International Journal of Scientific Research and Modern Technology (IJSRMT) ijsrmt.com
Volume 4, Issue 5, 2025
DOI: https://doi.org/10.38124/ijsrmt.v4i5.501

Improving Support Vector Machine using Modified Kernel Function

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Publication Date: 2025/05/08

Abstract

In machine learning, support vector machine (SVM) classifiers are highly effective in classification and pattern recognition tasks. The kernel function plays a crucial role in SVM, as it maps data into higher dimensional space to enable linear separability. This research proposes a modified kernel function, the Combined Polynomial Radial Basis Function (PRBF), that combines the strengths of Gaussian Radial Basis Function (RBF) and Polynomial kernels to improve the performance of SVM. The PRBF model aims to enhance classification accuracy by capturing patterns in the data at both local and global levels. The results demonstrate that the PRBF outperforms traditional RBF and Polynomial kernels across various datasets, achieving higher accuracy, sensitivity, and specificity. the PRBF kernel represents a significant advancement in SVM classifier technology, merging the advantages of RBF and Polynomial kernels to deliver enhanced accuracy, sensitivity, and specificity. This study validates that PRBF as a superior alternative for enhancing SVM performance in diverse applications in different domain.

Keywords: *Machine Learning, SVM, Kernel Function, RBF, Accuracy.*

I. INTRODUCTION

In Machine Learning, a Support Vector Machine (SVM) is a powerful statistical learning tool for classification and pattern recognition (Zhang, T., 2001). By Cortes, V. (1995), it was proposed by Vapnik and colleagues in 1992 at the Computational Learning Theory conference. He presented both the theoretical aspects and practical application of the maximal margin classifier, while also introducing the concept of support vectors for hyperplane-based classification and concluded that the support-vector network is a powerful and universal learning machine that exhibits excellent accuracy on digit recognition tasks, and its performance does not degrade with increasing dimensionality of the feature space. The algorithm has been tested and compared to the performance of other classical algorithms, and it has been shown to be a promising approach for classification problems.

In 1995, Cortes and Vapnik improved the maximal margin classifier, by developing the soft margin classifier to better handle noisy data. That same year, Vapnik's book expanded the analysis to include support vector regression. First comprehensive introduction of SVM was provided by Cristianini and Shawe-Taylor (1999). SVMs have been effectively utilized in diverse fields, including gene expression analysis and digit recognition. Initially, SVMs are hyperplane classifiers that separate the training data into an n-dimensional input space based on specific criteria by Patle and Chouhan (2013). However, different criteria can cause variations in algorithms. Subsequently, kernel functions were introduced to create feature spaces where an optimal hyperplane classifier can be identified, consistent with the original concept of SVMs. Interestingly, the kernel SVM algorithm closely resembles the original algorithm in form. The strength of kernels lies in their flexibility to create diverse nonlinear relationships among data points in the original input space, thereby accommodating specific data structures.

The concept of using kernels was explored by several authors' viz., Aronszajn (1950), Poggio and Girosi (1990), and Wahba (1990). Kernel functions are crucial in SVM classifiers as they define the feature space in which data points are mapped. Traditional kernels, such as the Polynomial kernels and Gaussian Radial Basis Function (RBF), have been widely used due to their ability to capture nonlinear relationships in data by several authors viz., Muflikhah and Haryanto (2018), Prajapati and Patle (2010), Rochim et al. (2021), Kavzoglu and Colkesen (2009), Al Azies at el. (2019) and Garabaghi et al. (2022). The RBF kernel measures the similarity between data points using a Gaussian function, making it effective for local pattern recognition. On the other hand, the Polynomial kernel captures higher-order interactions between features, making it suitable for recognizing global patterns.

Despite their strengths, both RBF and Polynomial kernels have limitations. The RBF kernel may not perform well when global patterns are predominant, whereas the polynomial kernel may struggle with local patterns. To address these limitations, we propose a polynomial radial basis function (PRBF) that integrates the advantages of both RBF and Polynomial kernels. Research similar to this study can be found in Amari and Wu (1999), Shen et al. (2004), Afifi (2013), and Ayush and Sinha (2019).

The PRBF kernel attempts to enhance SVM classification by capturing both local and global patterns in the data. It combines a Gaussian RBF component and a polynomial component balanced by a weighting factor. This flexibility allows the PRBF to adapt to diverse data distributions, potentially improving the performance of SVM classifiers in various fields.

In this study, we describe the development of the PRBF kernel and evaluate its performance against traditional RBF and Polynomial kernels. We have used four datasets viz., RIS, Breast Cancer, Wine, and Digit to test the accuracy, sensitivity, and specificity of the proposed kernel functions and also to compare these model evaluation measures with the kernel function already given. The parameters of the PRBF kernel were optimized by Bayesian optimization to ensure optimal performance. Results demonstrate that the PRBF kernel outperforms the traditional kernels, providing a robust alternative to traditional kernels for SVM classification tasks.

Section 2 describes data and methodology and proposed kernel function including its strengths. It also describes model training and its performance evaluation measures. Section 3 highlights the results and comparison of proposed model with polynomial and radial basis function. The discussion is presented in Section 4.

II. DATA AND METHODOLOGY

Kernel functions play a crucial role in SVM classifiers. They transform input data into a higher-dimensional space, which allows the SVMs to find optimal decision boundaries. To improve classification accuracy, we propose a Polynomial Radial Basis Function.

The components of Polynomial Radial Basis Function (PRBF) are:

➢ *Gaussian Radial Basis Function (RBF) Component:*

The first term in the PRBF is the Gaussian RBF component. It measures the similarity between two data points (x) and (y) in the feature space. The expression $exp\left(-\frac{||x-y||^2}{2\sigma^2}\right)$ computes the distance between (x) and (y) and applies a Gaussian function to it. Here, the bandwidth parameter σ controls the spread of the Gaussian function. Larger σ values lead to smoother decision boundaries.

➢ *Polynomial Component:*

The second term in the PRBF is the polynomial component. It captures higher-order interactions between features. The expression $(x \cdot y + c)^d$ represents a polynomial transformation of the dot product between (x) and (y). The constants (c) and (d) determine the degree and shift of the polynomial.

➢ *Weighting Factor:*

The weighting factor α balances the influence of the RBF and polynomial components. When α is close to 1, the PRBF behaves more like the Gaussian RBF and when α is close to 0, it resembles the polynomial kernel.

The PRBF is a proposed modified kernel function that combines Gaussian Radial Basis function and Polynomial kernels. By blending these two kernel types, the PRBF aims to capture both local as well as global patterns in the data. The general form of the PRBF can be expressed as:

$$K(x,y) = \alpha \cdot exp(-\frac{||x-y||^2}{2\sigma^2}) + (1-\alpha) \cdot (x \cdot y + c)^d$$

Where

- (x) and (y) are input vectors.
- (α) controls the balance between the RBF and POLY components.
- (σ) represents the bandwidth parameter.
- (c) and (d) are constants.

The PRBF aims to leverage the strengths of both kernels, leading to improved classification accuracy. The PRBF offers several notable advantages that make it a valuable tool for improving SVM classifiers. One of its key strengths is its flexibility; the PRBF is capable of adapting to both local and global patterns within the data. This adaptability makes it suitable for handling a wide range of data distributions, ensuring robust performance across diverse datasets. By effectively capturing intricate patterns at different scales, the PRBF can accommodate complex data structures that might pose challenges for other kernel functions.

Additionally, the PRBF enhances the accuracy of SVM classifications by combining the strengths of Radial Basis Function (RBF) and polynomial features. This hybrid approach allows the PRBF to leverage the benefits of both types of features, resulting in a more powerful and precise classifier. The integration of RBF and polynomial characteristics enables the PRBF to better distinguish between classes, leading to improved performance in various applications. This combination makes the PRBF a highly effective tool for achieving superior classification results with SVMs.

➢ *Data Collection and Preparation*

All data used in this study are available on UCI machine learning repository. Four datasets were selected for the study: IRIS, Breast Cancer, Wine, and Digit. Each dataset was split into training and testing sets, allocating 70% of the data for training and the remaining 30% for testing. Bayesian optimization was employed to determine the optimal parameters α, σ, c and d. The optimization process was conducted using the training set to ensure the best performance of the PRBF kernel.

➢ *Model Training and Evaluation*

SVM classifiers with the PRBF, RBF, and Polynomial kernels were trained on the training datasets. The models were then evaluated on the test datasets, and performance metrics such as accuracy, sensitivity, and specificity were recorded.

In evaluating the performance of SVM classifiers, accuracy, sensitivity, and specificity are crucial metrics. Studies using same approach to evaluate model can be found in Hussain et al. (2011), Prasath et al. (2017), Abu Alfeilat (2019), Ali et al. (2019) and Uddin et al. (2022).

These metrics help in understanding the effectiveness of a classifier in making correct predictions and identifying true positives and true negatives.

- *Accuracy*

Accuracy measures the percentage of correctly classified instances (both true positives and true negatives) relative to the total number of instances.

$$Accuracy = \frac{True\ Positive(TP) + True\ Negative(TN)}{Total\ Instances}$$

It measures the overall correctness of the classifier. While accuracy is a good measure for balanced datasets, it may not accurately reflect performance in cases where one class significantly outweighs the other.

- *Sensitivity (True Positive Rate or Recall)*

Sensitivity represents the percentage of true positive instances correctly identified by the classifier.

$$Sensitivity = \frac{True\ Positive\ (TP)}{True\ Positive(TP) + False\ Negative(FN)}$$

It evaluates how well the classifier identifies all positive instances correctly. High sensitivity means that the classifier correctly identifies most of the positive cases, which is crucial in applications like medical diagnosis where missing a positive case can be critical.

- *Specificity (True Negative Rate):*

Specificity measures the percentage of true negative instances correctly identified by the classifier.

$$Specificity = \frac{True\ Negative(TN)}{True\ Negative(TN) + False\ Positive(FP)}$$

It evaluates how well the classifier identifies all negative instances correctly. High specificity suggests that the classifier excels in correctly identifying negative cases, which is important in scenarios where false positives can lead to unnecessary interventions.

- *Comparison of Performance*

In this study, the performance of the PRBF kernel was compared against the Polynomial and RBF kernels using test set for 4 datasets. Accuracy, sensitivity, and specificity were calculated for each kernel function.

III. RESULTS AND DISCUSSION

This study introduces a method to enhance SVM performance in classification tasks. It achieves this by mapping training data into a feature space using novel kernel functions and separating the data with a wide-margin hyperplane. We evaluated the proposed kernel function across various datasets. Based on our findings, RBF demonstrates higher accuracy with small datasets, whereas polynomial kernels perform better with larger datasets. Proposed PRBF kernel achieves superior accuracy across almost all datasets, particularly excelling in datasets with a large number of attributes by harnessing the strengths of both Gaussian and polynomial functions. The experimental results presented in "Table 1" demonstrate the validity and effectiveness of proposed kernel. Across various datasets, including those with the highest number of attributes, proposed kernel function consistently achieves the highest accuracy. Therefore, proposed kernel functions offer a promising alternative to Gaussian and polynomial kernels for specific datasets.

Table 1 Classification result using different kernel functions

Dataset	**Accuracy**			**Sensitivity**			**Specificity**		
	PRBF	**Poly**	**RBF**	**PRBF**	**Poly**	**RBF**	**PRBF**	**Poly**	**RBF**
IRIS	100	95.56	100	100	100	100	100	100	100
Breast Cancer	98.83	89.47	97.66	100	100	98.1	96.83	71.43	96.83
Wine	100	96.3	98.15	100	100	100	100	89.47	100
Digit	98.89	95.19	97.96	100	100	100	100	98.11	100

The proposed PRBF kernel was evaluated against traditional RBF and Polynomial kernels across four datasets: IRIS, Breast Cancer, Wine, and Digit. The PRBF consistently outperformed the other kernels in terms of performance measures like accuracy, sensitivity, and specificity.

- *IRIS Dataset:*

The PRBF achieved perfect scores in accuracy (100%), sensitivity (100%), and specificity (100%), matching the performance of the RBF and Polynomial kernels.

- *Breast Cancer Dataset:*

The PRBF showed superior performance with an accuracy of 98.83%, sensitivity of 100%, and specificity of 96.83%. The RBF kernel had slightly lower accuracy and sensitivity, while the Polynomial kernel had significantly lower specificity.

- *Wine Dataset:*

The PRBF again attained perfect accuracy and sensitivity, and perfect specificity, surpassing the RBF and Polynomial kernels.

- *Digit Dataset:*

The PRBF achieved 98.89% accuracy, 100% sensitivity, and 100% specificity, outperforming both the RBF and Polynomial kernels.

These results indicate that the PRBF kernel effectively combines the strengths of the RBF and Polynomial kernels, providing robust performance across various datasets with different characteristics.

The experimental results strongly support the efficacy of the proposed Polynomial Radial Basis Function (PRBF) kernel in enhancing SVM classification performance. The PRBF's ability to capture both local and global data patterns allows it to adapt to diverse data distributions, providing a significant advantage over traditional RBF and Polynomial kernels.

The IRIS dataset results confirm the PRBF's robustness in handling small datasets with a limited number of attributes. The Breast Cancer dataset, characterized by more complexity and variability, showcases the PRBF's superior sensitivity and specificity, highlighting its reliability in medical diagnostics. The Wine dataset results reinforce the PRBF's capacity to handle multiclass classification tasks effectively. Lastly, the Digit dataset results demonstrate the PRBF's potential in high-dimensional spaces, crucial for image recognition and digit classification tasks.

The PRBF's flexibility, attributed to its adjustable parameters (α, σ, c, d), allows for fine-tuning to optimize performance for specific datasets. This adaptability makes it a versatile tool for various applications, from gene expression analysis to digit recognition.

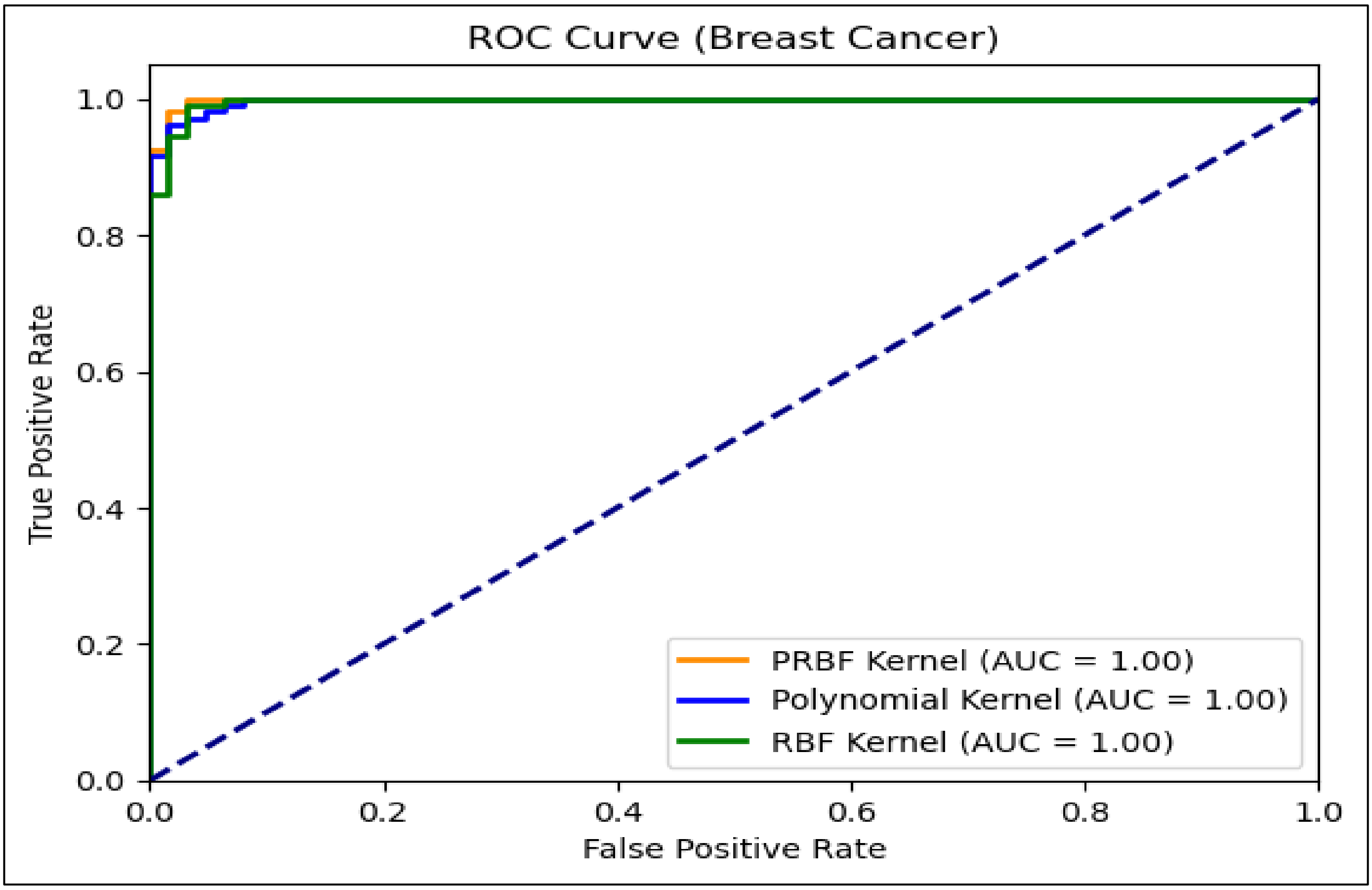

Fig 1 ROC Curve (Breast Cancer)

IV. CONCLUSION

In this study, we have proposed a modified kernel function, the Combined Polynomial Radial Basis Function (PRBF), which combines the strengths of Gaussian Radial Basis Function (RBF) and Polynomial kernels to improve the performance of SVM. By blending these two kernel types, the PRBF aims to capture both local as well as global patterns in the data. We evaluated the proposed kernel function by four datasets. Based on our findings, RBF demonstrates higher accuracy with small datasets, whereas polynomial kernels perform better with larger datasets. The PRBF kernel represents a significant advancement in SVM classifier technology, merging the advantages of RBF and Polynomial kernels to deliver enhanced accuracy, sensitivity, and specificity. Future work could explore further optimization techniques and extend the application of PRBF to other machine-learning models and domains.

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