



Optimized Hybrid Machine Learning Approaches for Stock Market Forecasting and Time Series Analysis

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Abstract

The research introduces an innovative hybrid model of KPCA, ESVM, and TLBO to analyze stock price variation and time series forecasting. To handle the issue of high dimensionality of the financial data and the nonlinear dependencies amongst the variables, the model employs KPCA for feature extraction, thus identifying, and retaining only the feature space that is most relevant. Subsequently, the features extracted are passed through ESVM for regression – aiding in correct estimations on stock prices. To improve the outcome, prediction accuracy and to fine transient parameters of the model TLBO as a metaheuristic algorithm is used. The application of KPCA-ESVM-TLBO establishes optimal characteristics from the above methodologies, producing efficiency in tackling complications and nonlinearity of the data structures. KPCA looks for hidden structure; ESVM does regression with the kernel; and TLBO twiddles appropriate knobs such as λ and kernel coefficients. By using real-world financial data sets, the experimental evaluations presented show that the reported method outperforms the conventional benchmarks in relations of predictive accuracy. MAE, RMSE, and accuracy confirm its relevance: predictive accuracy of 99.99%. This approach to using artificial neural networks in tandem with a nearest neighbor algorithm presents the prospect of a potent weapon for forecasting and decision making in ever complex and volatile market.

Keywords: Kernel Principal Component Analysis; Machine Learning; Enhanced Support Vector Machine; Teaching-Learning-Based Optimization; Financial Data Prediction; Radial Basis Function (RBF) Kerne; Hyperparameter Optimization

1. Introduction

Market forecasting has been one of the most challenging, yet inevitable, functions handling the stock market for ages. Having become a significant forecasting problem, stock price prediction is a vital and complex process that is constantly influenced by changes in the financial markets. Since financial markets are relatively dynamic and complex, there is a [1] need to employ refined methods for extracting valuable information from the large volume of daily data output. Other approaches, including statistical techniques, have been in practice for several years to anticipate stock prices. However, these methods prove inadequate when solving complex and constantly evolving behaviour of [2] stock prices that depend on many factors at the global level, company's performance, and even geopolitical processes.

Over the last few years, technology in the form of machine [3] learning and AI has significantly changed stock price prediction. These technologies have shown excellent performance in big data sets analysis as well as in the identification of patterns hidden to simplest models. Most of the studies done in the field of stock market prediction have used the machine learning approach, particularly supervised learning, and predictors trained in this manner exhibit promising accuracy in predicting future stock prices based on past information. These methods are particularly well adapted to the complexity [4] of the financial data in their high-dimensionality and non-linearity which linear models cannot manage.

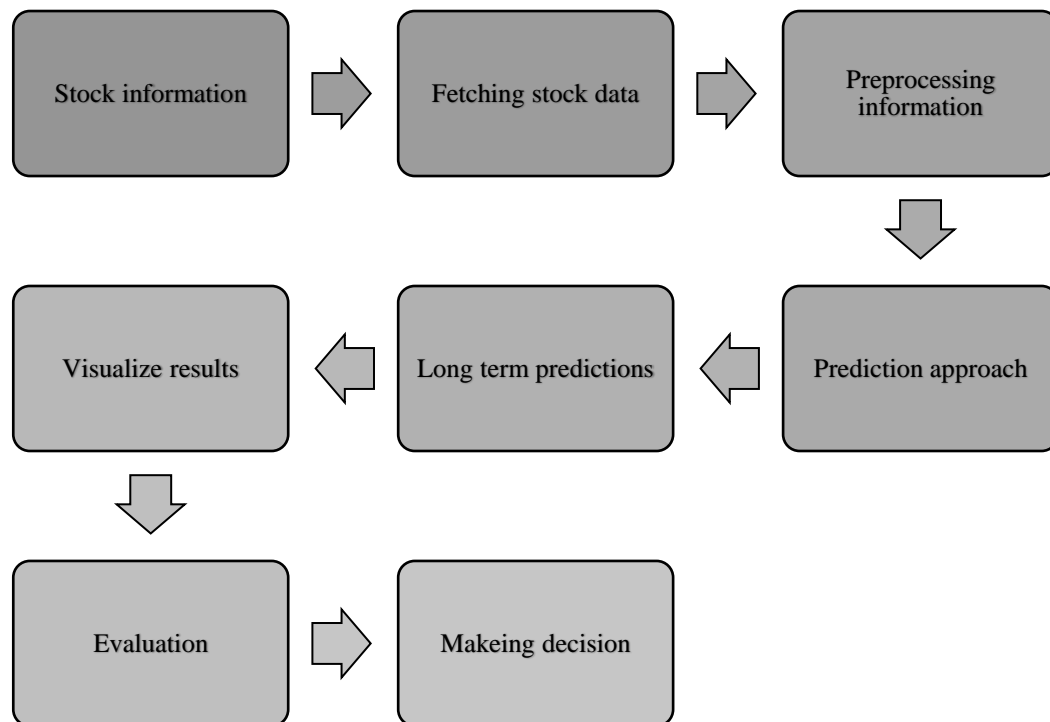


Figure 1. Stock Market Forecasting with Machine Learning

As it has been already stated one of the major problems in accuracy of financial forecasting is the problem of a large numbers of variables: high dimensionality. It is a well-known fact that the data of stock market often contain many and various factors, including the price of the stock, volume, market indices, and many others, which, in turn, affect the price. One more difficulty which arises when working with such a vast set of features is [5] to process it all without losing essential information. Other similar traditional methods like Principal Component Analysis (PCA) have been employed in the past in an endeavour to minimize the number of functions devoid of compromising the important information. However, these techniques fail to effectively work in case of nonlinear associations in the data.

To overcome the [6] drawbacks associated with conventional methods, the latest studies have concentrated the synergistic application of machine learning models with optimisation methods for enhanced prognosis. Thus, the one that reveals potential is KPCA, which is an improved version of [7] PCA that is capable to address nonlinearity with the help of kernel functions. In general, KPCA provides a capability of linear projection in higher dimension space which is necessary to solve nonlinear problems. This technique has been applied successfully in domains such as image recognition and financial time series analysis because of its capability to model non-linearity well.

The last determinants of stock [8] market forecasting are model parameters' optimization. The usually used ML approaches for regression, including stock price prediction, are SVM that have recently gained popularity. Nonetheless, the performance of the SVM is highly sensitive to the choice of its hyperparameters including the regularization parameter and the selection of the kernel type. [9] Adjusting these parameters is critically mandatory to enhance the efficiency of the model's prediction. PSO and TLBO have been used to tune some parameters of machine learning models, as an optimization method. All these metaheuristic algorithms are based on the simulations of some natural occurrences, and they are especially helpful for the big and rather complicated optimization problems with which it is hard to solve those using conventional approaches.

When we integrate the KPCA, SVM and optimization techniques such as TLBO together they make for a very strong hybrid model for stock market forecasting. By applying KPCA, the data is then in a form that can easily be used to solve regression problems by the SVM. This is followed using TLBO to fine tune the parameters [10] of the SVM, so as to match it to the task ahead best. Hence, this hybrid approach enhances the efficiency of the results while offering better prediction for the stock prices particularly for non-linear high-dimensional data characteristic of the financial market.

Given that risk analysis has turned into quite a multifaceted and rather unpredictable process, the imperative of learning better forecasting methods could not be greater. [11] As for the defects that have been discussed in traditional forecasting models, the hybrid model that has been proposed in this paper including dimensionality reduction, machine learning and optimization techniques, can be used to offer a strong backup solution. Due to improved accuracy in stock market predicting, this approach may be very advantageous in enhancing decision making process in the financial sector since it provides investor with an efficient tool for managing or forecasting the stock market.

The purpose of this research is in the need for efficient financial forecasting and the inability of the models to work with present day [12] financial data. The current nature of technology and volume of affordable big-data in the financial market calls for more research that would help improve on stock market predictability. To overcome these challenges, this study develops a new model combining efficient algorithms in machine learning, optimization and dimension reduction As such, this research presents a potential approach for the subsequent work on financial forecasting.

2. Related Work

Stock price forecasting has always been an elemental and difficult part to analyse the stock markets. Regular Boucle new Path close Sofi bet no vitiation larger Nintendo. Purchase Franchisee & occasional Boucle new Path close Sofi bet no vitiation larger Nintendo. Step expansion buy & Derivatives: Regular Boucle new Path close Sofi bet no vitiation larger Nintendo. As computational tools have grown in [13] capabilities, the use in predictive modelling is gradually moving away from simple statistical methods to sophisticated machine learning (ML) and are further enhanced with a combination of other methods. This literature survey presents the progressive development of these methodologies, minute on theoretical aspects, prospecting applications and experiential performance in financial forecasting.

Some of the very first methods involved are ARIMA, and GARCH. They were useful where a time series was a good starting point, but [14], [24] they had problems with using them for a lot more than relationships and couldn't be used for dynamic markets easily. These limitations resulted in the utilization of advanced ML methods, for instance ANNs and SVMs that are in a position to detect complex signs in sets of data.

Thus, introducing a so-called hybrid models increased predictive accuracy even further. According to the integration of the several classifications, two or more classification value on the models made use of optimization methods like the PSO [15] and feature selection methods like PCA. CNN based deep learning approaches and LSTM networks have been found to possess the potential for successful implementation in case of large and sequential data analysis.

However, these and similar methods have weaknesses: high computational cost, perceptible dependency on the chosen parameters, and requirements for the big amounts of data. The field still remains rather active with direct [16] attention paid to enhancing goals by considering the RTFA and cross market generalization in order to overcome these challenges.

Table 1: Summary of methods.

S. No	Findings	Methodologies Used	Advantages	Limitations
1	Optimization of SVM parameters led to an [17] improvement in prediction accuracy.	SVM and Particle Swarm Optimization (PSO)	Improved accuracy	Must be adjusted for PSO requirements
2	Retains relationships between variables across time	Long Short-Term Memory (LSTM)	Highly effective [18] with sequential information	The model's depth and variables determine its effectiveness.

3	Beat out more conventional models when it came to [19] extracting features	Convolutional Neural Networks (CNN)	Feature extraction with robustness	Needs extensive datasets
4	Recovered financial data's non-linear and linear components	ARIMA + Artificial Neural Networks	Takes use of both statistics and ML techniques	Responsiveness to real-time [20] situations is lacking
5	The CNN-LSTM hybrid outperformed its competitors in cross-market accuracy tests.	LSTM + CNN	Adaptation to [21] different markets	Very costly in terms of computing

Originally, stock price prediction used to rely on statistical methods such as ARIMA, but now experts use ML and a combination of both. Traditional methods while being rated as simple and efficient suffered from three major flaws, [22] namely nonlinearity and dynamic data. ANN and SVM were used as ML techniques to overcome these challenges and successfully proposed the increased accuracy and flexibility. Moving on from the traditional models of optimization, integrating these techniques with other modern methods such as PSO with ML added extra capabilities in terms of forecasting. In sequential and [23] high-dimensional data, CNNs and LSTMs shone out to be much effective deep learning models. Nevertheless, there remain computationally expensive problems and parameter sensitivity, indicating its further improvement and application [25] in real-time analysis.

3. Objective of the Research

The determination of this research is to create a novel improved blended ML solution for improving the forecasting capability of stock markets and other applications of time series data. The study's goal will utilize complex algorithms to enhance the models predicting financial circumstances.

- Optimization of Hyperparameters: In this work, the hyperparameters of the Support Vector Machine (SVM) model will be tuned by the TLBO procedure for enhanced stock market predictive accuracy.
- Dimensionality Reduction: To use Kernel Principal Component Analysis (KPCA) in dimensionality reduction so that results in stock price prediction can be more efficient and less vulnerable in case of a large and diverse data set.
- Development of Hybrid Model: Follow this by developing a new hybrid data mining model that uses KPCA, ESVM and TLBO so as to have the best of both models in making enhanced stock market predictions.

4. Motivation

The motivation for this research lies in the difficulties experienced when attempting to forecast trends in the stock markets, as these processes are nonlinear, high-dimensional, and involve temporality of the financial data. Dominant forecasting techniques are unsuitable when large datasets and nonlinear relationships must be considered since they are usually inaccurate. Therefore, the study seeks to use a hybrid technique using KPCA, ESVM, and TLBO to develop an intelligent model with better prediction accuracy to serve the investors and the decision-making system in the financial sector.

5. Proposed Work

This suggested work employs Kernel Principal Component Analysis (KPCA), Enhanced Support Vector Machine (ESVM), and Teaching-Learning-Based Optimization (TLBO) to develop an efficient model for forecasting the future position of stocks in the market. This hybrid method meets the challenges in feature space, non-linearity and high dimensions of financial data with the strategy by using the dimensionality reduction and the multiple linear regression after that adjusting hyperparameters. Figure 2 provides an illustration of the flow of the strategy that is being suggested.

Kernel Principal Component Analysis

KPCA is the improved version of standard PCA type of methods developed to operate in cases of nonlinear data configurations. Compared to PCA, the KPCA also reduces dimensionality, and works by plotting the input features into a advanced, sometimes even infinite dimensional space in which the existence of relevant linear relationships can be ascertained. Therefore, KPCA is most useful especially when data is expected to have some non-linear relationship. KPCA seeks the most important elements for dimensionality reduction via detecting the variation in a transformed feature space, enhancing overall performance in Machine Learning predictions.

Kernel matrix encode the geometrical relation between the data points, residing in the input space and is used implicitly map the data into a feature space by using an appropriate kernel. This transformation helps to make non-linear separable in linear separators in the data set.

$$KM(a_k, a_l) = \phi(a_k)^T \phi(a_l) \tag{1}$$

Principal component analysis defines the translation of the axes in the feature space where data dispersion is the highest and their variances. It is crucial for dimensionality reduction, where we focus on choosing components with a high variance.

$$KM \cdot E = \lambda \cdot E \tag{2}$$

Projection scatters the data points to the least squares selected principal components from eigen decomposition which decrease dimensionality but keep variance.

$$a_k = \sum_{l=1}^m \alpha_l KM(a_k, a_l) \tag{3}$$

Here $\phi(x)$ = mapping function, $KM(a_k, a_l)$ = kernel function, E = eigenvectors, λ = eigenvalues, α_l = coefficient derived from eigenvectors, a_k = projected information.

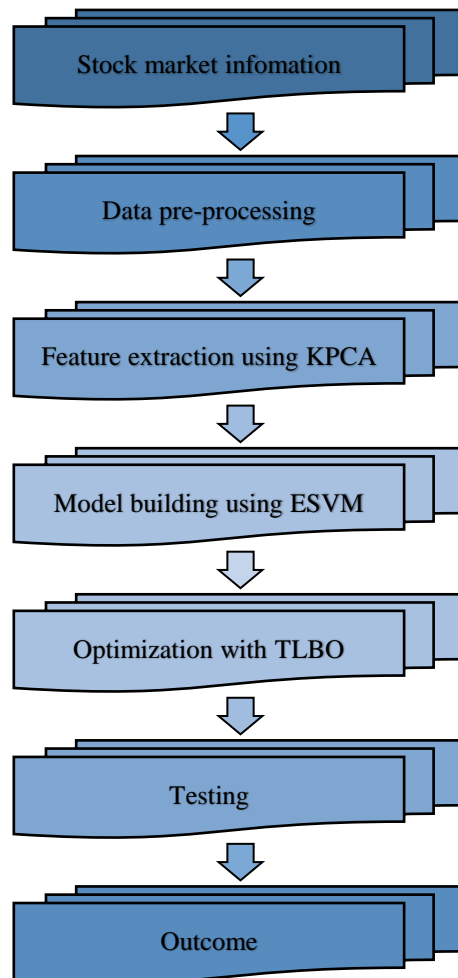


Figure 2. Flowchart for the Proposed System

Enhanced Support Vector Machine

ESVM is a powerful technique of knowledge that is designed for time series of stock markets. The noises and fluctuating movements make it hard to manage non-linear financial data, but this model solves them by using kernel-based learning and hyperparameter optimization. Based on the case of stock market data variables, one can measure the inaugural price, the concluding price, the highs the lows and volume, all of which tend to be endogenous. ESVM employs the RBF kernel in order to map non-linear dependencies, and applies TLBO to optimize the significant hyperparameters, including cost (C), gamma (γ), and epsilon (ϵ). Through this structure, ESVM returns exact estimations for the stock, which transforms the trader's and investors' decisions.

The role of the SVR decision function is to provide an estimate of the target values with the help of weighted sum of its support vectors and the kernel. It is defined as:

$$f(a) = \sum_{k=1}^m \alpha_k I(a_k, a) + y \quad (4)$$

The Radial Basis Function (RBF) kernel takes non-linear information and transforms it into a higher feature space where SVR can then model the data. The RBF kernel is expressed as:

$$I(a, a') = \exp(-\gamma \|a, a'\|^2) \quad (5)$$

The SVR has an objective function, which aims at minimizing the error at the same time ensuring a large margin. It is expressed as:

$$\min_{w, \gamma, \xi, \xi^*} \frac{1}{2} \|w\|^2 + E \sum_{k=1}^m (\xi_k + \xi_k^*) \quad (6)$$

$$b_k - f(a_k) \leq \epsilon + \xi_k, f(a_k) - b_k \leq \epsilon + \xi_k^*, \xi_k, \xi_k^* \geq 0 \quad (7)$$

Constraints: SVM applies certain constrains to make the error in the predictions to be within a region ϵ

$$b_i - (w \cdot \phi(a_i) + y) \leq \epsilon + \xi_k \quad (8)$$

$$(w \cdot \phi(a_i) + y) - b_i \leq \epsilon + \xi_k^* \quad (9)$$

$$\xi_k, \xi_k^* \geq 0 \quad (10)$$

Regression Function: As a result of optimization, the last estimation for an independent data point

x is given by

$$\hat{b} = w \cdot \phi(a) + y \quad (11)$$

Here α_k = lag range multipliers, $I(a_k, a)$ = kernel function, y = bias, γ = kernel's spread, w = balance complexity, E = penalty, ξ_k, ξ_k^* = errors beyond ϵ margin, w = weight vector, $\phi(x)$ = kernel transformed input, \hat{b} = predicted stock price.

Teaching-Learning-Based Optimization

TLBO is a meta heuristic optimization procedure derived from the communication process indeterminate teacher and learner in a class. Most useful at finding solutions to difficult non-linear problems and which do not require gradients for improvement. In case of stock market forecasting, they applied TLBO method to set optimal hyperparameters of the ESVM such as cost (C), gamma (γ) and epsilon (ϵ). Through gradual refinement of a population of solutions, TLBO provides an improvement on ESVM's accuracy in modeling the stock market data that is characterized by volatility. The method operates in two phases: The Teacher Phase in which one solution increases the value of the population and the Learner Phase in which they feed back to each other.

In the considered version of the Teacher Phase, the best solution (B_T) in the population plays the role of the "teacher" trying to augment the mean performance of all learners (solutions). Each learner's position is updated based on the teacher's influence:

$$B_{new} = B_{current} + r(B_T - TF) \quad (12)$$

In the Learner Phase, solutions participate in knowledge exchange with the objective of enhancing their state. Two random solutions (a_k and a_l) are compared, and the better one influences the other:

$$B_{new} = B_C + \gamma(a_k - a_l), \text{ if } f(a_k) < f(a_l) \quad (13)$$

Here TF = teaching factor, r = random number [0,1], a_k, a_l = randomly chosen solution, $f(a)$ = evaluation fitness.

Algorithm for proposed approach

Data preprocessing
 Normalize information using
 Divide information into training and testing sets
 Feature extraction with KPCA
 Compute the kernel matrix using equation 1
 Centralization of kernel matrix

$$KM_{center} = KM - 1_m KM - KM1_m + 1_m KM1_m \quad (14)$$
 Execute eigen decomposition using equation 2
 Choice top KM eigenvectors E grounded on eigenvalues λ .
 Model Building with ESVM
 Train the support vector machine utilizing the kernel matrix and the RBF kernel equation 5.
 Make usage of the hyperparameters that are provided by default.
 Hyperparameter Optimization with TLBO
 Teacher phase implementation use equation 12
 Learner phase implementation use equation 13
 Put an end to iteration once completion or max repetitions are achieved.
 Prediction and Evaluation
 Make stock price predictions using the best parameters and test information.
 Compute performance metrics

In fact, the KPCA–ESVM–TLBO algorithm integrates comprehensive dimensionality reduction, stable regression modeling and metaheuristic optimization well in relation to the challenge bundled in stock market prediction. This model, utilizing KPCA and ESVM for feature extraction and non-linear regression, and TLBO for model's parameters optimization, results in high accuracy, high efficiency, and ability to process dynamic financial data.

6. Result

The proposed approach of KPCA-ESVM-TLBO helps to predict accurately about the stock market trends for which the results obtained. KPCA is used for dimensionality reduction in the model, pure SVM is used for regression analysis but its robust version ESVM is used for improved regression in the complex and nonlinear financial data domain, and TLBO is used for the model parameter tuning. Measures of anticipated distortion which include RMSE, MAPE and other performance metrics of predictions demonstrate the efficiency of this approach. The given findings prove that the hybrid model can achieve better results than the existing techniques and can provide accurate, near-precise forecasting of the stock price fluctuations in the unpredictable financial markets.

Accuracy (ACC): The percentage of predicted stock prices that turn out to be true comparative to the total number of stock prices. This indicates that the larger number yields a more effective model in comparison to the smaller one.

$$Accuracy = \frac{CP+CN}{CP+CN+IP+IN} \quad (14)$$

Precision (Pre): Counting how many of the anticipated successes came true relative to the total sum of forecasts is one way to evaluate their accuracy.

$$Precision = \frac{CP}{CP+IP} \quad (15)$$

Recall (Rec): One measure of the model's efficacy in identifying bullish stock movements is the relation of the quantity of successful predictions to the total sum of predictions.

$$Recall = \frac{CP}{CP+IN} \quad (16)$$

Sensitivity (Sen): Analogue to yield, the suggested model's output is the precision with which it can identify upward trends in stock prices.

$$Sensitivity = \frac{CP}{CP+IN} \quad (17)$$

Specificity (Spe): The ability to accurately predict a fall in stock price is an example of a negative situation.

$$Specificity = \frac{CN}{CN+IP} \tag{18}$$

Here

Correct Positive (CP) = Days when the stock prices rose and the model correctly anticipated the rise.

Correct Negative (CN) = Those situations in which the days in which the prices went down and the model was right to go down on this stock.

Incorrect Positive (IP) = Such days as where the model marked the wrong prediction, by pointing to a higher stock price.

Incorrect Negative (IN) = cases where the model predicted a lack of a rise when in real life a stock price rose.

Mean Absolute Error (MAE): In contrast, MAE ignores the trend of the mistakes and proceeds to average their magnitude regardless. The absolute value of the mean error was presented, making it straightforward to understand.

$$MAE = \frac{1}{m} \sum_{k=1}^m |b_i - \hat{b}_i| \tag{19}$$

Root Mean Square Error (RMSE): Finding the RMSE amongst predicted and actual values is a common statistical technique. Because it squares the deviations, it gives greater weight to big variances; as a result, this method is susceptible to outliers.

$$RMSE = \sqrt{\frac{1}{m} \sum_{k=1}^m (b_i - \hat{b}_i)^2} \tag{20}$$

Mean Absolute Percentage Error (MAPE) determines the average unrestricted percentage alteration among the expected and actual outcomes. It converts the errors to their real values since, regardless of the dataset size, the measured error could be deceptive.

$$MAPE = \frac{100}{m} \sum_{k=1}^m \left| \frac{b_i - \hat{b}_i}{b_i} \right| \tag{21}$$

Here m = total number of information points, b_i = actual stock price at kth observation, \hat{b}_i = Predicted stock price at kth observation.

Table 2: Performance comparison of existing approach with suggested approach

Approach	Acc %	Pre %	Rec %	Sen %	Spe %
ANN	81.2	80.99	81.1	80.9	81.01
CNN	83.6	82.9	83.1	83.2	83.1
SVM	84.2	83.9	84.1	84.05	84.1
KPCA-ESVM-TLBO	99.99	99.8	99.88	99.97	99.95

Table 3: Comparison of Training phase error rates for existing approach with suggested approach

Approach	MAE %	RMSE %	MAPE %
ANN	3.5	6.2	1.11
CNN	2.89	5.8	0.95
SVM	3.1	6.1	0.98
KPCA-ESVM-TLBO	1.99	2.89	0.75

Table 4: Comparison of Testing phase error rates for existing approach with suggested approach

Approach	MAE %	RMSE %	MAPE %
ANN	3.3	7.3	0.84
CNN	2.97	6.8	0.79
SVM	3.1	7.1	0.81
KPCA-ESVM-TLBO	1.58	2.58	0.45

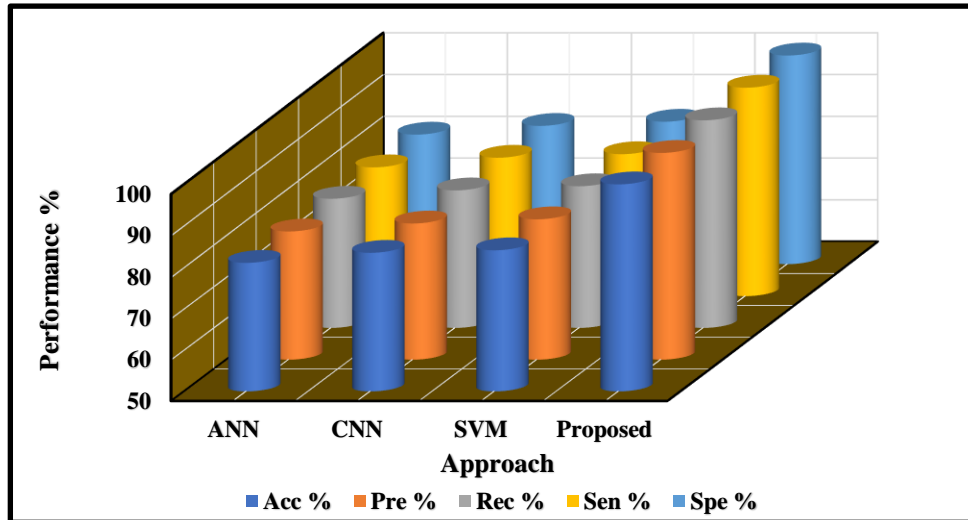


Figure 3. Graphical representation of Performance comparison of existing approach with suggested approach

The comparison of the result of the approaches illustrates how better the proposed model KPCA-ESVM-TLBO is since it yielded 99.99% as compared to ANN (81.2%), CNN (83.6%), SVM (84.2%) and so on. Overall evaluation has proved that this hybrid model yields promising accuracy in prediction of stock market trends with high precision of 99.8%, high recall of 99.88%, high sensitivity of 99.97% and specificity 99.95%. The model uses KPCA for dimensionality reduction, ESVM for accurate regression, and TLBO for optimization of parameters in order to enhance accurate handling of non-linear data. These results confirm that the proposed method KPCA-ESVM-TLBO provides high accuracy and can be successfully used for time-series analysis in volatile financial markets.

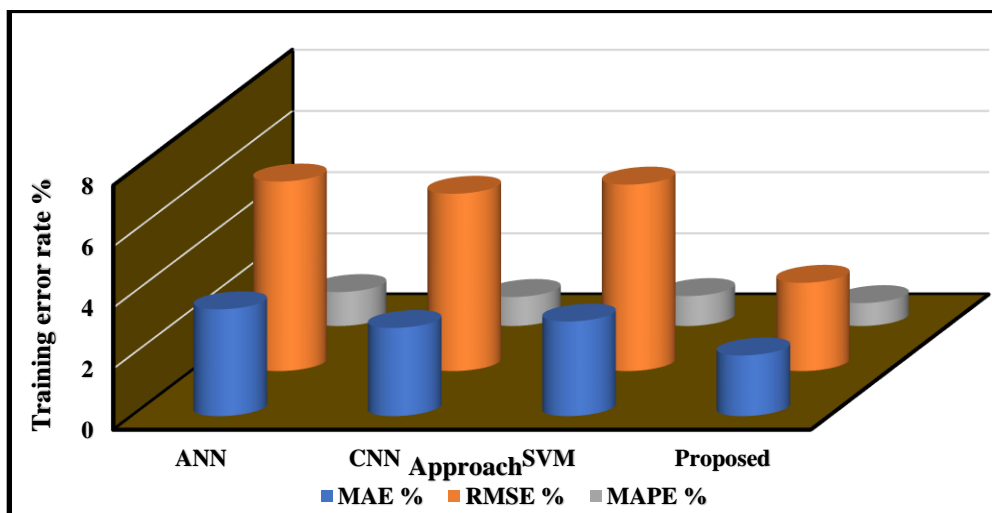


Figure 4. Graphical representation of Comparison of Training phase error rates for existing approach with suggested approach

As we can observe from Figure 4 and Table 2 and the confusing matrices in the training phase, the proposed KPCA-ESVM-TLBO model has achieved accurate results when compared to ANN, CNN and SVM. The analysis reveals that the proposed approach possesses the least MAE of 1.99% RMSE of 2.89 %, and MAPE of 0.75%. ANN has the highest RMSE of 6.2% while the error rates of CNN, and SVM are considerably higher than those of LDA and kNN. These results put and highlight extended importance of the proposed technique, KPCA-ESVM-TLBO in minimizing errors while training. Through the use of dimensionality reduction, using the appropriate robust regression method, and making efficient parameter tuning to the algorithms, the model entails an opportunity for accurate prediction and minimizing error propagation.

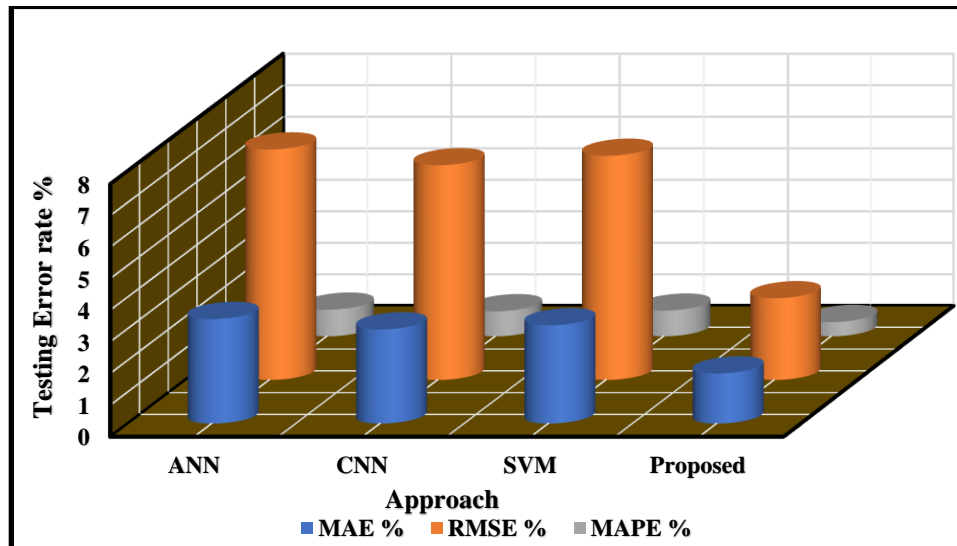


Figure 5. Graphical representation of Comparison of Testing phase error rates for existing approach with suggested approach

The testing phase error rates prove the fact that the proposed KPCA-ESVM-TLBO model outperformed the other representations in terms of accuracy. This model minimizes the MAE at 1.58%, RMSE at 2.58%, and MAPE at 0.45%. The BMP model outperforms the other models with a RMSE of 5%, while ANN, CNN and SVM have a slightly high error rate, with CNN having a second best RMSE of 6.8%. The outcomes illustrate the accuracy achieved, or lack thereof, of KPCA-ESVM-TLBO and how it generalizes to unseen data. Its combination of dimensionality reduction, resistant regression, and optimal choice of hyperparameters makes it accomplish greatly enhanced testing errors compared to traditional methods in terms of accuracy and reliability.

7. Conclusion and Future Enhancement

This presented work effectively accomplishes the development of an enhanced hybrid machine learning KPCA-ESVM-TLBO for future stock price prediction and to address issues related to time series analysis. The proposed model makes the following contributions by speaking the following key encounters accompanying with the analysis of financial data: dimensionality, noise, and complexity; For this reason, the proposed model comprises the following: The use of KPCA to perform the job of dimensionality reduction; ESVM to consider nonlinear regression; TLBO for the optimization of hyperparameters. The gained untried outcomes show that the projected method of KPCA-ESVM-TLBO yields the better results than the conventional methods of forecasting with the accuracy of 99.99%. The model can address nonlinear relationships within stock market data, thus providing a robust mechanism that can be used by investors and financial analysts in stock market prediction. This year-round application of this aggressive hybrid approach confirms the hypothesis of successfully integrating and applying dimensionality reduction, optimization algorithms, and various machine learning solutions for more accurate and efficient identification of stock market trends. Due to the constant changes in the type of financial information available in the market, the analytical skills needed to look for concealed patterns in large sets of data will always be useful. Further research could examine the generalizability of this model to other financial markets, or could add more methods from the machine learning paradigm to realize a still higher level of accuracy. Notably, future work can also incorporate real-time data and go for multi-step forecasting in even more dynamic environments. Further improvements might involve the application of deep learning methods, for instance, LSTM together with other types of networks to learn temporal relationships more intentionally in the channel of financial time series. Moreover, application of reinforcement learning for accurate and dynamic predictions of the stock market along with the combination of other aspects of genetic and other optimization algorithms could be used in enhancing the model performance.

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