Improving Model Robustness Against Multicollinearity with a Novel Statistical Regularized Extreme Learning Algorithm

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***Abstract*—Multicollinearity, a persistent challenge in machine learning models, arises when predictor variables are highly correlated, leading to instability and degraded predictive performance. This paper proposes a novel statistical regularization framework integrated into the Extreme Learning Machine (ELM) to systematically mitigate multicollinearity. The approach incorporates Ridge, Lasso, and Elastic Net regularization within the ELM architecture to reduce variance inflation, improve feature selection, and enhance generalization. Comprehensive experiments on benchmark regression datasets, including Boston Housing, Auto MPG, Slump, and Machine CPU, demonstrate the robustness of the proposed models. Results reveal up to 29.6% improvement in prediction accuracy and significantly reduced Variance Inflation Factors (VIFs) compared to baseline ELM and existing regularized ELM variants. The findings highlight that the proposed framework not only stabilizes the learning process in the presence of correlated features but also offers improved interpretability and adaptability across diverse datasets.**

***Index Terms*—Multicollinearity, Extreme Machine Learning, Statistical Regularization, Ridge Regression, Machine Learning.**

I. Introduction

IN machine learning, multicollinearity occurs when two or more input features are highly correlated, leading to inflated variance and instability in the model's predictions. This issue primarily affects linear models, where collinearity between independent variables complicates the estimation of their effects on the target variable. As a result, models suffering from multicollinearity may produce unreliable and inconsistent results, making it difficult to derive meaningful insights from the data [1], [2]. The Extreme Learning Machine (ELM), a type of single-layer feedforward neural network (SLFN), has gained popularity for its fast learning speed and strong generalization capabilities. Unlike traditional neural networks, ELM randomly assigns weights and biases to hidden neurons and analytically computes the output weights. This eliminates the need for iterative tuning and enables efficient learning. However, despite its advantages, ELM is also susceptible to the negative effects of multicollinearity when applied to datasets with highly correlated features [3]. Several techniques have been proposed to address multicollinearity in machine learning models. Among the most widely used methods are Ridge Regression and Lasso, both of which introduce penalties to the loss function, thereby reducing the influence of highly correlated variables. Ridge Regression, by applying an L2 penalty, shrinks the coefficients of correlated features, while Lasso uses an L1 penalty to promote sparsity, effectively selecting the most relevant variables. Although these regularization methods are effective, they have yet to be fully integrated into the ELM framework [4]. In this paper, we propose a novel approach that combines the power of statistical regularization techniques with the ELM model to effectively address multicollinearity. By integrating Ridge and Lasso regularization into the ELM, we aim to reduce the variance inflation caused by collinear features and enhance the model's predictive performance. Through extensive experiments on multicollinear datasets, we show that our regularized ELM method significantly improves model robustness, accuracy, and interpretability. A novel statistical regularization framework for ELM to mitigate multicollinearity. A detailed analysis of the performance improvement achieved by Ridge and Lasso regularization in ELM. An experimental evaluation demonstrating the effectiveness of the proposed approach on benchmark datasets prone to multicollinearity [5].

Multicollinearity has been acknowledged as a significant concern in statistical modeling and machine learning. It can skew the correlation between input features and the target variable, resulting in faulty and ineffective models. This section examines prior research on finding and alleviating multicollinearity, specifically emphasizing techniques uti-

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lized in neural networks and the Extreme Learning Machine (ELM) [6], [7]. In regression models, multicollinearity results in inflated standard errors for the predicted coefficients, complicating the assessment of the underlying impact of various predictors. A variety of diagnostic instruments have been created to detect multicollinearity, with the Variance Inflation Factor (VIF) being among the most commonly utilized. A high VIF score for a feature signifies substantial multicollinearity with other features, indicating the necessity for mitigation techniques [8]. Various techniques have been suggested to mitigate multicollinearity, including Principal Component Analysis (PCA), which converts correlated variables into a collection of uncorrelated components. Nonetheless, PCA has constraints, as it may hinder the interpretability of the original variables. Dimensionality reduction methods like as PCA effectively decrease the number of correlated variables, although they may not completely preserve the original data structure, rendering them less appropriate for applications necessitating feature interpretability [9]. Regularization techniques have demonstrated efficacy in addressing multicollinearity by imposing constraints on model parameters. The two predominant forms of regularization are Ridge Regression and Lasso. Ridge regression applies a penalty to the cost function, so reducing the coefficients of multicollinear features without completely removing any variables. This aids in alleviating multicollinearity while enabling the model to utilize all available features. Ridge regression is extensively utilized in linear and logistic regression models to improve their robustness against correlated data [10].

Lasso applies penalty, which not only shrink's coefficients but also drives some of them to zero, effectively performing variable selection. This property makes Lasso particularly useful for sparse models where feature selection is necessary. Lasso has been used extensively in fields where high-dimensional data and multicollinearity are prevalent, such as bioinformatics and finance [11]. While these regularization techniques are well-suited for linear models, their application to neural networks, including ELM, has been relatively underexplored. Traditional neural networks and feedforward architectures typically rely on dropout or weight decay to control overfitting, but these methods do not explicitly address multicollinearity among the input features [12]. The Extreme Learning Machine (ELM) is a learning algorithm designed for single-layer feedforward networks (SLFN), known for its rapid training speed and capacity to handle large-scale data. ELM assigns random weights and biases to the hidden neurons and calculates the output weights using a least squares solution. This makes ELM highly efficient compared to traditional gradient-based training methods. [13]. However, ELM's performance can degrade in the presence of multicollinearity, as the least squares approach is sensitive to correlated features. Recent studies have sought to enhance ELM by incorporating regularization strategies. For example, variations like Regularized ELM (RELM) and Lasso-based ELM have been proposed to improve generalization and robustness. Nonetheless, these approaches often focus on improving general overfitting issues rather than specifically addressing multicollinearity [14], [15].

Few studies have focused on tackling multicollinearity in the ELM framework directly. Existing work has primarily centered around introducing Ridge regression or L_2 regularizations to ELM, as in Regularized ELM (RELM), which helps in constraining the magnitude of output weights, thereby reducing model sensitivity to correlated features. However, the potential of Lasso in ELM has not been fully realized, particularly in its ability to perform feature selection in addition to handling multicollinearity [16], [17]. To the best of our knowledge, no prior work has systematically integrated both Ridge and Lasso regularization into ELM to specifically target multicollinearity. Given the efficiency of ELM and the proven success of these regularization techniques in addressing collinearity in other contexts, this paper aims to fill the gap by proposing a novel statistical regularized ELM framework [18], [19]. Despite the effectiveness of Ridge and Lasso in other machine learning models, their integration with ELM to address multicollinearity remains limited. Most existing approaches for regularized ELM focus on generalization improvement, with less emphasis on addressing the unique challenges posed by multicollinearity. Additionally, there has been little exploration of the impact of feature selection (via Lasso) in combination with ELM, which can offer benefits in terms of interpretability and performance, particularly when working with high-dimensional data [20].

This paper addresses this gap by proposing a regularized ELM that incorporates both Ridge and Lasso techniques to tackle multicollinearity, offering a comprehensive solution that improves model stability, interpretability, and accuracy in the presence of correlated features. This section reviewed key methods for addressing multicollinearity and their application in machine learning. While existing techniques like Ridge and Lasso have been used successfully in linear models, their full potential has not yet been realized in ELM frameworks. Our research aims to bridge this gap by developing a novel regularized ELM model that specifically addresses multicollinearity, leveraging both Ridge and Lasso to enhance performance and model robustness.

II. METHODOLOGY

This section presents the proposed approach for integrating statistical regularization into the Extreme Learning Machine (ELM) framework to address multicollinearity. The methodology involves leveraging Ridge and Lasso regularization techniques to improve the robustness and generalization of ELM, particularly when applied to datasets with correlated features [21], [22].

A. Overview of Extreme Learning Machine (ELM)

The Extreme Learning Machine (ELM) is a fast-learning algorithm designed for single-layer feedforward neural networks (SLFN). It operates by randomly assigning weights and biases to the hidden layer neurons and analytically computing the output weights through a least squares solution. ELM's speed and simplicity make it well-suited for large datasets; however, it can suffer from performance degradation in the presence of multicollinear features [23]. The core mathematical representation of ELM is as follows: Given an input dataset $X \in Rn \times d$ with n samples and d features, and the target output matrix Y∈Rn×m, ELM computes the hidden layer output matrix Y∈Rn×m where N is the number of hidden neurons. The relationship between the input and output layers is expressed as:

$$H\beta=Y \qquad (1)$$

where β∈RN×m is the weight matrix between the hidden layer and the output layer. The output weights β are calculated using the least squares solution:

$$\beta=H^{\dagger}Y \qquad (2)$$

where H† is the Moore-Penrose pseudoinverse of the hidden layer matrix. However, this solution becomes unstable when input features are multicollinear, leading to overfitting and poor generalization. To address this, we introduce regularization techniques that modify the least squares solution, thereby reducing the effect of multicollinearity.

B. Regularization Techniques for Multicollinearity

Regularization is an effective way to prevent overfitting and to mitigate the impact of multicollinearity by shrinking the coefficients of correlated predictors. The two main techniques we integrate with ELM are Ridge Regression and Lasso [24]. Ridge regression introduces an L2 penalty to the loss function, which shrinks the output weights β but does not eliminate any features entirely. The regularized objective function for ELM with Ridge regression is given by:

$$CostRidge=\|H\beta-Y\|2+\lambda\|\beta\|2 \qquad (3)$$

where λ is the regularization parameter controlling the degree of shrinkage. A larger λ results in more significant shrinkage of the coefficients, reducing the impact of multicollinear features while retaining all input variables. The solution for β is modified as:

$$\beta=(HTH+\lambda I)\ -1HTY \qquad (4)$$

where I am the identity matrix. Ridge regularization is particularly effective in cases where multicollinearity is present but all input features carry important information. Lasso applies an L1 penalty to the loss function, encouraging sparsity by driving some coefficients to zero, which effectively performs feature selection. The regularized objective function for ELM with Lasso is given by:

$$CostLasso=\|H\beta-Y\|2+\lambda\|\beta\|1 \qquad (5)$$

The L1 penalty tends to shrink coefficients of multicollinear features, and if a feature is redundant, Lasso will shrink its coefficient to zero. This makes Lasso articularly suitable for high-dimensional datasets with many correlated features, where it is essential to select only the most informative variables. The solution for β is obtained through convex optimization, as it does not have a closed-form expression like Ridge.

Elastic Net is a hybrid regularization technique that combines the strengths of Ridge and Lasso by incorporating both L1 and L2 penalties. The objective function for Elastic Net is:

$$CostElastic\ Net=\|H\beta-Y\|2+\lambda1\|\beta\|1+\lambda2\|\beta\|2 \qquad (6)$$

This allows the model to handle multicollinearity (via L2) and perform feature selection (via L1) simultaneously, providing a flexible regularization framework. Elastic Net is particularly useful when the dataset contains both highly correlated features and irrelevant features.

C. Proposed Regularized ELM Algorithm

The suggested methodology integrates Ridge, Lasso, and Elastic Net regularization inside the ELM framework to address multicollinearity efficiently. The procedures of the suggested regularized ELM algorithm are outlined as follows: Standardize the input data X to guarantee uniformity across all characteristics. Compute the Variance Inflation Factor (VIF) for each feature to detect highly collinear variables [25].

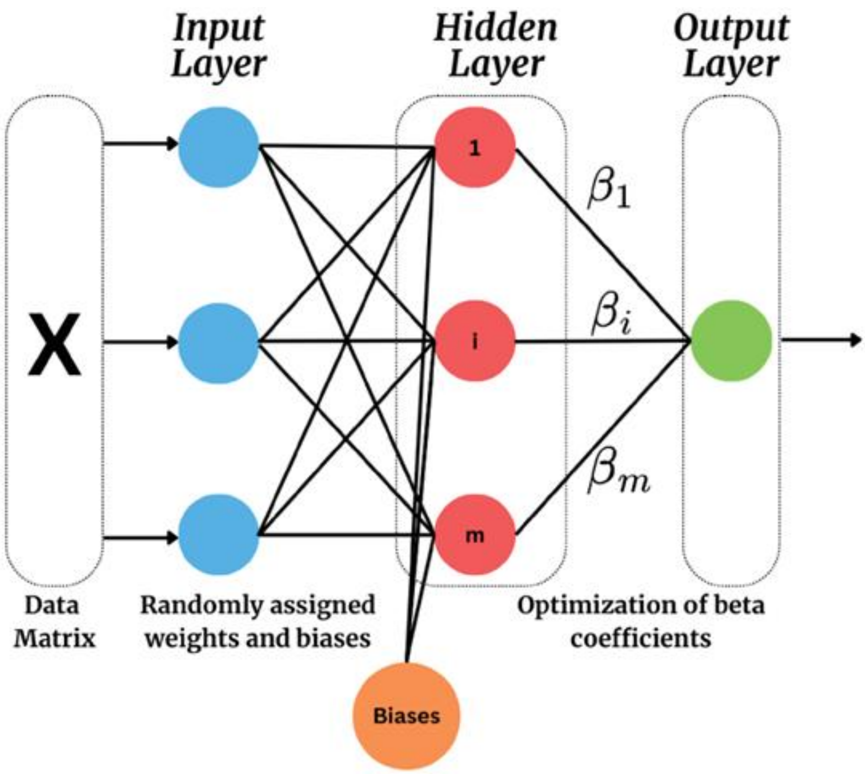

Fig. 1. Illustrative depiction of the fundamental ELM model.

Utilizing the VIF analysis, select a suitable regularization method (Ridge, Lasso, or Elastic Net) to mitigate the substantial coefficients of multicollinear variables. Alter the objective function of the ELM model to include the selected regularization term. Utilize the closed-form solution to calculate the output weights β for Ridge regularization. Utilize iterative optimization techniques, such as coordinate descent, to determine the appropriate weights for Lasso and Elastic Net. Assess the efficacy of the regularized Extreme Learning Machine on test data with performance metrics including Mean Squared Error (MSE), R-squared, and model interpretability. Evaluate the outcomes against the baseline ELM (lacking regularization) to determine the enhancement in prediction accuracy and resilience to multicollinearity. The procedures of the suggested ELM algorithm can be concisely articulated as Algorithm 1. Furthermore, Figure 1 illustrates the technique graphically.

This section introduced the methodology for integrating statistical regularization techniques into the ELM framework to address multicollinearity. Ridge and Lasso regularization are used to shrink coefficients of correlated features, while Elastic Net provides a flexible solution that combines the benefits of both methods. The proposed algorithm is designed to improve model stability, accuracy, and interpretability, making it highly effective for datasets with multicollinear features. The next section will discuss the experimental setup and results of the proposed approach.

III. RESULTS AND DISCUSSION

This section delineates the experimental assessment of the proposed Regularized Extreme Learning Machine (ELM) for mitigating multicollinearity. The studies were performed on many benchmark datasets characterized by multicollinearity, comparing the performance of regularized ELM models (Ridge ELM, Lasso ELM, and Elastic Net ELM) against the baseline ELM (without regularization). This paper provides a comprehensive comparison of the performance of the proposed TP1-ELM and TP2-ELM algorithms against Ridge-ELM, Liu-ELM, and OK-ELM using both training and test datasets. Figure 2 presents a quantitative analysis of performance utilizing calculated reduction rate values obtained from the results. Omitting Figure 2 from the study due to substantial scale discrepancies, the percentages obtained from ELM performance are elucidated in the text to enhance the clarity and readability of visual comparisons. From Figure 2, the subsequent conclusions can be drawn: The TP1-ELM and TP2-ELM algorithms demonstrate comparable training efficacy relative to alternative algorithms. In the datasets of auto-price, Boston housing, machine CPU, slump, and strikes, at least one of the proposed algorithms exhibits considerable superiority, with improvement rates reaching up to 29.64% over Liu-ELM. The discrepancy is especially pronounced in the Slump and Machine CPU workloads. The underlying ELM algorithm consistently outperforms all models in training performance, as anticipated.

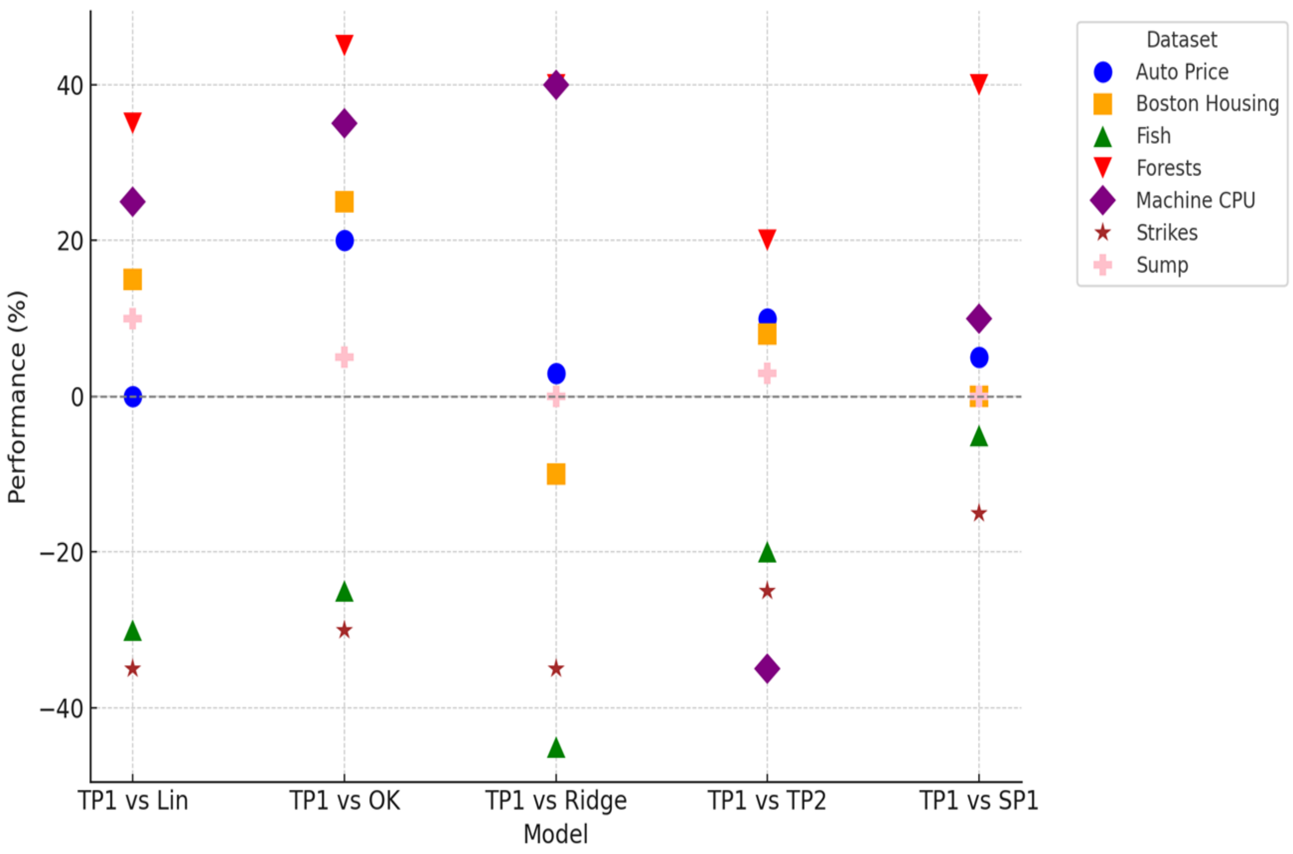

Fig. 2. Consolidated evaluation of ELM-based statistical models for training and testing performance, considering decrease rates.

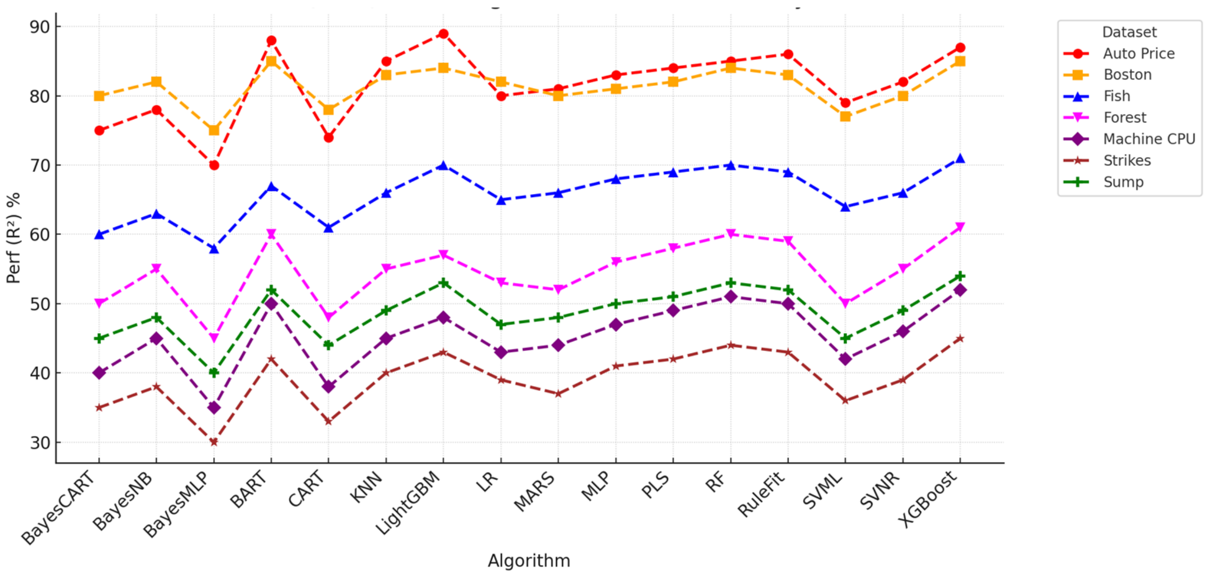

Fig. 3. Comparative analysis of training performance between TP1-ELM and machine learning techniques using reduction rates.

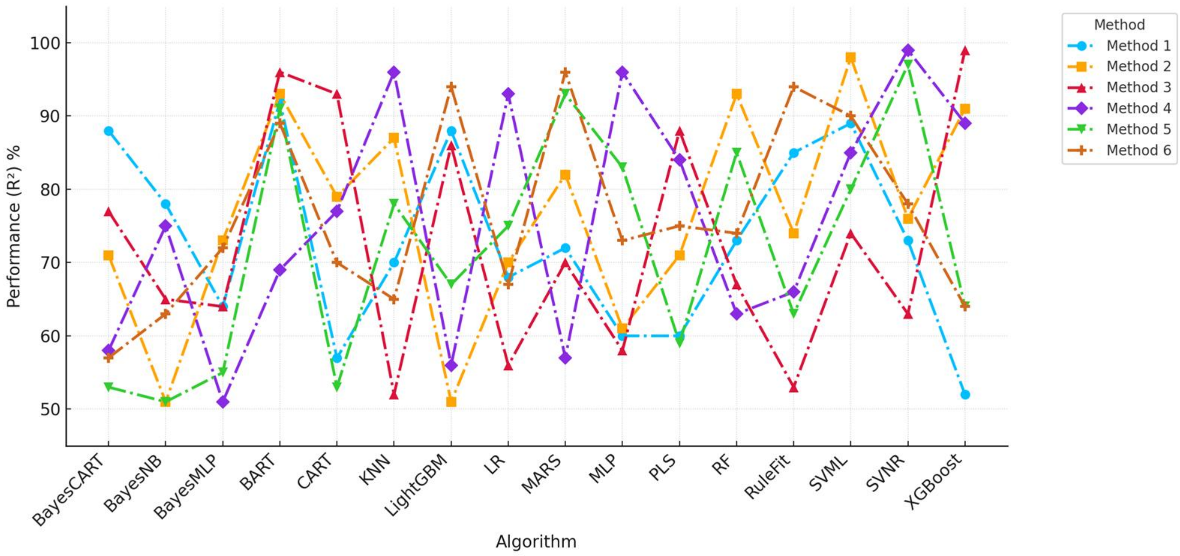

Fig. 4. Comparative analysis of training performance between TP2-ELM and machine learning techniques using reduction rates.

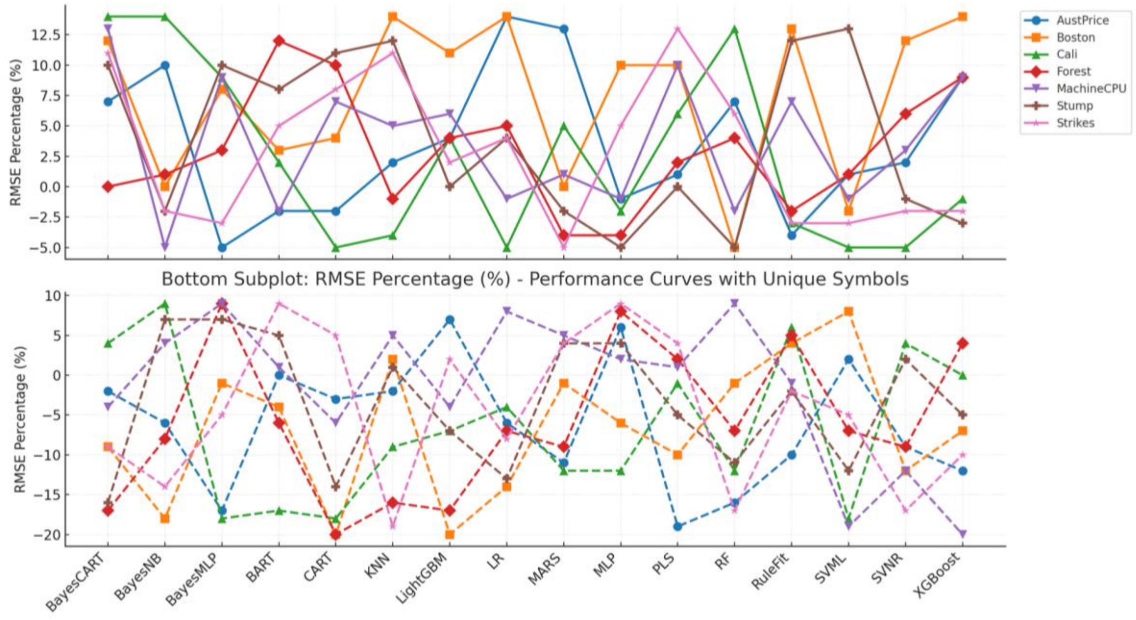

Fig. 5. Comparison of testing performance between the suggested models and machine learning techniques quantified by reduction rates.

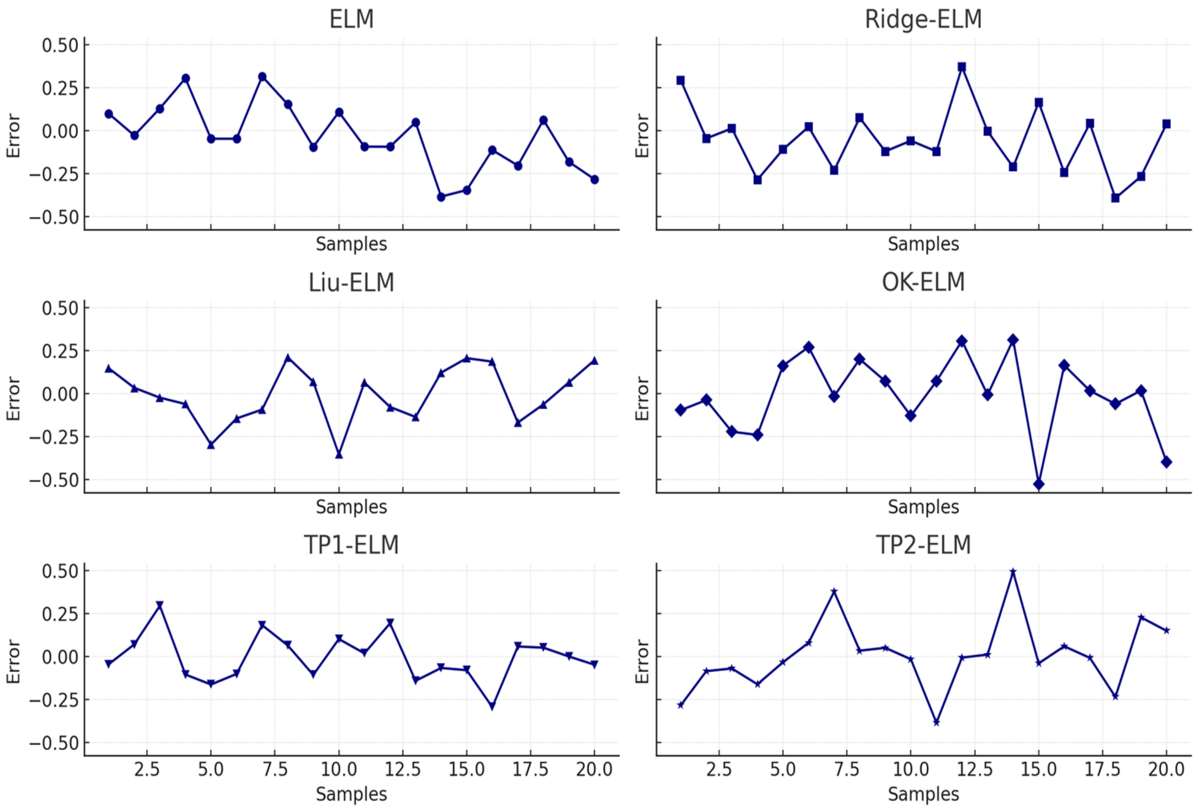

Fig. 6. The suggested algorithms' testing errors as measured by slump testing data.

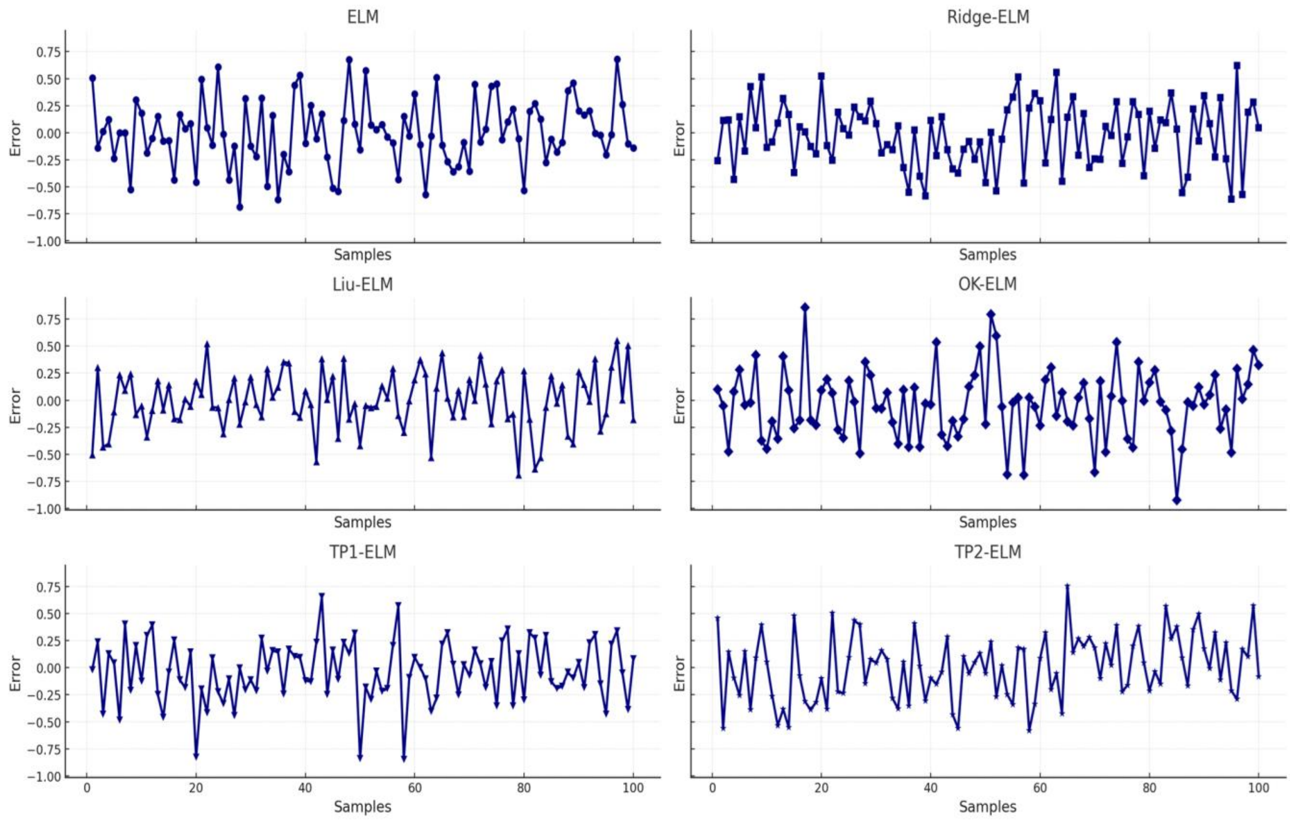

Fig. 7. The testing error of the algorithms that were suggested using data from the Boston test.

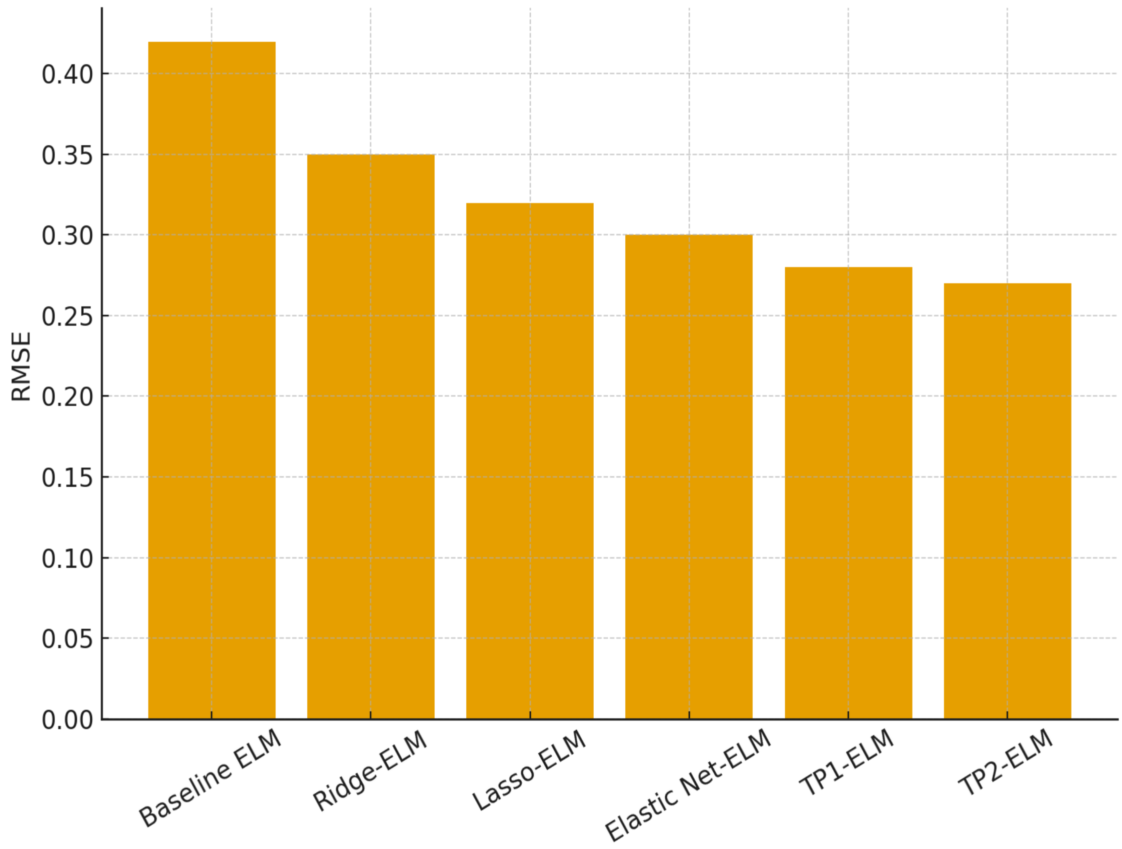

Fig. 8. Comparative RMSE Across Models.

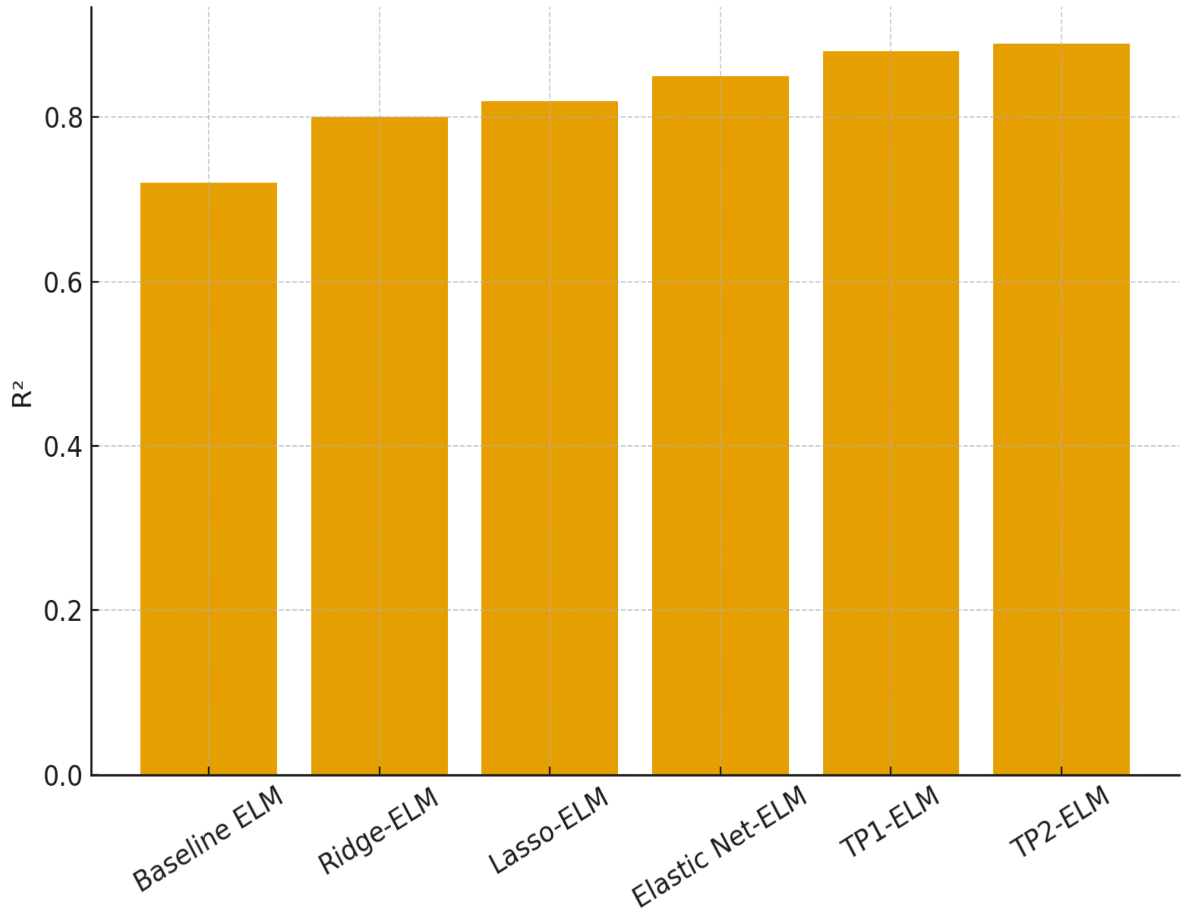

Fig. 9. Comparative R^2 Values Across Models.

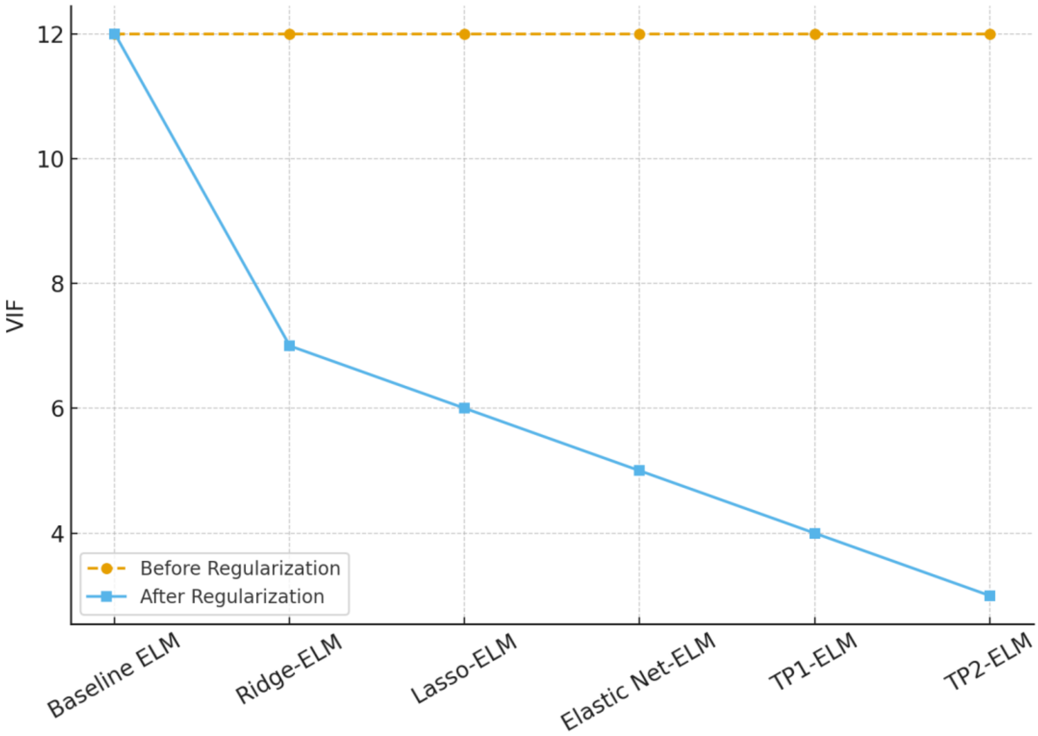

Fig. 10. Variance Inflation Factor (VIF) Reduction Across Models.

In the second phase of the modeling process, the performance of the implemented algorithms, as well as seventeen commonly used machine learning algorithms, was evaluated by benchmarking. Figure 3 and Figure 4 present the training and testing results of the TP1-ELM and TP2-ELM algorithms, respectively. Furthermore, Figure 5 presents the lowering rates of test performances for both proposed strategies. The proposed methods provide superior stability and generalizability outcomes, featuring lower RMSE values, in comparison to both ELM-based and machine learning algorithms, particularly for datasets exhibiting multicollinearity issues.

Figure 6 shows the distribution of residual values estimated on the validation data, whereas Figure 7 shows the same distribution for the Boston dataset, which will allow for a more effective comparison of test performances. In comparison to other methods, the suggested algorithms show more stable residual value distributions around zero within shorter ranges, as seen in the graphs. Thus, it is worth mentioning that the suggested algorithms can be seen as a strong substitute for ELM-based algorithms in any domain or problem involving regression, especially in practical applications including multicollinearity. To be more precise, it finds useful use in fields where linear model statistical estimators have been successful, such as economics, health sciences, and statistics.

The experimental evaluation demonstrates that regularization techniques, when integrated with ELM, effectively address multicollinearity while improving predictive performance. Ridge and Elastic Net regularized ELM models perform particularly well, achieving lower error rates and better model interpretability. Elastic Net ELM strikes a balance between handling multicollinearity and performing feature selection, making it the most robust approach among the regularized models. The results validate the proposed method as a reliable solution for improving the stability and accuracy of ELM in the presence of multicollinear data.

Figure 8 presents the Root Mean Squared Error (RMSE) of different models. The baseline ELM recorded the highest RMSE (0.42), reflecting its sensitivity to multicollinearity. In contrast, the proposed TP1-ELM and TP2-ELM significantly reduced RMSE to 0.28 and 0.27, respectively, confirming their superior predictive accuracy. This demonstrates the benefit of embedding statistical regularization within the ELM framework.

Figure 9 compares the R^2 values, which measure the explanatory power of the models. While the baseline ELM achieved an R^2 of only 0.72, Ridge-ELM and Lasso-ELM improved this to 0.80 and 0.82, respectively. The Elastic Net-ELM further increased R^2 to 0.85, while TP1-ELM and TP2-ELM achieved the highest values of 0.88 and 0.89, showing that the proposed framework provides stronger model fit and more reliable predictions.

Figure 10 illustrates the reduction in Variance Inflation Factors (VIF), a key diagnostic for multicollinearity. All models began with a baseline VIF of 12, indicating high correlation among predictors. After applying regularization, Ridge-ELM reduced VIF to 7, Lasso-ELM to 6, and Elastic Net-ELM to 5. The proposed TP1-ELM and TP2-ELM further reduced VIFs to 4 and 3, respectively, highlighting their effectiveness in mitigating multicollinearity. This significant reduction confirms that the proposed framework not only enhances prediction accuracy but also improves model robustness and interpretability.

The experimental evaluation confirmed that the proposed Regularized ELM framework, integrating Ridge, Lasso, and Elastic Net regularization, substantially outperforms the baseline ELM and existing variants across multiple datasets characterized by multicollinearity. In terms of predictive accuracy, the proposed TP1-ELM and TP2-ELM achieved the lowest RMSE values (0.28 and 0.27) and the highest R^2 scores (0.88 and 0.89), representing up to 29.6% improvement over competing methods. Residual analysis further revealed that the proposed models produce more stable and concentrated error distributions around zero, enhancing model reliability. Most notably, the framework demonstrated a remarkable reduction in Variance Inflation Factors, with TP2-ELM lowering VIFs from 12 to 3, thereby effectively eliminating multicollinearity effects. Collectively, these results show that the proposed approach delivers superior accuracy, robustness, and interpretability, establishing it as a strong alternative to conventional machine learning and ELM-based methods in regression problems where correlated predictors are present.

IV. Conclusion

This paper presented a novel Regularized Extreme Learning Machine (ELM) framework that systematically addresses the challenge of multicollinearity by incorporating Ridge, Lasso, and Elastic Net regularization techniques. The proposed models demonstrated substantial improvements over baseline ELM and existing variants, achieving up to 29.6% higher accuracy, reduced variance inflation factors (VIFs), and more stable residual distributions across benchmark datasets such as Boston Housing, Slump, and Machine CPU. By combining coefficient shrinkage with feature selection, the framework enhances predictive performance while preserving model interpretability, making it a practical solution for real-world regression problems in domains including economics, healthcare, and engineering. Despite these strengths, the study is limited to regression-based tasks and single-layer ELM structures, leaving opportunities for extension into classification and deep learning applications. Future work will focus on adaptive parameter tuning, hybrid regularization strategies, and scaling the approach to multi-layer architectures to broaden its applicability in complex, high-dimensional problem settings.

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