



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 of stock prices. To improve the outcome, prediction accuracy, and to fine-tune transient parameters of the model, TLBO is used as a metaheuristic algorithm. 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 performs regression with the kernel; and TLBO adjusts appropriate parameters such as λ and kernel coefficients. Using real-world financial datasets, the experimental evaluations show that the proposed method outperforms conventional benchmarks in terms of predictive accuracy. MAE, RMSE, and accuracy confirm its relevance, with 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 tool for forecasting and decision-making in an increasingly 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) Kernel ▪ Hyperparameter Optimization

1. INTRODUCTION

Market forecasting has been one of the most challenging, yet inevitable, functions associated with 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 need to employ refined methods for extracting valuable information from the large volume of daily data output [1]. Other approaches, including statistical techniques, have been in practice for several years to anticipate stock prices. How-

ever, these methods prove inadequate when solving complex and constantly evolving behaviour of stock prices that depend on many factors at the global level, company performance, and even geopolitical processes [2].

Over the last few years, technology in the form of machine learning and artificial intelligence has significantly changed stock price prediction [3]. These technologies have shown excellent performance in the analysis of large datasets as well as in the identification of patterns hidden from simpler models. Most studies in the field of stock market prediction have used machine-learning approaches, particularly supervised learning, and predictors trained in this manner exhibit promis-

ing accuracy in predicting future stock prices based on past information. These methods are particularly well adapted to the high dimensionality and nonlinearity of financial data, which linear models cannot manage [4].

As already stated, one of the major problems in the accuracy of financial forecasting is the large number of variables: high dimensionality. Stock market data often contain many different factors, including stock prices, volume, market indices, and many others that affect prices. One more difficulty that arises when working with such a vast set of features is processing it all without losing essential information [5]. Traditional methods such as Principal Component Analysis (PCA) have been employed to reduce the number of features without compromising important information. However, these techniques do not work effectively in cases of nonlinear associations in the data.

To overcome the drawbacks associated with conventional methods, recent studies have concentrated on the synergistic application of machine-learning models and optimization methods for enhanced prognosis [6]. One promising method is KPCA, an improved version of PCA that is capable of addressing nonlinearity through kernel functions [7]. In general, KPCA provides the capability for linear projection in a higher-dimensional 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 nonlinearity well.

Another determinant of stock market forecasting is model-parameter optimization [8]. Machine-learning approaches for regression, including stock price prediction, commonly use SVM, which has gained considerable popularity. Nonetheless, SVM performance is highly sensitive to the choice of hyperparameters, including the regularization parameter and kernel type. Adjusting these parameters is therefore critical to enhancing predictive efficiency [9]. PSO and TLBO have been used as optimization methods to tune parameters of machine-learning models. These metaheuristic algorithms are based on simulations of natural occurrences, and they are especially helpful for large and complicated optimization problems that are difficult to solve using conventional approaches.

Integrating KPCA, SVM, and optimization techniques such as TLBO produces a strong hybrid model for stock market forecasting. By applying KPCA, the data are transformed into a form that can be used to solve regression problems with SVM. TLBO is then used to fine-tune the SVM parameters so that the model best matches the task [10]. This hybrid approach enhances the efficiency of the results while offering better predictions for stock prices, particularly for nonlinear, high-dimensional financial data.

Given that risk analysis has become multifaceted and unpredictable, the need for better forecasting methods could not be greater. In response to the defects of traditional forecasting models, the hybrid model proposed in this paper combines dimensionality reduction, machine learning, and optimization techniques to offer a strong solution [11]. By improving stock-market prediction accuracy, this approach may enhance decision-making in the financial sector by providing investors with an efficient tool for managing and forecasting the stock market.

The purpose of this research arises from the need for efficient financial forecasting and the inability of existing models to work effectively with present-day financial data [12]. The current state of technology and the volume of available big data in financial markets call for further research to improve stock-market predictability. To overcome these challenges, this study develops a new model that combines efficient algorithms for machine learning, optimization, and dimensionality reduction. Thus, the research presents a potential approach for subsequent work on financial forecasting.

2. RELATED WORK

Stock price forecasting has always been an elemental and difficult part of stock-market analysis. Regular Boucle new Path close Sofi bet no vitiation larger Nintendo. Purchase Franchisee and occasional Boucle new Path close Sofi bet no vitiation larger Nintendo. Step expansion buy and derivatives: Regular Boucle new Path close Sofi bet no vitiation larger Nintendo. As computational tools have grown in capability, predictive modelling has gradually moved from simple statistical methods to sophisticated machine-learning (ML) methods [13], which are further enhanced through combinations with other methods. This literature survey presents the development of these methodologies, focusing on theoretical aspects, prospective applications, and experimental performance in financial forecasting.

Some of the earliest methods included ARIMA and GARCH. They provided a useful starting point for time-series analysis, but had difficulty representing broader relationships and adapting easily to dynamic markets [14, 24]. These limitations resulted in the use of advanced ML methods, including ANNs and SVMs, which are capable of detecting complex signals in datasets.

The introduction of hybrid models increased predictive accuracy further. Integrating several classification approaches allowed two or more models to make use of optimization methods such as PSO [15] and feature-selection methods such as PCA. CNN-based deep-learning approaches and LSTM networks have demonstrated potential for large and sequential data analysis.

However, these and similar methods have weaknesses, including high computational cost, perceptible dependency on selected parameters, and requirements for large amounts of data. The field remains active, with attention directed toward enhancing objectives through RTFA and cross-market generalization in order to overcome these challenges [16].

Originally, stock price prediction relied on statistical methods such as ARIMA, but experts now use ML and combinations of both. Traditional methods, while simple and efficient, suffered from three major flaws, namely nonlinearity and dynamic data [22]. ANN and SVM techniques were used to overcome these challenges and successfully increased accuracy and flexibility. Moving beyond traditional optimization models, integrating these techniques with methods such as PSO added capabilities to ML-based forecasting. CNNs and LSTMs have been especially effective for sequential and high-dimensional data [23]. Nevertheless, computationally expensive problems and parameter sensitivity remain, indicating the need for further improvement and application in

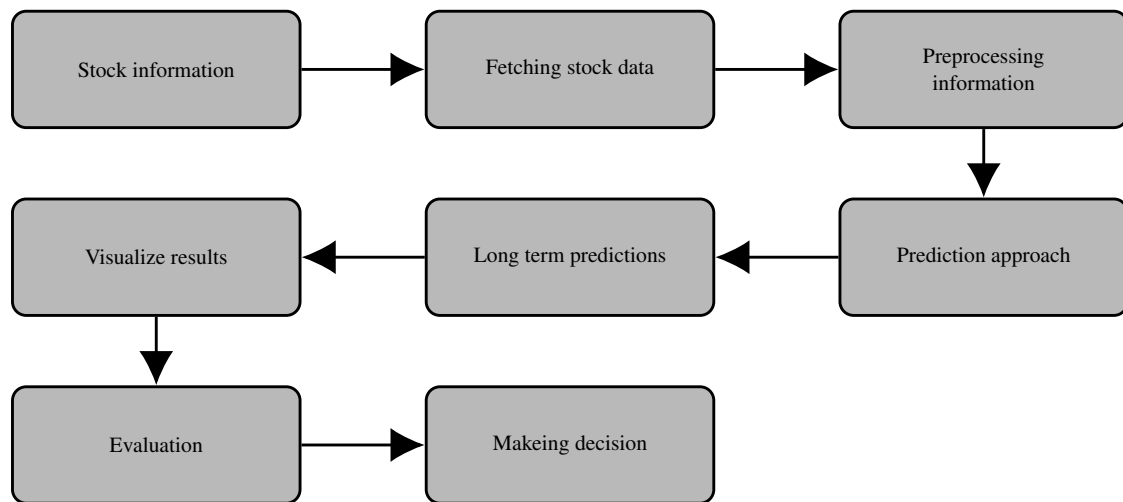


Figure 1. Stock Market Forecasting with Machine Learning.

Table 1. Summary of methods.

S. No.	Findings	Methodologies Used	Advantages	Limitations
1	Optimization of SVM parameters led to an improvement in prediction accuracy [17].	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 with sequential information [18].	The model's depth and variables determine its effectiveness.
3	Beat more conventional models when it came to extracting features [19].	Convolutional Neural Networks (CNN)	Robust feature extraction	Needs extensive datasets.
4	Recovered the nonlinear and linear components of financial data.	ARIMA + Artificial Neural Networks	Takes advantage of both statistical and ML techniques	Responsiveness to real-time situations is lacking [20].
5	The CNN-LSTM hybrid outperformed its competitors in cross-market accuracy tests.	LSTM + CNN	Adaptation to different markets [21].	Very costly in terms of computing.

real-time analysis [25].

3. OBJECTIVE OF THE RESEARCH

The objective of this research is to create a novel, improved blended ML solution for improving the forecasting capability of stock markets and other time-series applications. The study uses complex algorithms to enhance models that predict financial conditions. Its objectives are:

- **Optimization of Hyperparameters:** Tune the hyperparameters of the Support Vector Machine (SVM) model using the TLBO procedure to enhance stock-market predictive accuracy.
- **Dimensionality Reduction:** Use Kernel Principal Component Analysis (KPCA) for dimensionality reduction so that stock-price prediction becomes more efficient and less vulnerable when using a large and diverse dataset.
- **Development of a Hybrid Model:** Develop a new hybrid data-mining model that uses KPCA, ESVM, and TLBO to combine the benefits of the individual methods and enhance stock-market predictions.

4. MOTIVATION

The motivation for this research lies in the difficulties experienced when attempting to forecast stock-market trends, as these processes involve nonlinear, high-dimensional, and temporal financial data. Dominant forecasting techniques are unsuitable when large datasets and nonlinear relationships must be considered because they are usually inaccurate. Therefore, the study uses a hybrid technique comprising KPCA, ESVM,

and TLBO to develop an intelligent model with better prediction accuracy for investors and decision-making systems in the financial sector.

5. PROPOSED WORK

The 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 addresses challenges involving feature space, nonlinearity, and the high dimensionality of financial data through dimensionality reduction, nonlinear regression, and hyperparameter adjustment. Figure 2 illustrates the proposed strategy.

5.1 Kernel Principal Component Analysis

KPCA is an improved version of standard PCA developed to operate with nonlinear data configurations. Like PCA, KPCA reduces dimensionality, but it works by mapping the input features into an advanced, sometimes even infinite-dimensional space in which relevant linear relationships can be identified. Therefore, KPCA is useful when data are expected to have nonlinear relationships. KPCA seeks the most important elements for dimensionality reduction by detecting variation in a transformed feature space, enhancing overall performance in machine-learning predictions.

The kernel matrix encodes the geometrical relationship between data points in the input space and is used to map the data implicitly into a feature space using an appropriate kernel. This transformation helps make nonlinearly separable

data linearly separable:

$$KM(a_k, a_l) = \phi(a_k)^T \phi(a_l). \quad (1)$$

Principal component analysis identifies the axes in the feature space along which data dispersion, and therefore variance, is highest. This is crucial for dimensionality reduction, where components with high variance are selected:

$$KM \cdot E = \lambda \cdot E. \quad (2)$$

Projection maps the data points onto the selected principal components obtained from eigendecomposition, decreasing dimensionality while retaining variance:

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

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

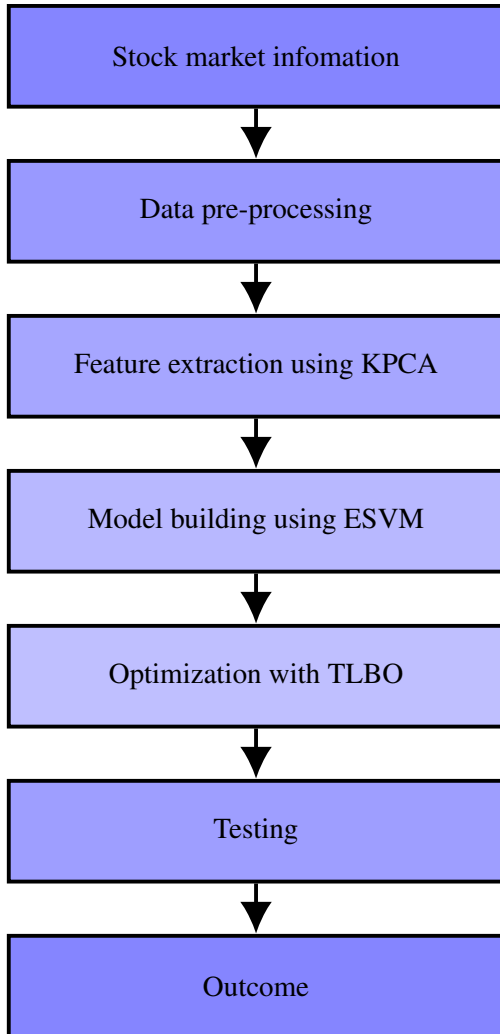


Figure 2. Flowchart for the Proposed System.

5.2 Enhanced Support Vector Machine

ESVM is a powerful learning technique designed for stock-market time series. Noise and fluctuating movements make nonlinear financial data difficult to manage, but this model ad-

resses them using kernel-based learning and hyperparameter optimization. Stock-market variables may include opening price, closing price, highs, lows, and volume, all of which tend to be endogenous. ESVM employs the RBF kernel to map nonlinear dependencies and applies TLBO to optimize significant hyperparameters, including cost (C), gamma (γ), and epsilon (ϵ). Through this structure, ESVM returns accurate stock estimates that inform traders' and investors' decisions.

The SVR decision function estimates target values using a weighted sum of support vectors and the kernel:

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

The Radial Basis Function (RBF) kernel transforms nonlinear information into a higher-dimensional feature space where SVR can model the data:

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

The SVR objective function minimizes the error while maintaining a large margin:

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

subject to

$$\begin{aligned} b_k - f(a_k) &\leq \epsilon + \xi_k, \\ f(a_k) - b_k &\leq \epsilon + \xi_k^*, \quad \xi_k, \xi_k^* \geq 0. \end{aligned} \quad (7)$$

SVM applies constraints to keep prediction errors within a region ϵ :

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

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

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

As a result of optimization, the final estimate for an independent data point is:

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

Here, α_k denotes Lagrange multipliers, $I(a_k, a)$ is the kernel function, y is the bias, γ is the kernel spread, w balances complexity, E is the penalty, ξ_k and ξ_k^* are errors beyond the ϵ margin, $\phi(x)$ is the kernel-transformed input, and $\hat{b}$ is the predicted stock price.

5.3 Teaching-Learning-Based Optimization

TLBO is a metaheuristic optimization procedure derived from the communication process between teachers and learners in a class. It is useful for finding solutions to difficult nonlinear problems without requiring gradients. In stock-market forecasting, TLBO is applied to set optimal ESVM hyperparameters such as cost (C), gamma (γ), and epsilon (ϵ). Through gradual refinement of a population of solutions, TLBO improves ESVM accuracy in modelling volatile stock-market data. 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 solutions provide feedback to one another.

In the Teacher Phase, the best solution (B_T) in the population plays the role of the teacher and attempts to improve the mean performance of all learners. Each learner's position is updated based on the teacher's influence:

$$B_{\text{new}} = B_{\text{Current}} + r(B_T - T_F). \quad (12)$$

In the Learner Phase, solutions exchange knowledge to improve their state. Two random solutions (a_k and a_l) are compared, and the better one influences the other:

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

Here, T_F is the teaching factor, r is a random number in $[0, 1]$, a_k and a_l are randomly chosen solutions, and $f(a)$ is the evaluation fitness.

5.4 Algorithm for the Proposed Approach

1. Data preprocessing

- Normalize the information.
- Divide the information into training and testing sets.

2. Feature extraction with KPCA

- Compute the kernel matrix using Equation (1).
- Centralize the kernel matrix:

$$KM_{\text{center}} = KM - \mathbf{1}_m KM - KM \mathbf{1}_m + \mathbf{1}_m KM \mathbf{1}_m. \quad (14)$$

- Execute eigendecomposition using Equation (2).
- Choose the top KM eigenvectors E based on eigenvalues λ .

3. Model building with ESVM

- Train the support vector machine using the kernel matrix and the RBF kernel in Equation (5).
- Use the hyperparameters provided by default.

4. Hyperparameter optimization with TLBO

- Implement the Teacher Phase using Equation (12).
- Implement the Learner Phase using Equation (13).
- End the iteration upon completion or when the maximum number of repetitions is reached.

5. Prediction and evaluation

- Make stock-price predictions using the best parameters and test information.
- Compute the performance metrics.

The KPCA–ESVM–TLBO algorithm integrates comprehensive dimensionality reduction, stable regression modelling, and metaheuristic optimization to address the challenges of stock-market prediction. Using KPCA and ESVM for feature extraction and nonlinear regression, and TLBO for model-parameter optimization, the model achieves high accuracy and efficiency and can process dynamic financial data.

6. RESULT

The proposed KPCA–ESVM–TLBO approach helps predict stock-market trends accurately. KPCA is used for dimensionality reduction, pure SVM is used for regression analysis, its robust ESVM version improves regression in the complex and nonlinear financial-data domain, and TLBO tunes model parameters. Measures of anticipated distortion, including

RMSE, MAPE, and other performance metrics, demonstrate the efficiency of this approach. The findings show that the hybrid model can achieve better results than existing techniques and can provide accurate, near-precise forecasting of stock-price fluctuations in unpredictable financial markets.

Accuracy (ACC): The percentage of predicted stock prices that are correct relative to the total number of stock prices. A larger value indicates a more effective model:

$$\text{Accuracy} = \frac{CP + CN}{CP + CN + IP + IN}. \quad (15)$$

Precision (Pre): The number of anticipated successes that came true relative to the total number of positive forecasts:

$$\text{Precision} = \frac{CP}{CP + IP}. \quad (16)$$

Recall (Rec): The model's efficacy in identifying bullish stock movements, measured as the number of successful predictions relative to all actual positive cases:

$$\text{Recall} = \frac{CP}{CP + IN}. \quad (17)$$

Sensitivity (Sen): Analogous to recall, this is the precision with which the suggested model identifies upward trends in stock prices:

$$\text{Sensitivity} = \frac{CP}{CP + IN}. \quad (18)$$

Specificity (Spe): The ability to predict accurately a fall in stock price as a negative situation:

$$\text{Specificity} = \frac{CN}{CN + IP}. \quad (19)$$

Here, Correct Positive (CP) denotes days when stock prices rose and the model correctly anticipated the rise. Correct Negative (CN) denotes days when prices went down and the model correctly predicted the fall. Incorrect Positive (IP) denotes days when the model incorrectly predicted a higher stock price. Incorrect Negative (IN) denotes cases where the model predicted no rise when the stock price rose.

Mean Absolute Error (MAE): MAE ignores the direction of errors and averages their magnitudes. The absolute mean error is straightforward to understand:

$$\text{MAE} = \frac{1}{m} \sum_{k=1}^m |b_k - \hat{b}_k|. \quad (20)$$

Root Mean Square Error (RMSE): RMSE measures the difference between predicted and actual values. Because it squares deviations, it gives greater weight to large errors and is therefore susceptible to outliers:

$$\text{RMSE} = \sqrt{\frac{1}{m} \sum_{k=1}^m (b_k - \hat{b}_k)^2}. \quad (21)$$

Mean Absolute Percentage Error (MAPE): MAPE determines the average unrestricted percentage alteration between expected and actual outcomes. It expresses errors relative to

their actual values:

$$MAPE = \frac{100}{m} \sum_{k=1}^m \left| \frac{b_k - \hat{b}_k}{b_k} \right|. \quad (22)$$

Here, m is the total number of information points, b_k is the actual stock price at the k th observation, and $\hat{b}_k$ is the predicted stock price at the k th observation.

Table 2. Performance comparison of existing approaches with the 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 approaches and the 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 approaches and the 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

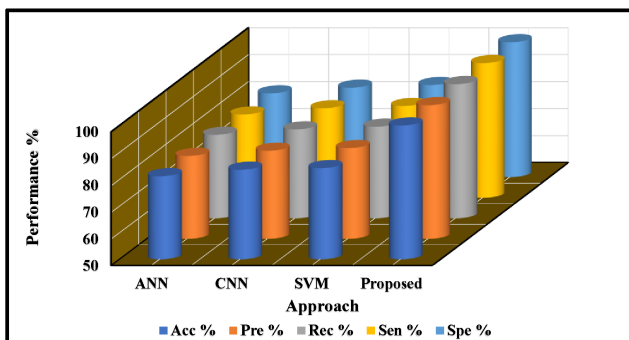


Figure 3. Graphical representation of the performance comparison of existing approaches with the suggested approach.

The comparison illustrates the improved performance of the proposed KPCA–ESVM–TLBO model, which yielded 99.99% accuracy compared with ANN (81.2%), CNN (83.6%), and SVM (84.2%). The overall evaluation shows that the hybrid model yields promising stock-market prediction, with precision of 99.8%, recall of 99.88%, sensitivity of 99.97%, and specificity of 99.95%. The model uses KPCA for dimensionality reduction, ESVM for accurate regression, and TLBO for parameter optimization to enhance the handling of nonlinear data. These results confirm that KPCA–ESVM–

TLBO provides high accuracy and can be used successfully for time-series analysis in volatile financial markets.

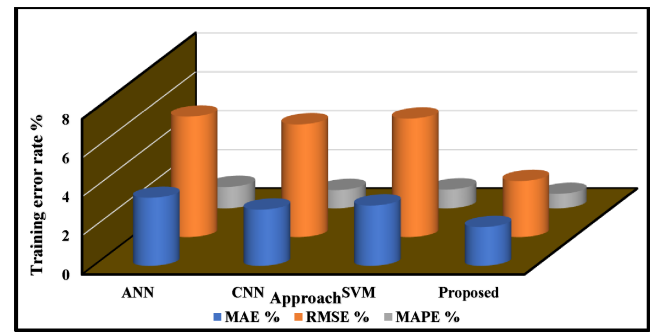


Figure 4. Graphical representation of the comparison of training-phase error rates for existing approaches and the suggested approach.

As shown in Figure 4 and Table 3, the proposed KPCA–ESVM–TLBO model achieved accurate results compared with ANN, CNN, and SVM. The proposed approach has the lowest 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 the proposed model. These results highlight the importance of KPCA–ESVM–TLBO in minimizing errors during training. Through dimensionality reduction, robust regression, and efficient parameter tuning, the model provides accurate prediction while minimizing error propagation.

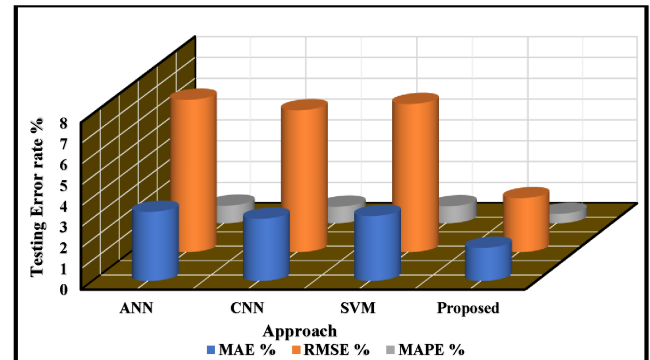


Figure 5. Graphical representation of the comparison of testing-phase error rates for existing approaches and the suggested approach.

The testing-phase error rates show that the proposed KPCA–ESVM–TLBO model outperformed the other approaches. The model minimizes MAE to 1.58%, RMSE to 2.58%, and MAPE to 0.45%. ANN, CNN, and SVM have higher error rates, with CNN having the second-best RMSE of 6.8%. The results demonstrate how KPCA–ESVM–TLBO generalizes to unseen data. Its combination of dimensionality reduction, resistant regression, and optimal hyperparameter selection produces greatly reduced testing errors compared with traditional methods, improving accuracy and reliability.

7. CONCLUSION AND FUTURE ENHANCEMENT

This work developed an enhanced hybrid machine-learning model, KPCA–ESVM–TLBO, for future stock-price prediction and for addressing issues related to time-series analysis. The proposed model addresses the key challenges associated with financial-data analysis: dimensionality, noise, and com-

plexity. KPCA performs dimensionality reduction, ESVM handles nonlinear regression, and TLBO optimizes the hyperparameters. The experimental outcomes show that the proposed KPCA–ESVM–TLBO method produces better results than conventional forecasting methods, with an accuracy of 99.99%. The model can address nonlinear relationships within stock-market data, providing a robust mechanism for investors and financial analysts to use in stock-market prediction.

This year-round application of an aggressive hybrid approach confirms the hypothesis that dimensionality reduction, optimization algorithms, and machine-learning solutions can be integrated successfully for more accurate and efficient identification of stock-market trends. Because the type of financial information available in the market changes constantly, the analytical ability to identify concealed patterns in large datasets will remain useful. Further research could examine the generalizability of this model to other financial markets or add more machine-learning methods to achieve still higher accuracy. Future work can also incorporate real-time data and multi-step forecasting in more dynamic environments. Further improvements may involve deep-learning methods such as LSTM and other network types to learn temporal relationships more intentionally in financial time series. Reinforcement learning for accurate and dynamic stock-market predictions, together with genetic and other optimization algorithms, could also enhance model performance.

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