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# An AI-enabled Design Framework for Price Intelligence and Trend Prediction Based on Machine Learning and Particle Swarm Optimisation

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**Abstract:**

The stock market exhibits extreme volatility, nonlinearity, and changes in the internal and external environment. Artificial intelligence (AI) methods can be used to find this non-linearity, which dramatically improves forecast accuracy. This study reviews 148 studies that use neural and hybrid-neuro techniques to forecast stock markets. 43 automatically generated themes are used to group the papers. Study features and performance outcomes are the two main categories into which we split the papers that were surveyed. While the data pre-processing method, artificial intelligence approach, training algorithm, and standard performance have been categorised under "model characteristics," the stock market covered, the necessary information, and the type of study are further classified under "study characteristics."Our findings show that employing AI techniques, stock market behaviour may be successfully examined and assessed.

**Keywords:** artificial intelligence; neural networks; training algorithm; stock market forecast

## Introduction

Artificial neural network development is promoting customer dependability in the stock market. The growth of financial investment in the stock market is accelerated by the reliability factors. Due to the non-linear and volatile nature of time series data, managing and making decisions in the dynamic stock market are still difficult. However, modelling supervised and unsupervised artificial neural networks with numerous layers decreases the influence factors of stock market price prediction. The difference between a stock's opening and closing values is a significant factor in stock market forecasting. Since the stock market is vital to a nation's economic development, several academics and mathematicians have developed reliable models for predicting stock values.However, despite numerous price prediction models, price stability fluctuates greatly, which discourages market investment. Artificial neural networks and machine learning forecasting techniques like support vector machines, LSTMs, and CNN have excellent potential for price prediction in the current decade.

Popular theories claim that stock markets, especially the Iranian stock market, which operates under some rules depending on the previous day's close price, are primarily a random walk. Predicting stock prices is difficult because the majority of conventional time series prediction algorithms are based on static patterns. Furthermore, because there are so many variables at play, forecasting stock values is a challenging topic in and of itself.There is potential for forecasting market movements over a longer time horizon since the market behaves like a voting machine in the short term but like a weighing machine in the long run. The most potent technology is machine learning (ML), which employs a variety of algorithms to improve its performance in a particular case study.

It is widely believed that ML has a significant capacity to find meaningful information and uncover patterns in datasets. Ensemble models, a type of machine learning-based strategy that combines several widely used algorithms to address a particular problem, have been proven to perform better than individual methods at predicting time series, in contrast to traditional ML approaches.Time series data, such as stock data, include many components that make prediction difficult. The researchers created various prediction methods based on autoregressive integrated moving average. There are, nevertheless, still unpredictable stock market circumstances that cause sporadic volatility. The results of comparing the predictive abilities of the ARIMA and artificial neural network (ANN) models revealed that the ANN model performed better. Many experts have compared the many machine learning algorithms that are being developed to predict stock prices and trends.

A machine learning strategy using sentiment analysis, along with LR and support vector machine (SVM) models, was used to predict stock market movements. The public mood was determined from Twitter data.The results showed that random forest gave the best performance when compared to ensemble techniques and single classifier models. Swarm intelligence was also included in the suggested stock market forecast algorithm for optimization. A variation of particle swarm intelligence was used during the attribute optimization procedure. PSO and multi-objective particle swarm optimization are two of the particle swarm intelligence types used here. The procedure of selecting the best attributes for the process of classification and prediction is redefined by the multi-objective particle swarm optimization. The cascading of machine learning algorithms is an incremental advance in machine learning. The sample size and rate of stock market prediction are increased through cascading.

The impact of accurate stock price forecast on the national stock market. Machine learning offers ensemble classifier approaches for precise stock market forecasting. Several techniques, including bagging, boosting, stacking, and random forest, are used in the ensemble process. The suggested ensemble classifier uses boosting techniques. Support vector machine and decision tree are two classifiers that are combined in the boosting process.

**Literature Review**

Nti et al. [2010] GASVM is a brand-new homogeneous ensemble classifier that predicts the stock market using support vector machine enhancements including Genetic Algorithm (GA) for feature selection and SVM kernel parameter optimization. To simultaneously optimise the various SVM design variables, the GA was used in this study. Results from experiments using historical stock data from the Ghana Stock Exchange (GSE) were convincing. The results demonstrate that in terms of forecasting a 10-day-ahead stock price movement, the suggested model—dubbed GASVM—performed better than other traditional ML techniques, including Decision Tree (DT), Random Forest (RF), and Neural Network (NN). In comparison to RF, DT, and 80.1%, the proposed (GASVM) showed a superior prediction accuracy of 93.7%. (NN).Accordingly, it can be inferred from the results that the suggested (GASVM) technique offers a workable method for feature-selection and parameter optimisation of the various design elements of the SVM and thereby eliminates the requirement for labor-intensive parameter optimisation.

Reddy et al. [2011] Data mining techniques combined with artificial intelligence and machine learning techniques are utilised in a variety of situations to address a wide range of issues. These machine learning approaches and methods have previously shown to be very accurate, efficient, and time-saving. People have recently begun investing in stocks and shares since it is a beneficial strategy for raising one's income. There is a potential to double the annual revenue from the stock market returns with careful planning and sound advice. However, many people still believe that stock investments are risky even today.Due to the substantial income earned by investment professionals and the general public's inexperience of financial matters, many consumers are discouraged from investing in stocks. The fear of losing the money invested also acts as a deterrent to people. These facts serve as the driving force behind the use of machine learning's ability to forecast stock movement. The tweets acquired by using the Twitter API are subjected to sentiment analysis. For stock investors to make thoughtful selections and invest in lucrative stocks, such projections are quite useful.

Shi et al. [2012] Using deep neural networks, a novel sentiment analysis method was developed for stock comments, and it was used to forecast stock movement using estimated sentiment. The empirical findings demonstrated that our method of deep sentiment categorization outperformed the logistic regression algorithm by 9% and delivered a precise sentiment extractor for the subsequent prediction phase. Additionally, among 150 Chinese equities in the testing sample, our new hybrid features that combine stock trading data and sentiment information improved by 1.25%. For American stocks, the sentiment data would lessen the accuracy of the predictions. For companies with a higher price to book value and a lower beta risk value, we discovered that emotion traits extracted from comments are effective.

Mehtab et al. [2013] a collection of deep learning-based stock price prediction algorithms. For training and testing the models, we use the historical data for the NIFTY 50 index listed on the National Stock Exchange (NSE) of India from December 29, 2008 to July 31, 2013. Three long-and short-term memory (LSTM) network-based predictive models and two convolutional neural network (CNN)-based regression models are included in our proposal. We used a multi-step prediction technique with walk-forward validation to project the open values of the NIFTY 50 index records.The open values of the NIFTY 50 index are forecast using this method across a time horizon of one week, and once that week has passed, the actual index values are added to the training set before the model is retrained and forecasts for the following week are created. We provide comprehensive findings on the predicting accuracy of each model we've suggested. According to the results, the univariate encoder-decoder convolutional LSTM with the prior two weeks' worth of data as the input is the most accurate model, even though all of them are quite accurate at predicting the NIFTY 50 open values.On the other hand, a univariate CNN model that uses data from the prior week as input is discovered to be the model with the fastest execution time.

Sen et al. [2014] provide a collection of models for predicting stock price that are based on deep learning. We create and test the models using data from the NIFTY 50 index listed on the National Stock Exchange (NSE) of India between December 29, 2008 and May 15, 2014. Three long-and short-term memory (LSTM) network-based predictive models and two convolutional neural network (CNN)-based regression models are included in our proposal. We used a multi-step prediction technique with walk-forward validation to project the open values of the NIFTY 50 index records.The open values of the NIFTY 50 index are forecast using this method across a time horizon of one week, and once that week has passed, the actual index values are added to the training set before the model is retrained and forecasts for the following week are created. We provide comprehensive findings on the predicting accuracy of each model we've suggested. The findings indicate that while all of the models are quite good at predicting the NIFTY 50 open values, the CNN model—which takes data from the previous week as an input—is the quickest to execute and the most precise.The encoder decoder CNN-LSTM model, on the other hand, is discovered to be the least accurate one and takes the data from the previous two weeks as input.

**Objective of the study**

We defined the following goals for our research after determining the need for development in the area of machine learning-based option price prediction:

1. To research and have a basic understanding of stock market forecasting.
2. To create and deploy a feature re-education system for predicting option prices.
3. Create and use a prototype classification algorithm for predicting option prices.

**Research Methodology**

The two sections that make up the suggested method of stock price prediction. I go into detail about the attribute optimization of NSE data in section. Describe the cascaded classifier's ultimate stock price prediction procedure. The accuracy of the stock price forecast was diminished by attribute fluctuation. Particle swam optimization was used to reduce attribute variance. Iterative optimization strategies are used in particle swarm optimization. The acceleration factor and constant factors c1 and c2 are the two primary derivates of data processing used in particle of swarm optimization. The derivation and mapping of the particle swarm optimization technique using NSE stock data show

$$Pk_{\cdot}\frac{FSk - FSb}{FSmax - FSmin} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.5.1)$$

Define the process of data movement (Velocity)

$$V_{k,d} = \beta \times V_{k,d} + c \times r1 \times \left(x_{best,d} - x_{k,d}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.5.2)$$

The set of variance data is

D=1, 2,M……………………………(4.5.3)

Update the position of new data

$$x_{k,d} = x_{k,d} + V_{k.d} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.5.4)$$

The process of designing precise algorithms for stock price prediction is known as cascading machine learning. Three levels of support vector machines were used during the cascade process. Support vector machines are classified into three levels: C0, C1, and Cn. Particle swarm optimization is used to standardise and optimise the processing of NSE data. Here is a description of the cascade support vector machine processing. We establish t levels with $t \geq 3$ in each level, one or more classes predict the dataset, and then process the prediction result in the next level of class for a dataset described by a raw attribute vector of dimension (f*1).

**Data Analysis and Discussion**

Table 1: Performance comparison of the suggested technique with the algorithms EM, ML, SVM, SOM, and ANN using the parameters RMSE, NMSE, MAE, and MI analysis of the axis bank dataset using 0.1, 0.2, 0.3, 0.4, and 0.5 settle prices

| SETTLE PRICE | METHOD | RMSE | NMSE | MAE | MI |
|---|---|---|---|---|---|
| 0.1 | EM | 7.34 | 7.21 | 8.56 | 7.54 |
| | ML | 7.46 | 7.24 | 8.57 | 7.59 |
| | SVM | 7.31 | 7.38 | 8.64 | 7.83 |
| | SOM | 7.24 | 7.01 | 8.51 | 8.10 |
| | ANN | 7.08 | 7.43 | 8.34 | 8.14 |
| | PROPOSED | 6.99 | 6.84 | 8.23 | 8.24 |
| 0.2 | EM | 7.21 | 7.19 | 7.89 | 7.63 |
| | ML | 7.53 | 7.16 | 7.74 | 7.68 |
| | SVM | 6.95 | 7.34 | 7.51 | 7.89 |
| | SOM | 7.13 | 6.98 | 7.24 | 8.12 |
| | ANN | 7.03 | 7.49 | 7.31 | 8.27 |
| | PROPOSED | 6.89 | 6.69 | 6.89 | 8.65 |
| 0.3 | EM | 7.01 | 7.13 | 7.61 | 7.88 |
| | ML | 7.39 | 7.28 | 7.35 | 7.94 |
| | SVM | 7.25 | 7.42 | 7.54 | 8.01 |
| | SOM | 7.38 | 7.09 | 7.29 | 8.16 |
| | ANN | 7.28 | 7.39 | 7.14 | 8.31 |
| | PROPOSED | 6.71 | 6.63 | 6.87 | 8.71 |
| 0.4 | EM | 6.99 | 7.09 | 7.24 | 7.81 |
| | ML | 7.19 | 7.11 | 7.41 | 7.86 |
| | SVM | 7.32 | 7.45 | 7.21 | 8.06 |
| | SOM | 7.19 | 7.2 | 7.01 | 8.19 |
| | ANN | 7.47 | 7.31 | 6.94 | 8.37 |
| | PROPOSED | 6.64 | 6.57 | 6.81 | 8.89 |
| 0.5 | EM | 6.74 | 7.14 | 7.14 | 7.95 |
| | ML | 7.08 | 7.23 | 7.20 | 8.11 |
| | SVM | 7.12 | 7.01 | 7.36 | 8.26 |
| | SOM | 7.27 | 6.99 | 6.32 | 8.59 |
| | ANN | 7.65 | 7.29 | 6.47 | 8.69 |
| | PROPOSED | 6.51 | 6.49 | 6.78 | 8.97 |

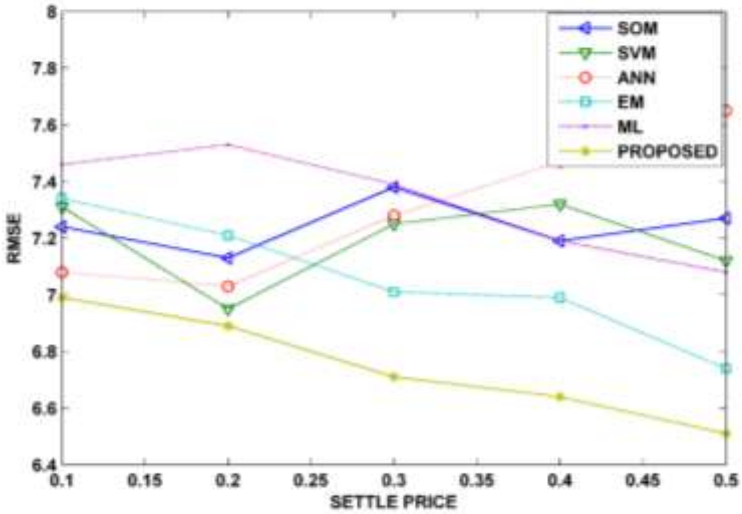


Fig 1: RMSE vs. Settle price.

This graph compares the root mean square error for the AXIS Bank dataset using SOM, SVM, ML, EM, ANN, and the suggested technique. The variation's distribution across different settle prices, such as 0.1, 0.2, 0.3, 0.4, and 0.5, shows that the suggested method's optimization process and improved prediction have improved the value of RMSE. Here, we see that the proposed method's root mean square error value is superior to that of previous approaches.

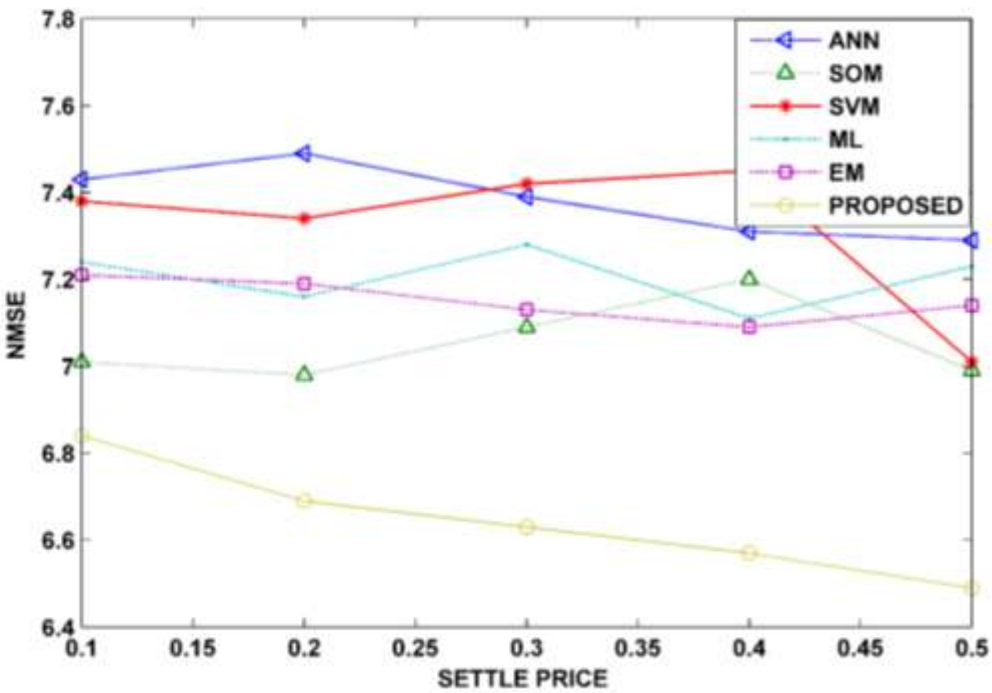


Fig 2 : NMSE vs. Settle price.

The normalised mean square error for the AXIS Bank dataset is compared in this graph using SOM, SVM, ML, EM, ANN, and the recommended method. The variation's distribution over a range of settle prices, including 0.1, 0.2, 0.3, 0.4, and 0.5, demonstrates how the optimisation process of the suggested method has raised the value of NMSE. Here, we see that the proposed method's normalised mean square error value is superior to previous approaches.

**Conclusion**

The stock market is a crucial component of any nation's financial development. When making investments, buyers and sellers engage with the stock market's dependability. Customers' investing decisions are unpredictable due to the fluctuating nature of the stock market. When deciding whether to buy or sell stocks, stock price patterns are a major factor. The stock market's price patterns determine its potential for investment. Future stock market trends determine the actions taken at market opening and closure. Artificial neural network models as well as linear and non-linear regression were used in the non-parametric stock price prediction models.Artificial neural network models must carefully consider parameters like input, learning rate, number of hidden layers, and connections between hidden layers in order to provide the intended outputs, which include a stock price. The standardisation and transformation of stock data increase the neural network models' capacity for learning. The prediction depends heavily on the choice and extraction of stock market data's properties. The stock price prediction ratio was reduced as a result of human intervention.

The prediction ratio is improved by the proposed prototype classifier, which is based on a machine learning algorithm. The higher value of MI supports the classification process by reducing the number of data iterations and minimising various error metrics like RMSE and MSE, according to the improved prediction ratio. SVR and support vector machines were compared with the suggested algorithm. A static classifier and regressive function, respectively, are the SVR and supports vector machine. According on the experimental results, the suggested cascaded classifier outperforms SVR and SVM. The intricacy of the class level rises with the level of cascading. Future classifiers will use new mechanisms and have less complex architectures.

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