The Effect of Hybrid RBF-Polynomial Kernel on the Accuracy of Mathematical Models in Data Forecasting and Classification

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Abstract. As a recent development in machine learning methods, the hybrid RBF-polynomial kernel has shown significant potential in enhancing model performance in various complex data applications. This study aims to analyze the impact of the RBF-polynomial hybrid kernel on the accuracy of mathematical models in forecasting and data classification. The methodology used in this research is a qualitative approach with a Systematic Literature Review (SLR), examining indexed literature in databases such as Scopus, DOAJ, and Scispace with a publication range between 2014 and 2024. Based on the evaluation of the application of the RBF-polynomial kernel and its relevance across various fields, it can be concluded that the RBF-polynomial hybrid kernel combination demonstrates significant potential in improving model accuracy for complex data. The main advantage of this model lies in its ability to handle high data variation, noise, and irregular data distributions. However, the use of this hybrid model also faces challenges, particularly in terms of higher computational complexity, longer training times, and the optimal selection of parameters to avoid overfitting or under-fitting issues. This study is expected to contribute to the development of more efficient algorithms, especially for real-time applications and large datasets, and to open opportunities for further research into the automation of parameter selection and the reduction of class imbalance impacts in mathematical models.

Keywords: Hybrid Kernel; RBF-Polynomial, Mathematical Models, Forecasting, Classification

1. Introduction

The development of forecasting and data classification methods has become a primary focus across various disciplines, particularly with the utilization of mathematical models and machine learning techniques. One widely used approach is the Support Vector Machine (SVM)-based method and regression models, where the selection of kernel functions plays a crucial role in determining the model's accuracy. Kernels serve to transform data into a higher-dimensional space, enabling more optimal separation or modelling [1]. In the context of regression, kernels are also employed to handle non-linear data, such as in the Gaussian Process Regression model, which is frequently applied in spatial data analysis and time series [2].

Traditional kernels such as Radial Basis Function (RBF) and polynomial kernels are often used in modelling due to their ability to handle non-linear data [3]. However, each has limitations in handling complex variations within the data, especially when the data structure is highly heterogeneous or contains significant noise [4]. To address these limitations, several studies have proposed hybrid approaches that combine two or more kernels to enhance the flexibility and accuracy of the model. For instance, the combination of RBF and polynomial kernels can capture both local and global patterns simultaneously, which has proven to improve classification performance in various applications, including pattern recognition and anomaly detection [5]. Furthermore, recent research indicates that the use of multiple kernel learning can adaptively adjust the kernel weights, allowing the model to handle high data complexity more effectively [6].

The Hybrid RBF-Polynomial kernel approach combines the strengths of the Radial Basis Function (RBF) kernel in handling non-linear data with the flexibility of the polynomial kernel in accommodating broader structural variations [7]. This approach is designed to overcome the limitations of individual kernels, particularly when dealing with data exhibiting complex and irregular patterns [8]. Recent studies show that the use of hybrid kernels like RBF can enhance model accuracy in classification and regression tasks, particularly in pattern recognition, image analysis, and signal processing [9]. Moreover, this method has demonstrated superior performance in handling high-dimensional data compared to single kernel-based approaches, such as SVM with either RBF or polynomial kernels alone [10].

The application of hybrid kernels in economics and geography has shown significant promise in improving model accuracy across various predictive tasks. In the field of economics, hybrid kernels are highly effective in financial forecasting, credit risk analysis, and anomaly detection, where they skilfully capture complex non-linear patterns within the data. For example, a hybrid model integrating LSTM and reinforcement learning has achieved high accuracy in stock price prediction, with an R^2 value reaching 0.94 [10]. Furthermore, predictive modelling techniques, including hybrid approaches, have enhanced credit risk assessment by analyzing customer behaviour patterns, as well as leveraging multiple machine learning algorithms to improve fraud detection [11]. Hybrid kernels are also utilized in financial forecasting, such as predicting stock prices and market trends, where the combination of kernels can capture non-linear patterns in macro and microeconomic data [13]. In geography, hybrid kernels facilitate better handling of spatial-temporal data, which is crucial for accurate land-use change mapping, achieving 98.7% accuracy on the MNIST dataset. Improved geospatial modelling through hybrid approaches has also enhanced the prediction of events such as earthquakes and floods, with a 35% reduction in computational time compared to traditional methods [13]. This model has also been used in natural disaster prediction, such as earthquakes and floods, improving the accuracy of geospatial data-based modelling [15]. Despite these advancements, the effectiveness of hybrid kernels depends on data type and model parameters, requiring thorough evaluation to optimize their performance across both fields. However, the reliance on complex models may pose challenges in interpretability and computational efficiency, which could hinder their broader adoption.

This article aims to analyze the impact of the Hybrid RBF-Polynomial kernel on the accuracy of mathematical models in forecasting and data classification. This approach was developed to address the limitations of single kernels by combining the flexibility of the Radial Basis Function (RBF) kernel in handling non-linear data with the power of the polynomial kernel in accommodating broader structural variations. This research will evaluate the advantages and potential of hybrid kernels in improving model performance, both in forecasting and classification scenarios. The analysis will focus on how this kernel combination can capture more complex data patterns, enhance model generalization, and optimize prediction results across various application domains. Furthermore, this study will identify implementation challenges and opportunities for further development, providing a comprehensive insight into the effectiveness of the hybrid ERH kernel compared to single kernel approaches across various disciplines.

2. Method

This research uses the Systematic Literature Review (SLR) approach to analyze the effect of hybrid RBF-Polynomial kernel on the accuracy of mathematical models in forecasting and data classification. The SLR approach was chosen because it can identify, evaluate, and interpret related studies in a systematic and transparent manner. Research data was obtained from three major academic databases, namely Scopus, DOAJ, and Scispace. The search was conducted using keyword combinations such as "Hybrid RBF-Polynomial Kernel AND accuracy AND forecasting AND classification", "Machine Learning Kernel Methods AND Polynomial-RBF Hybrid AND performance evaluation", and "Hybrid

Kernel Methods AND mathematical modeling AND data prediction". The selected articles must meet several inclusion criteria, namely published in the 2015-2024 timeframe, written in English or Indonesian, have Open Access status, and discuss the use of hybrid RBF-Polynomial kernels in data forecasting or classification. Articles that did not discuss kernel combinations or that used only one of the kernels (RBF or Polynomial) without combinations, limited access articles, or that did not include model accuracy evaluation were excluded from the analysis.

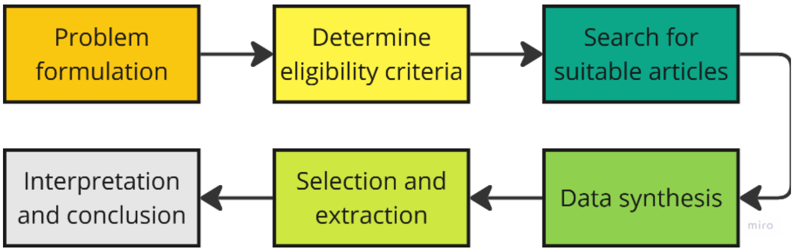

Figure 1. Research procedure

Figure 1 shows that this research was conducted in several stages. First, an initial search was conducted to extract publications from the mentioned databases. Next, title and abstract screening was conducted to select articles that fit the predefined criteria. Articles that passed this stage were then thoroughly evaluated to ensure the relevance of the methodology and results presented. Relevant data was then extracted, including information on the methods used, datasets used, model parameters, and accuracy evaluation results. In the final stage, a synthesis of findings was conducted to analyze patterns that emerged in the study, such as trends in the use of hybrid kernels, factors affecting model performance, and recommendations for further development. All these stages were conducted to ensure transparency and accuracy in the research process. The data analysis techniques used are descriptive and comparative analysis to compare the accuracy results of models using hybrid RBF-Polynomial kernels with other models, as well as to identify factors that affect the performance of hybrid kernels in various types of datasets.

3. Results and Discussion

Based on our research, we have identified several studies that are highly relevant and contribute significantly to our research focus and objectives. The information gained from these studies has substantially expanded our understanding of the topic under investigation. We have compiled and summarized the findings of these studies in Table 1.

Table 1. Summary of Research Focus, Authors, and Insights

No	Research Focus/Variables	Author(s)	Insight/Description
1	Use of RVM Kernels in Data Forecasting and Classification	Hussain (2019), Giang et al. (2020), Mathew et al. (2018)	RVM kernels are increasingly popular in data forecasting and classification, especially in biomedical applications and imbalanced data scenarios. RVM has shown improved accuracy in classifying diseases such as Alzheimer's and cancer. However, challenges remain with high-dimensional biomedical data and imbalanced datasets.
2	Use of CRRBF and MV-RBF Kernels for Hyperspectral	Niazmardi (2024), Lv et al. (2023)	The CRRBF kernel performs better than traditional RBF kernels in hyperspectral data classification, while the MV-RBF model with attribute-weighting mechanisms improves

No	Research Focus/Variables	Author(s)	Insight/Description
	Data		prediction accuracy by leveraging multiple data attributes.
3	Use of Tensor Kernel Learning for Multimodal Data	Thanh et al. (2024)	Tensor Kernel Learning (TKL) enhances classification performance in multimodal data integration, particularly in Alzheimer's disease assessment.
4	Implementation of Hybrid RBF-Polynomial Kernels in Mathematical Models	Fu et al. (2015), Hagen et al. (2016), Nouri et al. (2018), Varma et al. (2019)	Hybrid RBF-Polynomial kernels are used to enhance mathematical modeling in various applications, such as differential equations and numerical relativity. In fields like epidemiology and agriculture, hybrid models have also proven effective in analyzing infectious diseases and predicting agricultural yields.
5	Application of Hybrid RBF-Polynomial Kernels in Applied Sciences	Fujiwara et al. (2022), Masrur Ahmed et al. (2022), Koch & Lado (2021)	Hybrid RBF-Polynomial kernels show significant potential in applied sciences like epidemiology, agriculture, and quantum physics. Their use in SIR models for infectious disease and wheat yield prediction demonstrates notable error reduction.
6	Comparison of Model Accuracy with RBF, Polynomial, and Hybrid RBF-Polynomial Kernels	Hussain (2019), Rendall et al. (2019), Pilario et al. (2020), Z. Lin & Yan (2016), Razaque et al. (2021), Zhang et al. (2020), Zaiane et al. (2017)	Comparing RBF and polynomial kernels shows that while RBF is effective for non-linear patterns and polynomial provides greater flexibility, both have limitations. The RBF-Polynomial hybrid kernel combination demonstrates superior performance in handling complex data and reducing overfitting risks.
No	Research Focus/Variables	Author(s)	Insight/Description

Table 1 summarizes key research on the use of RVM, RBF, polynomial, and hybrid RBF-Polynomial kernels in data forecasting, classification, and mathematical modelling. Several studies highlight the growing application of RVM kernels, particularly in biomedical fields, where they have shown improved accuracy in classifying diseases like Alzheimer's and cancer, although challenges such as high-dimensional data and imbalanced datasets remain. The CRRBF kernel outperforms traditional RBF kernels in hyperspectral data classification, while the MV-RBF model leverages multiple data attributes to enhance prediction accuracy. Furthermore, advancements like Tensor Kernel Learning (TKL) have proven effective in integrating multimodal data for applications such as Alzheimer's disease assessment. The integration of hybrid RBF-Polynomial kernels into mathematical models has also been valuable, particularly in solving differential equations and simulating phenomena in fields such as epidemiology, agriculture, and quantum physics. These hybrid models show promise in improving predictive accuracy and computational efficiency, addressing complex data patterns. Lastly, the RBF-Polynomial hybrid kernel has proven to be particularly effective in comparison studies, enhancing model performance by handling complex data and mitigating overfitting.

3.1. Trends and Challenges in the Use of RVM Kernels for Data Forecasting and Classification

The application of Relevance Vector Machine (RVM) kernels in data forecasting and classification has gained increasing attention due to their effectiveness in handling high-dimensional and complex datasets. This is particularly evident in biomedical applications and scenarios involving imbalanced data, where specific trends and challenges have emerged. One significant trend is the integration of biomedical data, where RVMs have been successfully utilized for patient stratification in diseases such as Alzheimer's and cancer. By incorporating diverse data types, including gene expression profiles and MRI images, RVM-based models have demonstrated improved accuracy in disease classification [16]. Additionally, advancements in high-dimensional data handling have enhanced RVM performance, particularly in domains such as text classification and social network analysis, where conventional methods often struggle to produce reliable results [18]. Despite these advancements, several challenges remain in the utilization of RVM kernels. One key issue is the dimensionality and complexity of biomedical data, which introduces significant computational challenges. This necessitates the development of more efficient frameworks for data integration and dimensionality reduction to enhance processing efficiency [16]. Another major challenge involves imbalanced data, as RVMs often struggle to classify datasets with uneven class distributions, leading to biased predictions. To address this, techniques such as weighted kernel-based oversampling have been proposed as potential solutions [19]. These ongoing trends and challenges highlight the need for continued research and methodological improvements to optimize the effectiveness of RVM kernels in diverse applications.

Recent advancements have demonstrated notable trends in RBF kernel utilization. The CRRBF kernel has shown comparable or superior performance to traditional RBF kernels in hyperspectral data classification, exhibiting robustness against parameter variations [20]. Additionally, multiview lerning approaches, such as the MV-RBF model, incorporate a view-weighting mechanism to improve prediction accuracy by leveraging multiple data attributes [21]. In more complex scenarios, Tensor Kernel Learning (TKL) facilitates multimodal data integration, enhancing classification performance, particularly in fields like Alzheimer’s disease assessment [22]. Despite these advancements, several challenges persist. The need for extensive parameter tuning in traditional RBF kernels often requires cross-validation, making the process computationally intensive and potentially leading to suboptimal results. Additionally, imbalanced datasets can significantly degrade classification performance, necessitating adaptive techniques for improved accuracy [23]. Furthermore, noise sensitivity in standard hinge loss functions affects model stability, prompting the development of alternative loss functions such as the ℓ_0-norm hinge loss to enhance robustness [24].

The increasing application of RVM kernels highlights the growing need for flexible and scalable machine learning models capable of handling multimodal data. The ability of RVMs to integrate diverse information sources suggests their potential in fields requiring complex decision-making, such as medical diagnostics and financial forecasting. Additionally, improvements in high-dimensional data processing indicate a shift towards more adaptive learning mechanisms, allowing RVMs to outperform traditional classifiers in specific domains. Despite these advancements, the reliance on manual parameter tuning and cross-validation poses challenges in real-world implementation. The need for extensive computational resources makes RVM-based models less practical for large-scale applications, particularly in industries requiring real-time decision-making. Moreover, class imbalance continues to impact prediction accuracy, emphasizing the need for adaptive learning frameworks that can automatically adjust to varying data distributions. While RVM kernels have demonstrated clear advantages, their effectiveness depends on addressing fundamental efficiency and scalability issues. The improvements in multi-view learning approaches and tensor-based methods suggest that future models will focus on integrating multiple learning perspectives to enhance performance. However, the computational cost of these methods remains a concern, as higher model complexity often leads to slower processing times and increased resource consumption. Furthermore, the challenge of noise sensitivity in classification tasks suggests that existing loss functions may not be entirely optimal for all datasets. Alternative loss functions and adaptive weighting mechanisms could improve model resilience, but their implementation requires further refinement. Automation in parameter tuning is also crucial to reduce reliance on trial-and-error methods, making RVM-based models more efficient for practical use.

3.2. Analysis of Hybrid RBF-Polynomial Kernel Implementation in Mathematical Models

The implementation of hybrid kernel RBF-polynomials in mathematical models has gained considerable attention due to their versatility and effectiveness across various applications. By integrating the strengths of radial basis functions (RBFs) with polynomial kernels, these hybrid approaches enhance the modelling of complex phenomena by capturing both non-linear relationships and linear dependencies [25]. This methodology has been particularly effective in differential equations, where hybrid models have demonstrated flexibility in solving fractional differential equations and simulating neuronal activity, as seen in neuroscience research [26], [27]. Additionally, in numerical relativity, hybrid models improve the efficiency of waveform simulations, which are crucial for gravitational wave analysis [28]. These implementations highlight the adaptability of hybrid kernels in addressing diverse mathematical challenges, with error analysis showing optimal convergence properties that contribute to numerical stability.

Beyond mathematical modelling, hybrid kernel RBF-polynomials have also contributed significantly to applied sciences, including epidemiology, agriculture, and quantum physics. In epidemiology, hybrid models have been integrated into SIR frameworks to analyze the impact of non-pharmaceutical interventions (NPIs) on infectious disease dynamics, demonstrating their utility in public health strategies [29]. In agriculture, the GWO-CEEMDAN-KRR model, which combines kernel ridge regression with decomposition techniques, has improved wheat yield predictions by reducing errors by approximately 20%, underscoring the effectiveness of kernel methods in predictive analytics [30]. Furthermore, in quantum many-body systems, hybrid neural-network approaches enhance the computation of dynamical distributions, addressing computational challenges through the integration of kernel polynomial techniques with deep learning [31]. While hybrid kernel RBF-polynomial models hold significant promise in enhancing computational efficiency and predictive accuracy, challenges remain, particularly regarding computational costs and the need for extensive data, necessitating further research to optimize their broader applications.

The successful implementation of hybrid kernel RBF-polynomials across various disciplines demonstrates the advantages of this approach in addressing complex problems. In differential equations, the flexibility of this method enables more accurate problem-solving by accounting for nonlinear aspects that are often challenging for conventional techniques. In epidemiology, the integration of hybrid kernels into SIR models illustrates that this approach not only serves as a predictive tool but also facilitates the quantitative analysis of public health policies. In the agricultural sector, the enhanced accuracy of crop yield predictions achieved by the GWO-CEEMDAN-KRR model highlights the substantial potential of hybrid kernel RBF-polynomials in data-driven modeling that demands high precision. Similarly, in quantum physics and numerical relativity, the application of hybrid kernels has been shown to improve computational efficiency, which is a critical factor in handling large datasets and simulating complex equation-based systems. Overall, this hybrid methodology demonstrates superiority in both predictive accuracy and computational efficiency compared to single-kernel approaches. Despite these advantages, several challenges must be addressed in the implementation of hybrid kernel RBF-polynomials. One of the primary concerns is the increased computational complexity resulting from the combination of two distinct kernels. This can lead to longer processing times and higher computational resource demands, particularly when applied to large datasets or high-dimensional models. Additionally, parameter selection remains a significant challenge. Key parameters, such as the bandwidth of the RBF kernel and the polynomial degree, must be carefully adjusted according to the dataset characteristics to ensure optimal model performance. Inappropriate parameter selection may lead to overfitting or under-fitting, ultimately compromising predictive accuracy. Furthermore, although research has yielded promising results across multiple disciplines, further validation is necessary using broader datasets and real-world conditions. For instance, in epidemiology, developed models should be tested with data from diverse regions and different intervention scenarios to verify their reliability on a larger scale. Similarly, in agricultural yield prediction, models must be calibrated while considering climate variability and other environmental factors to ensure robustness in practical applications.

3.3. Comparison of Model Accuracy with Hybrid RBF, Polynomial, and RBF-Polynomial Kernels

The Radial Basis Function (RBF) kernel and polynomial kernel have long been used in various machine learning model applications, particularly in the classification and regression of non-linear data. The RBF kernel is known for its ability to handle more complex patterns by mapping data into higher-dimensional spaces, enabling better separation between classes or patterns [18]. On the other hand, the polynomial kernel offers the ability to handle structural variations in the data, providing flexibility in capturing broader relationships between data points [32]. However, both kernels have certain limitations. While the RBF kernel is effective in addressing non-linear patterns, it can struggle in situations where the data is highly heterogeneous or contains significant noise [33]. This can cause the model to overfit or fail in generalization. Meanwhile, the polynomial kernel, despite its high flexibility, can become overly complicated or less effective when handling highly non-linear data or data with irregular distributions.

The use of the hybrid RBF-Polynomial kernel has emerged as a solution to address the limitations of single kernels in handling more complex data. The combination of RBF and polynomial kernels offers advantages by merging the ability of the RBF kernel to handle local non-linear patterns with the polynomial kernel's capacity to capture broader structural variations [34]. This hybrid approach has proven to be more effective in improving model accuracy for various classification and regression tasks, especially in applications involving data with high variation and significant noise [35]. Recent studies indicate that models with the RBF-Polynomial hybrid kernel can better handle data complexity compared to single-kernel-based models. For example, in pattern recognition and image analysis applications, this kernel combination can capture both local and global patterns simultaneously, enhancing model performance in predictions [36]. Furthermore, research involving high-dimensional data and irregular distributions shows that models with this hybrid kernel have a greater ability to address generalization challenges and reduce the risk of overfitting [37]. In other words, the RBF-Polynomial hybrid kernel not only enhances accuracy but also improves model stability in handling various types of complex and unstructured data.

The use of both RBF and polynomial kernels each presents distinct advantages and limitations. The RBF kernel is effective for local non-linear data and class separation in high-dimensional space, but it is prone to overfitting and struggles with generalization when the data contains significant noise or heterogeneity. On the other hand, the polynomial kernel is more flexible in handling broader structural relationships between data; however, it can become overly complex and less effective for non-linear or poorly structured data. The RBF-Polynomial hybrid approach combines the strengths of both kernels, enabling it to better handle data complexity and variation, while also improving generalization capabilities with a lower risk of overfitting. Models utilizing the hybrid kernel have proven more effective in enhancing accuracy for data with high variation and significant noise, as well as being more stable for high-dimensional data with irregular distributions. However, challenges remain regarding computational complexity, as hybrid models tend to be more intricate and require longer training times, especially when applied to large datasets or real-time applications.

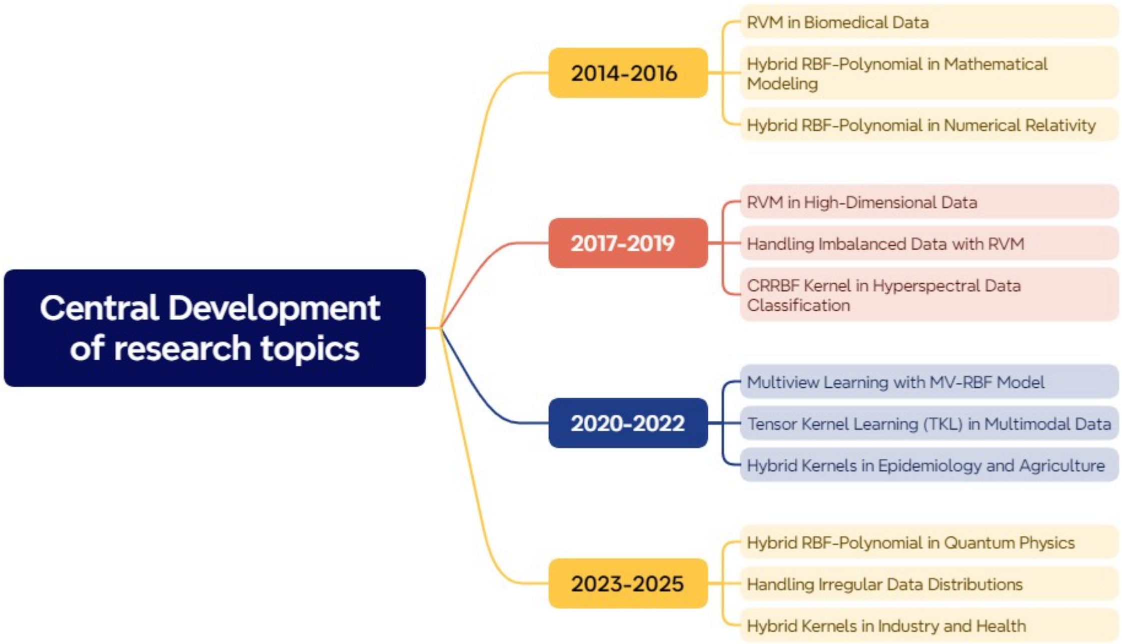

Figure 2. Development of research topics over the last 10 years

Figure 2 shows that the research on the hybrid RBF-Polynomial kernel has evolved significantly over time, addressing a wide range of applications and challenges. From 2014 to 2016, the primary focus was on utilizing the hybrid kernel for mathematical modelling, such as solving fractional differential equations and simulating neuronal activity, as well as its use in biomedical data like Alzheimer's and cancer classification. Between 2017 and 2019, advancements were made in applying RVM to high-dimensional and imbalanced data, particularly in text classification and social network analysis, while the CRRBF kernel was introduced for hyperspectral data classification. From 2020 to 2022, research shifted towards multiview learning and Tensor Kernel Learning (TKL) to enhance prediction accuracy, especially in Alzheimer's analysis, as well as incorporating hybrid kernels in epidemiology for disease dynamics and agriculture for crop yield predictions. The most recent developments from 2023 to 2025 focus on applying hybrid RBF-polynomial kernels in quantum physics and industries like healthcare, agriculture, and technology, with an emphasis on improving model stability, handling irregular data distributions, and enhancing computational efficiency. This progression highlights the growing versatility and importance of hybrid kernels across diverse fields.

4. Conclusions and Suggestions

Based on the evaluation of the application of RBF-polynomial kernels and the relevance of kernels across various fields, it can be concluded that the RBF-polynomial hybrid kernel combination demonstrates significant potential in enhancing model accuracy for complex data, with its strengths in handling high data variation, noise, and irregular data distributions. However, the use of this hybrid model is not without challenges, particularly regarding higher computational complexity, longer training times, and the need for optimal parameter selection to avoid overfitting or underfitting. While efforts have been made to address these issues, such as the development of kernel-based oversampling techniques and tensor-based approaches, problems related to imbalanced data and noise sensitivity remain key concerns that need further attention.

The identified gap lies in the limited research focused on automating adaptive kernel parameter selection, which could reduce reliance on trial-and-error methods and improve model efficiency. Furthermore, despite the development of various techniques to mitigate the impact of imbalanced data, further research is needed to develop more effective methods to tackle this issue, particularly in datasets with highly uneven class distributions. Therefore, urgent research topics for future investigation include the development of adaptive algorithms for automatic parameter selection in hybrid kernel models, as well as the exploration of new, more robust techniques for addressing class imbalance and noise sensitivity in real-time applications and large datasets. Such research is expected to accelerate the implementation of these models in practical applications, such as medical diagnostics, social data analysis, and predictions in sectors that demand high accuracy and computational efficiency.

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