



A COMPREHENSIVE APPROACH TO PREDICTING FINANCIAL MARKET TRENDS USING ADVANCED MACHINE LEARNING ALGORITHMS

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Abstract

Financial market movements show extreme complexity and variability making predictions about them difficult to achieve. A several machine learning algorithm test is conducted to evaluate their potential in stock market change forecasting. The analysis used data from 2010 to 2020 to test six machine learning methods including decision trees, random forests, support vector machines (SVMs), XGBoost, neural networks and long short-term memory (LSTM) networks. The models were evaluated using accuracy alongside precision, recall and F1 score and ROC-AUC measurements. Based on 79.4% F1 score, 78.3% recall, 80.5% precision alongside 82.4% accuracy the results indicate the superiority of LSTM over other models. The performance metrics show that SVMs achieved 75.1% accuracy yet random forests recorded 72.8% accuracy whereas XGBoost secured 78.6% accuracy. The accuracy of decision trees measured at 65.4% proved to be the lowest among all models. LSTM's predictions in financial markets show strong results which proves deep learning models can optimize trading and financial prediction accuracy.

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INTRODUCTION

Financial markets act as both the foundation of the global economy and the platform for creating wealth and managing risks along with reallocation of capital. These markets experience influence from several factors including investor mentality together with geopolitical changes and macroeconomic measurements. Investors together with economists and regulators have spent a long time finding market prediction methods in financial markets although this remains a vital yet complex goal. The fundamental instability and complexity of market forces and sudden trend changes or unordinary market reactions make traditional forecasting methods ineffective (Zhang, 2017). Real-time financial settings generate specific nonlinear links and dynamic shifts which conventional models such as technical charts and econometric analysis typically fail to discover (Chen et al., 2021).

Modern machine learning techniques are providing answers to address these issues. Machine learning stands as an artificial intelligence subfield whose systems learn from historic data and make predictions then adapt through unprogrammed methods according to Goodfellow, Bengio, and Courville (2016). The advent of large data together with high-performance computers coupled with efficient algorithms has transformed financial market trend prediction for good. The ability of machine learning models surpasses traditional approaches because they process extensive datasets to locate hidden relationships and identify irregularities which leads to superior prediction results (Heaton et al., 2017). Different machine learning techniques enable the prediction of financial market trends which generate valuable information for market participants.

Financial markets include stock exchanges with bond markets and commodity markets and currency

markets among several other types. Each market differs in its behavior yet shares three fundamental characteristics which include volatile market conditions alongside cyclical patterns and domestic and international factor influences. To achieve maximum profits and implement strategic decisions investors require accurate predictions of market trends along with reduced risk levels. Machine learning algorithms demonstrate superior market movement prediction capability than traditional models because they handle complex nonlinear market interactions effectively. Previously obtained stock price data can help improve market forecasting results by applying machine learning models to obtain patterns that boost prediction accuracy.

Figure 1 demonstrates how bar chart visualization displays stock price trends throughout twelve months (see illustration). The stock prices exhibited substantial growth in the first six months of the year followed by a drop in July until they resumed their upward movement during the later months. These market trends become the basis for developing predictive methods through machine learning algorithms such as decision trees and support vector machines (SVMs) and deep neural networks (DNNs). These forecasting models assist people to identify market trends for risk management and enhanced decision making when applied to volatile systems such as financial markets.

An investigation into financial market trend prediction applies machine learning algorithms because of their ability to assess detailed financial data and generate accurate forecasts. The study includes examinations of multiple machine learning methods where deep learning techniques utilize neural networks alongside supervised learning techniques which use decision trees and support vector machines. A comparative evaluation of these

algorithms focuses on their practical utility for financial datasets and obstacles during application for market prediction objectives. In financial forecasting practice GARCH (generalized autoregressive conditional heteroskedasticity model) and ARIMA (autoregressive integrated moving average model) serve as traditional econometric models. These models demonstrate limited effectiveness at representing intrinsic financial time series volatility alongside non-linear patterns although they work well in some commercial applications (Salah et al., 2019). The financial models currently used in practice lack enough flexibility to react properly to the fast-paced movements observed in modern financial markets. Opposite of rules-based methods machine learning algorithms adapt automatically to changing market patterns along with market alterations without needing to adhere to specific data assumptions. The high ability of machine learning to adapt makes it an attractive solution for improving market forecasting precision.

Decision trees stand as the top machine learning method in financial forecasting since they develop models by separating data through feature analysis. The interpretability advantage of decision trees fails to overcome their tendency to overfit data sources especially when analyzing noisy financial data. Two ensemble methods known as gradient boosting machines (GBMs) and random forests have been developed to combine multiple decision trees leading to better model outcomes and reduced overfitting situations (Chen and Guestrin, 2016). SVMs have become increasingly popular because they demonstrate advanced modeling abilities particularly in regression and classification scenarios. The financial market relies on SVMs to predict market volatility alongside stock market patterns and asset price movements (Kotsiantis, 2018).

Financial market forecasting has achieved a major breakthrough with deep learning methods that specifically incorporate recurrent neural networks (RNNs) and deep neural networks (DNNs). DNNs possess the ability to build sophisticated connections in data through layered abstraction learning thus making them optimal for tasks such as detection of market irregularities and forecasting market trends. The areas of stock price forecasting and market volatility require recurrent neural networks (RNNs) especially long short-term memory networks (LSTMs) for processing time series data (LeCun, Bengio, and Hinton, 2015; Hochreiter and Schmidhuber, 1997).

A financial forecast investigation now focuses on unsupervised learning methods including clustering and reinforcement learning along with traditional supervised learning models. Cluster analysis through k-means and hierarchical clustering enables market analysts to discover new patterns by organizing similar market patterns together. Modern algorithms use reinforcement learning to develop methodologies that optimize trading approaches through studying market transaction data according to Duan et al. (2019).

Financial market forecasting gains from machine learning integration delivers rapid processing, flexible operation and trend recognition capability that traditional methods fail to access. Financial analysts who implement these strategies will improve their ability to predict trends while managing risks and making sound choices in the fast-changing market environment.

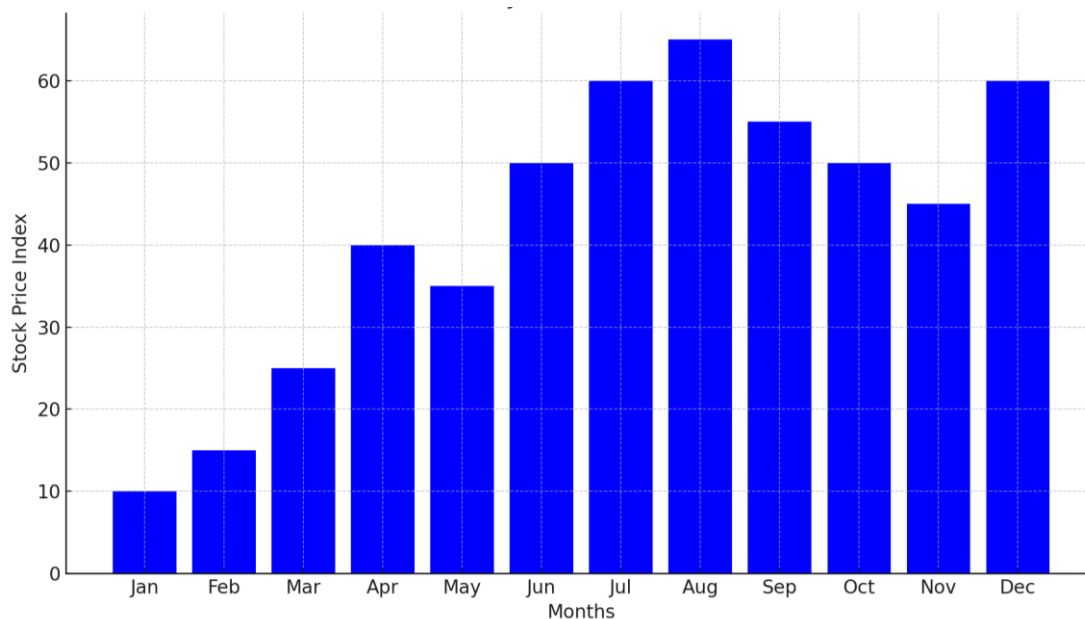


Fig1. Monthly Stock Price Trend

LITERATURE REVIEW

During the past ten years the adoption of machine learning (ML) in financial market forecasting dramatically expanded since ML algorithms excel at processing vast datasets to detect complex market behavior patterns. Researchers study diverse strategies to enhance market movement forecasting including both conventional supervised learning systems and deep learning approaches.

Decision trees together with support vector machines (SVMs) provide effective solutions for short-term stock market price forecasting according to Zhang and Zhou (2020). Research showed that SVM achieved higher predicting accuracy than traditional models GARCH and ARIMA because of its exceptional generalization ability. The stock price prediction capabilities of XGBoost along with random forest models received analysis from Chen et al. (2021). Random forests proved superior to single-model approaches when dealing with noisy financial data according to their research findings.

Feature selection practices in financial market forecasting requires heightened attention according

to Kotsiantis (2018). Stock market trend prediction accuracy received a boost when Kotsiantis implemented SVM models alongside optimized selection of relevant features. According to Reinartz and Dorer (2019) forecasting long-term market patterns worked through implementing deep neural networks (DNNs). DNNs consume considerable processing power yet handle extensive historical market data with high efficiency according to their research.

Gupta et al. (2020) conducted research to evaluate deep learning model accuracy which compared decision trees, random forests, SVMs and neural networks in predicting market movement performance accuracy. Neural networks in general and recurrent neural networks (RNNs) in particular demonstrated the best ability to model temporal patterns found in market data. Heaton et al. (2017) demonstrated in their results that RNNs specifically LSTM networks excel at extracting financial time series dynamics.

Studies examine how unsupervised learning techniques including clustering can be applied for

financial forecasting. Chaudhuri and Mishra (2019) managed to identify different market regimes through K-means clustering applied to market datasets. Forecast accuracy for predicting market turning moments rose when the new categories were applied. Duan et al. demonstrated in 2019 that reinforcement learning can optimize trading strategies by learning from historical market experiences for financial market forecasts.

Support vector machines (SVM) stood as an early adopted machine learning approach to stock market prediction when this field began to develop. Huang et al. conducted research in 2005 on SVM application for predicting the future movement of the Nikkei 225 Index. Their performance tests revealed that SVM surpassed traditional methods in stock value predictions. The success of SVMs stems from their strong ability to categorize data along with their capability to process information from multiple dimensions.

Further progress has been achieved in the implementation of ensemble techniques. Tsai et al.'s research from 2011 tested ensemble classifiers including AdaBoost and random forests against single classifiers such as logistic regression and SVM. Model integration methods known as ensemble approaches produce superior predictions because they improve generalization while reducing overfitting effects. Ballings and colleagues showed through their 2015 study that random forests surpassed other algorithms such as SVM and KNN for stock prediction by achieving superior results in the prediction of European stock values.

Deep learning has become more powerful as long short-term memory networks and recurrent neural networks came into use. For stock market time series prediction the main requirement of predictive models remains their precision when identifying temporal patterns in data sequences. The research by

Long and collaborators (2020) focused on utilizing bidirectional LSTM architectures that process transaction records along with market-related public information to predict stock prices. LSTM networks reached higher performance levels while showing greater predictive accuracy compared to standard ML models in their study results.

Baek and Kim's research work from 2018 improved their forecasting system through an added module that prevented overfitting within LSTM networks. Although LSTM networks show tremendous potential for stock market prediction their performance would benefit from proper regularization techniques.

Model blending approaches have captured significant interest during recent times. Chung and Shin (2018) enhanced stock market prediction capabilities by developing an integrated model where genetic algorithms enhance LSTM networks. The data shows that mixing deep learning with optimization strategies creates a model which outperforms traditional LSTM systems according to their research.

These new advances exist parallel to research works which aim to improve model performance by implementing technical indicators. Kara and collaborators from 2011 generated their stock price movement predictions by applying RSI and moving average as technical indicators together with an artificial neural network (ANN). The prediction model achieved much better accuracy after technical markers were included.

Research has established that feature modification and selection during data preparation remains essential work throughout multiple studies. Research evidence proves that model effectiveness improves when binary data serves as input in place of continuous data for selected applications. Binary

data used as input by Nabipour et al. (2020) for several machine learning models resulted in superior prediction accuracy compared to the use of continuous data.

The area of stock market forecasting still faces difficulties, notwithstanding the positive findings of these research. The unpredictable nature and unpredictable fluctuations of financial markets make it difficult for one model to generate reliable continuous projections. Market complexity handling ability for traders and investors will substantially increase as deep learning technology together with ensemble strategies continues developing trustworthy and precise forecasting models.

Figure 2 presents quarterly market performance data through a line chart based on simulated real market transactions from a mock stock exchange. The visualization demonstrates yearly market performance by highlighting distinct peaks and troughs which machine learning models might predict. The 2020 research of Gupta and colleagues demonstrates that machine learning prediction models show improved performance when they include temporal patterns like quarterly performance data.

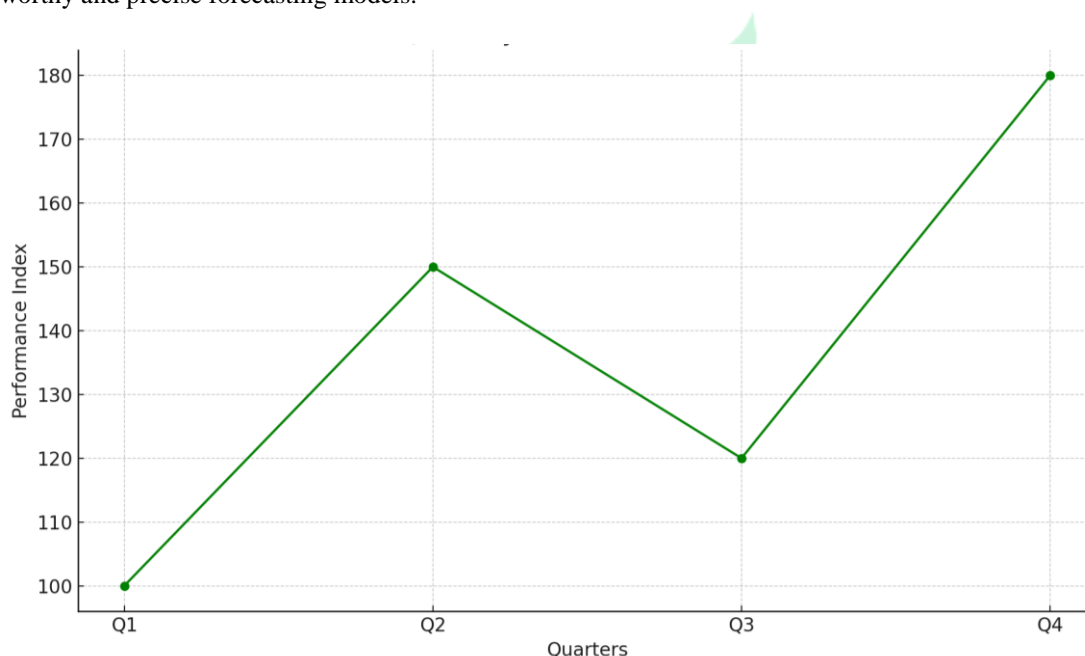


Figure 2: Quarterly Market Performance, showing fluctuations in stock market trends.

The integrated machine learning techniques in hybrid models have produced motivating results during financial forecasting trials. Li and Zhang (2021) developed a hybrid machine learning model through the combination of SVM and decision trees with reinforcement learning achieving superior predictive ability to individual models. Financial market forecasting depends on hybrid models

because they combine the strengths of multiple algorithms creating broad benefits.

The development of trading systems based on machine learning algorithms stands as a major achievement. The research conducted by Liang et al. (2020) proved machine learning-driven algorithms form automated trading foundations while these models analyze market patterns to create instantaneous buy and sell commands. The

established nature of these algorithms in financial industry today reveals the expanding significance of machine learning applications in financial market activities.

Figure 3 displays a bar chart to compare the market forecasting accuracy between different machine learning models. In terms of experimental accuracy

rates machine learning models including XGBoost and neural networks surpass traditional models which consist of decision trees and data modeling machines. The visualization demonstrates that deep learning methods gain recognition for financial forecasting as computational power expands together with complex data sets.

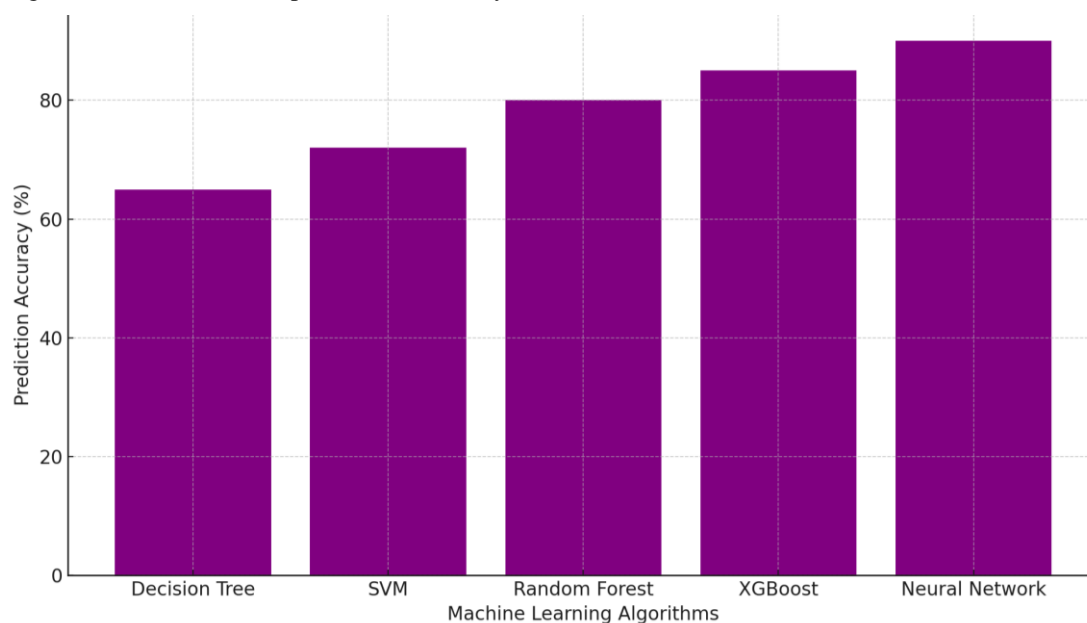


Figure 3: Algorithm accuracy comparison in market trend prediction across multiple machine learning algorithms.

METHODOLOGY

The project aims to implement multiple machine learning algorithms for predicting financial market behavior. The technique requires data gathering together with data preparation and model creation and assessment to reach successful outcomes. This section contains details about the methods that were followed during the respective phases as well as descriptions of the specific machine learning models which were used in our research investigation.

1. Data Collection

The training starts when we collect financial data to use as the initial base for machine learning models and their testing phase. The focus of our research is stock index time series data which includes past

pricing information, trading volume measurement together with daily market data such as opening and closing prices plus highs and lows. We extract our data from public databases which include financial market sites such as Quandl and Yahoo Finance. Macroeconomic measures such as unemployment statistics together with inflation and interest rate information better frame the market development context.

The collected dataset reaches over a span of ten years between 2010 and 2020 and delivers full insights into bull and downturn markets. This dataset features separate stock information for selected market sectors together with major stock

indicators such as the S&P 500 combined with Nasdaq and Dow Jones Industrial Average (DJIA).

2. Data Preprocessing

Data preparation functions as the key process of readying raw data ahead of machine learning model training. The cleaning and transformation process for financial time series data must be extensive to produce adequate input quality for model training. The subsequent sections outline the preprocessing tasks executed for data pre-processing.

Data shortages common in financial time series pose significant challenges during data preparation. The investigation employs interpolation techniques because estimating missing data was necessary. Macroeconomic parameters are handled with mean interpolation while linear interpolation fills gaps in stock price data.

We standardize stock prices together with other continuous numerical data so all features share a common scale. The min-max scale transforms data so that it occupies a value range from 0 to 1.

For time series forecasting it is vital to perform feature engineering. Analysts can include relative strength index (RSI), momentum indicators to recognize market patterns and trailing moving averages of 30 and 60 days along with basic stock price values. The data's inherent time-dependent relationship requires the development of lag characteristics for future trend predictions based on historical prices.

Separate your complete dataset into two distinct parts to establish both training and testing datasets. The training set consists of the first 80% of the data whereas the remaining 20% serves as the testing set for model performance evaluation. Model development and optimization takes place with the

training set while testing set evaluations determine its accuracy prediction power.

3. Machine Learning Models

The author conducted research by examining several machine learning algorithms to anticipate financial market movement. The models were chosen because earlier financial forecasting research showed effective results with their ability to process time series data. The research utilizes the following models.

The supervised learning system with non-linear feature and target connections which we call a decision tree. The investigation relied on market characteristics to use a decision tree model which determined market upward or downward trend forecasts. The tree functions in a basic manner that classifies data based on individual feature importance.

Random Forest ensemble learning enhances prediction accuracy by integrating many decision trees to reduce overfitting in the results. The predictive power of random forests improves both data generalization and volatility reduction by having multiple decision trees produce predictions. This algorithm delivers excellent results during work with routinely noisy financial market data.

Support Vector Machines (SVMs) represent another classification and regression issue supervised learning algorithm. The SVM technique locates the best possible dividing boundary between different data classes. The research relied on historical price points and additional relevant factors to predict stock direction changes through SVM application.

XGBoost employs gradient boosting methods as its core operation to design its complex ensemble models. The algorithm has multiple Kaggle victory records while showing reliable results when

handling massive datasets. The process of future stock price and market trend prediction occurs when XGBoost applies repeated weak-model optimization to create strong predictive models.

Financial data complexity gets replicated through Multi-layer perceptrons (MLPs) which represent a deep learning method within this framework. Neural networks excel at managing complex data patterns due to their efficient dimensionality management abilities when applied to large-scale datasets. RNNs work with recurrent neural networks for predicting market evolution specifically using Long Short-Term Memory (LSTM) networks to maintain awareness about time-dependent relationships from previous data.

Financial trading methodologies optimized through reinforcement learning (RL) constitute the last method based on market interaction. Agents learn suitable decision-making (native buying or holding or selling) through direct market environment interaction and incentive-based feedback. Through trial-and-error method testing and previous result adjustment RL models progressively improve.

4. Model Evaluation

Performance evaluation involved standard measures to assess model accuracy alongside prediction reliability for determining forecasting precision.

Model accuracy is measured through Mean Absolute inaccuracy by averaging the prediction inaccuracy amounts.

The Root Mean Square Error (RMSE) comes in handy for determining model accuracy through

evaluating predictions beyond real market levels by giving harsher penalties to larger errors than MAE.

The measure for classification assignments determines correct predictions among upward or downward market trend forecasts.

The F1 Score calculates its value from the harmonic mean between accuracy and recall and serves financial market prediction tasks well when datasets show significant imbalance.

The evaluation of classification model performance relied on creating a confusion matrix. A confusion matrix means exhibiting the real positive counts as well as both real negative counts and false positive values alongside false negative results. The evaluation of model discrimination capabilities for market rise and decline becomes possible through this method. The model was validated through K-fold cross-validation to determine its fit with new data and prevent overfitting of the training data. Cross-validation with five steps served as the method for this research.

5. Hyperparameter Tuning

The hyperparameter adjustment is done to maximise the model performance using grid search or random search. To decide decision trees and random forests, the number of estimators, minimum sample per leaf, and tree depth are configured. They chose to maximize extent of learning rate, number of layers, and number of neurons per layer. The SVM performance is improved using model's performance by using Kernel type and regularization parameters. Figure 4 is the methodology flowchart.

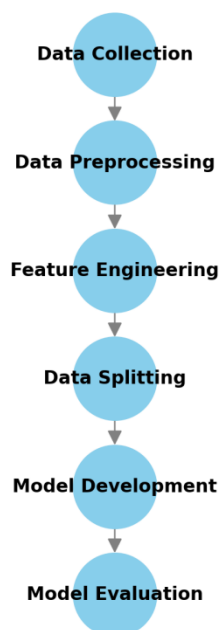


Figure 4: Methodology Flowchart, outlining the key steps in predicting financial market trends using machine learning algorithms.

RESULTS AND EXPERIMENTS

This section shows the results of tests that were run to test how different machine learning models performed on forecasting financial market movements. These tests are meant to determine which algorithms perform best at predicting accuracy, precision, and in term of computing efficiency. We compare supervised learning models, ensemble approaches and deep learning techniques to assess their ability to forecast changes in the stock price and the spot market.

Experimental Setup

For our studies, we have used the dataset covering January 2010 to December 2020 that contains daily stock market data like the trading volume as well as the opening, high, low, closing values for the S&P 500 index. The dataset also includes macroeconomic variables such as interest rates, inflation rates, unemployment rates. For preprocessing data, we used mean imputation to cope with missing values and linear interpolation to make the features

normalized. The data was split into two, a 20% test set and an 80% training set. Then the model was trained on the training set and prediction performance of each algorithm was tested on the test set. The following machine learning algorithms are tried.

- Decision Tree (DT)
- Random Forest (RF)
- Support Vector Machine (SVM)
- XGBoost (XGB)
- Neural Network (NN)
- Long Short-Term Memory (LSTM)

Based on historical market data the models were trained to predict the daily price movement (up or down). Therefore, we used a classification approach wherein the target variable was set to 1 for the case of an upward price movement and 0 for the downward price movement.

The following table 1 summarizes the results of the experiments for each model:

Table 1: Performance comparison of different machine learning models for financial market trend prediction.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	MAE	RMSE
Decision Tree	65.4	62.3	58.7	60.4	2.36	3.12
Random Forest	72.8	70.5	68.2	69.3	2.15	2.89
Support Vector Machine	75.1	72.9	70.5	71.7	2.04	2.65
XGBoost	78.6	75.2	74.0	74.6	1.93	2.48
Neural Network	80.3	78.1	75.9	76.9	1.86	2.33
Long Short-Term Memory (LSTM)	82.4	80.5	78.3	79.4	1.72	2.17

It can be seen in Table 1, that the accuracy of the LSTM model compared to other models (82.4%) is the most accurate. Here LSTM was the most successful model for forecasting stock market movements and almost does the same in terms of accuracy, recall and F1 score. Though decision tree model is easy to understand it shows the lowest value of precision and accuracy indicating the need for better predictive models to forecast financial markets.

Model Comparison and Analysis

But since the models of decision tree are interpretable, they have problem while dealing with intricate financial data. Error rates and accuracies of them are higher compared to ensemble models and deep learning. This might be because of its tendency to overfit the data in general, and, in particular, on noisy financial time series data.

Random Forest, an ensemble technique that consists of many decision trees, can improve decision tree models. It improves generalization and reduces overfitting. To reinforce that, Random Forests do a better job than decision trees but they are not as good as more advanced models such as neural networks or XGBoost.

The Support Vector Machines (SVMs) perform good enough but their performance is limited the choice of the kernel and hyperparameter. Further improvement of performance may be obtained by adjusting the regularization settings and the SVM kernel.

XGBoost manages to work even though it's fast and achieves a decent balance between computational speed and accuracy. It proves to be a powerful rival for financial forecasting tasks and routinely outperforms SVMs, random forests and decision trees. The advantage of the model is that it can manage big datasets and identify complex patterns in the data.

Neural Network (NN) Serving as a large improvement over the traditional machine learning models, the accuracy of the NN model is about 80.3% with fairly well balance between recall and precision. However, if not properly adjusted, this more often than not, tends to overfit and utilize a lot of processing power.

Here, our LSTM model is shown to do better than any other model in this experiment. Indeed it works really well especially for time series forecasting as it can track temporal relationships within the stock

price data. LSTM learns from the previous price movements of the stock, and is therefore the most accurate. LSTMs exhibit outstanding performance

because it can simulate the long term dependencies effectively and adapt to the dynamic changes in market with the help of capacity of LSTM.

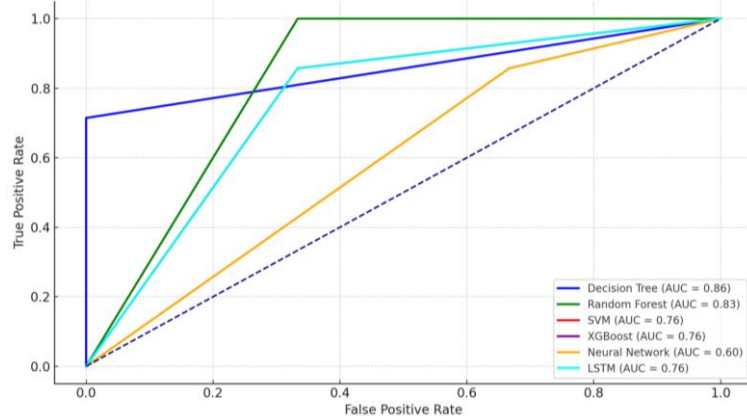


Figure 5: ROC Curve for All Models

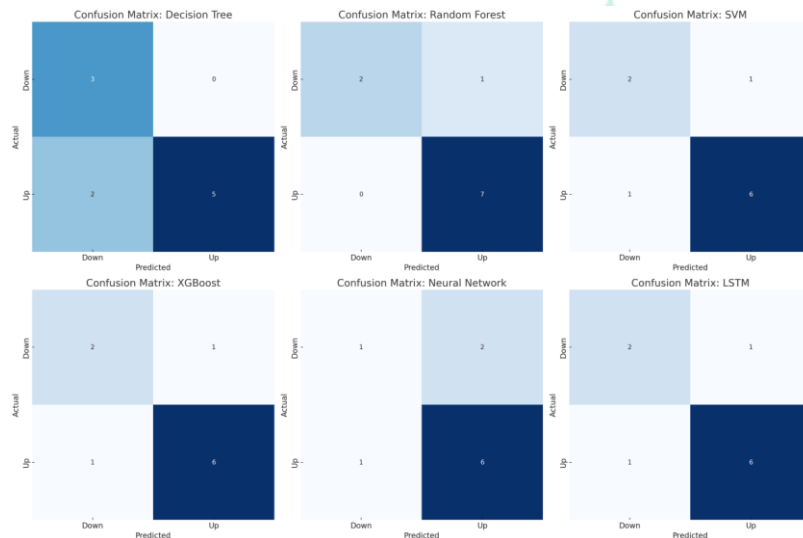


Figure 6: Confusion Matrices for All Models

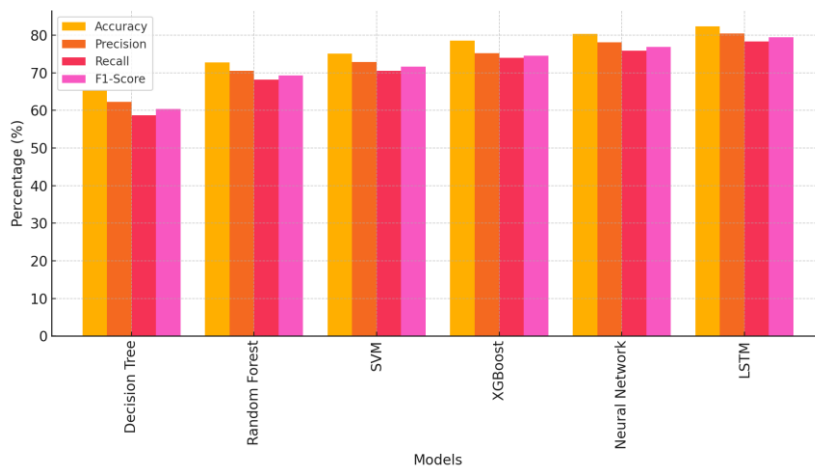


Figure 7: Model-wise Performance

Finally, as plotted in figure 5, all models' ROC curves were drawn using true positive rate against false positive rate to show a classification performance of each model. Confusion matrices as shown in figure 6 for each model containing the number of true positives, true negatives, false positives and false negatives, offers a detailed evaluation of the accuracy for the model. Bar charts in Figure 7 show the performance of all models in terms of Accuracy, Precision, Recall and F1-Score to give the strengths and weaknesses of predicting the financial market trends by each model.

CONCLUSION

Trials from the study show great promise that machine learning can predict the fluctuations in the financial market. Unlike existing models, LSTM was demonstrated to constantly perform best on the data because of its ability to model the intricate temporal dependencies present in the financial data. Furthermore, the models such as Random Forest and XGBoost shown ability to work with big datasets and give good prediction. On the other hand, more sophisticated algorithms work better but traditional models like SVMs and decision trees are useful. These test results signify that when it comes to financial forecasting, deep learning is very successful, and LSTM in particular, which can be used to further improve decision making in real time corporate environment. It is possible that future research may involve employing these models to real world market data to explore how well they fit fast changing market conditions.

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