3%, focusing on preprocessed datasets and applying algorithms such as Support Vector Machines. Malti Bansal et al. [3] explored machine learning models like K-Nearest Neighbors, Linear Regression, Support Vector Regression, Decision Tree Regression, and Long Short-Term Memory (LSTM) to predict stock prices for twelve major Indian companies. LSTM was found to be the most effective, with the least error in stock price predictions.
Junaid Maqbool et al. [4] proposed a model combining financial news and historical stock price data, achieving an accuracy of 90% for trend prediction. Manish Agrawal et al. [5] used an Evolutionary Deep Learning Model (EDLM) to predict stock trends for banking organizations, demonstrating accuracy rates of 63.59%, 56.25%, and 57.95% for HDFC, Yes Bank, and SBI, respectively. Gurjeet Singh et al. [6]

used eight supervised machine learning models, including AdaBoost, Random Forest, and Support Vector Machine, to predict the Nifty 50 Index and found that Stochastic Gradient Descent outperformed the others as the dataset size increased. Further, Bharat Kumar Meher et al. [7] employed the Random Forest model to predict stock prices for solar energy companies, obtaining a coefficient of determination between 0.9928 and 0.9939, though Adani Green Energy Ltd. showed more fluctuations in accuracy. Somenath Mukherjee et al. [8] compared Feed-forward Neural Networks and Convolutional Neural Networks (CNN), concluding that CNN offered better prediction accuracy for stock prices, with a 98.92% accuracy. Zahra Fathali et al. [9] focused on predicting NIFTY 50 stock prices using Recurrent Neural Networks (RNN), LSTM, and CNN, with LSTM proving to be the best model for time-series forecasting. Wasiat Khan et al. [10] analyzed social media and financial news data's impact on stock market prediction, achieving a maximum prediction accuracy of 83.22% using the Random Forest classifier. Shouvik Banik et al. [11] developed a Decision Support System based on LSTM, providing technical indicators and predictive analysis for stock prices, achieving high accuracy metrics. Tinku Singh et al. [12] proposed a hybrid model combining incremental learning and Offline-Online learning for real-time stock price forecasting, which outperformed traditional models in predicting stock price movements. Payal Soni et al. [13] compared various algorithms, including Deep Learning models like CNN and LSTM, for stock price forecasting. Ranjan Kumar Dash et al. [14] applied Support Vector Regression with fine-tuned parameters for predicting stock market trends with higher accuracy and reduced overfitting. Dushmanta Kumar Padhi et al. [15] presented a two-stage framework for stock prediction, integrating the mean-variance approach and machine learning models like the perceptron. Finally, Mahinda Mailagaha Kumbure et al. [16] reviewed 138 journal articles on machine learning techniques applied to stock market prediction, examining input variables and predictive performance metrics, while Parshv Chhajer et al. [17] explored the strengths and weaknesses of AI and machine learning tools for stock market prediction, highlighting the effectiveness of neural networks.

Deepak Kumar et al. [18] provided an extensive review of stock market prediction methodologies, focusing on ANN and NN techniques, which are widely used for precise forecasting.

A General Architecture of Stock Market Prediction Using ML

The philosophy behind machine learning is to extract knowledge from data. Supervised learning is the most widely used machine learning techniques in stock market prediction. Figure 9 illustrates a general workflow of a supervised learning-based approach applied for stock market prediction. The process starts with choosing time-series data (e.g., stock price and/or return) and/or relevant information (e.g., financial news) from a specific time period. If the task is a classification problem, the target class is either known or needs to be predicted.

First, the corresponding data require pre-processing, which initially includes the cleaning and removal of incomplete or obviously irrelevant data (such as identifiers). Next, technical indicators can be calculated based on the underlying time-series data, such as close price information. Once the cleaned data including technical indicators are obtained, the data are pre-processed further through scaling and dimensionality reductions (i.e., feature selection, feature extraction, and feature generation) to obtain relevant variables and to filter out irrelevant ones.

Using pre-processed data often leads to effective predictions. In Figure 9, however, this step is shown as optional because it usually depends on the selected domain and is also up to the author’s choice. Once the input data are ready, the task is to select an existing or novel machine learning technique to predict the target variable. For this purpose, input data are usually divided into training data (to train the model with certain parameters and structure of the model), validation data (to evaluate the performance of all trained models and select the best model structure and parameters), and test data (to evaluate the generalization performance of the final model on observations that it has not encountered before during training and validation). Since feature selection in its simplest form (i.e., filter methods) can be used independently of the learning algorithm, it is listed as a data preprocessing step. However, it may be connected to model training by using the learning algorithm's performance to perform feature selection (wrapper method) or may be integrated in the model construction itself (embedded method). To account for this potential link between feature selection and model training, the training step is connected with the pre-processing step via a dashed line in the flow chart. Lastly, prediction is performed using the trained classification model or in regression using the trained regression model.

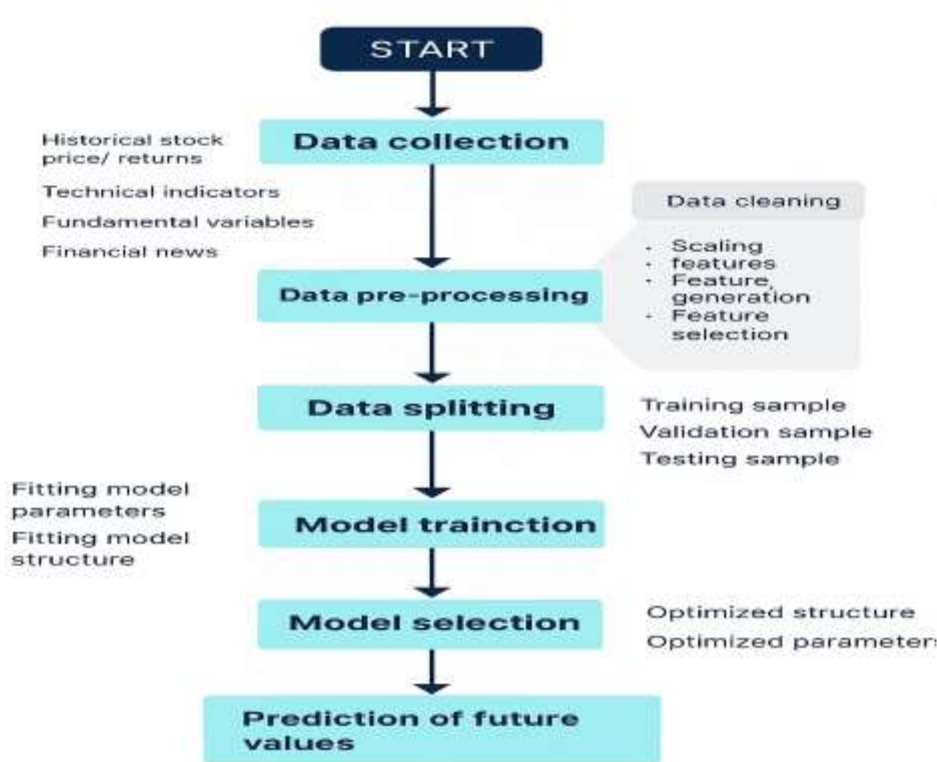

Figure 9: Workflow of a stock market prediction model with supervised learning.

Challenges and Limitations in Stock Price Prediction

1) Market Volatility and Noise- Stock prices are extremely volatile and influenced by unpredictable factors such as news events, political changes, and investor sentiment. This randomness creates "noise" that makes it difficult for models to distinguish between meaningful patterns and short-term fluctuations.

2) Non-Linear and Dynamic Relationships- The connection between input features (like volume, sentiment, or indicators) and future stock prices is rarely linear. Financial markets behave in complex and evolving ways, requiring sophisticated models that can adapt to changing patterns over time.

3) Data Quality and Availability- Historical data may include missing values, outliers, or inaccuracies that can degrade model performance. Moreover, access to high-quality, high-frequency data is often restricted or expensive, limiting the ability of many to build effective models.

4) Overfitting- Many models perform well on historical (training) data but fail to generalize to future unseen data. This is because they may overfit—learning noise instead of signal—leading to poor real-world predictive performance.

5) Feature Selection Complexity- Choosing the right set of predictive features is challenging. Adding too many features can introduce noise, while omitting key variables may cause the model to miss important trends. Balancing relevance and redundancy are crucial.

6) Influence of External, Unquantifiable Events- Unpredictable events such as natural disasters, policy decisions, or geopolitical tensions often impact stock prices, but these events are hard to model due to their qualitative nature and lack of structured data.

7) Latency and Real-Time Processing- In high-frequency trading, every millisecond counts. Even a highly accurate model may become ineffective if it cannot process data and make predictions quickly enough to act in real-time.

8) Lack of Interpretability in Complex Models- Advanced models like deep learning or ensemble methods often operate as "black boxes," making it difficult to understand how they arrive at predictions. This lack of transparency can be problematic for trust, accountability, and compliance.

9) Non-Stationarity of Market Data- Market behavior changes over time, meaning the patterns learned by a model today may not hold in the future. Models must be frequently retrained and monitored to stay relevant in evolving market conditions.

10) Ethical and Legal Constraints- Stock prediction models must operate within regulatory and ethical boundaries. Using insider information, violating privacy rules, or developing manipulative trading strategies can lead to legal consequences and reputational damage.

Conclusions and Future Scopes

Stock market prediction remains an inherently complex yet vital domain in financial analytics, where the integration of machine learning has significantly advanced predictive performance and decision accuracy. The comprehensive analysis presented in this paper reveals that ML-based models outperform traditional statistical methods by learning intricate, non-linear relationships within market data. Among the reviewed techniques, deep learning architectures such as LSTM and CNN have demonstrated superior capability in handling time-series data and capturing long-term dependencies. The general architecture proposed illustrates the systematic process of ML-driven prediction, encompassing crucial stages of data preprocessing, feature engineering, model selection, and validation. However, the limitations identified—such as market volatility, overfitting, and limited interpretability—highlight the need for ongoing innovation in hybrid modeling, real-time adaptation, and explainable AI approaches. Future work should focus on integrating alternative data sources like sentiment analysis, financial news, and social media indicators to enrich predictive context. Additionally, establishing standardized frameworks for evaluation and interpretability will enhance the reliability of ML-based forecasting in practical trading and investment systems. Overall, the study reinforces that while machine learning has revolutionized stock market analysis, continuous refinement and ethical implementation are essential for sustainable, accurate, and trustworthy financial forecasting.

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