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Revolutionizing Healthcare: Comprehensive Evaluation and Optimization of SVM Kernels for Precise General Health Diagnosis

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Abstract.
Purpose: This study is driven by a two-fold objective. Firstly, it seeks to optimize the Support Vector Machine (SVM) algorithms in machine learning, comprehensively evaluating diverse SVM kernel variants to enhance their versatility and applicability across various domains, which is beyond the healthcare sector. Secondly, in the context of general health diagnosis, it aims to assess the suitability of SVM kernels for achieving precision in predictive modeling. The choice of SVM is rooted in its effectiveness, proven in classification and regression within data mining. SVMs excel in high-dimensional problem classification, demonstrating superior accuracy, making them invaluable in refining machine learning methodologies and advancing diagnostic systems, promising implications for healthcare and beyond. The chosen SVM model, distinguished by its exceptional performance, is then implemented in real-world applications, particularly in wireless, non-invasive healthcare devices. This deployment signifies a substantial stride toward advancing healthcare practices and holds promising implications for various fields.
Methods: Data for this study was collected from publicly accessible datasets on Kaggle, encompassing a comprehensive array of general health-related information. This dataset, comprised of clinical data and vital signs data, underwent meticulous preprocessing, such as data cleaning, feature extraction, and categorization of health status into ‘healthy’ and ‘requiring further attention’. Subsequently, predictive models were constructed employing Support Vector Machine (SVM) algorithms with various kernel functions, such as Linear, RBF, Polynomial, and Sigmoid. They were trained and tested on the preprocessed dataset to assess their efficacy in general health diagnosis. Model performance was rigorously evaluated using established metrics, including accuracy, precision, recall, F-1 score, Area Under the Curve (AUC), Receiver Operating Characteristic (ROC) curve, and cross-validation. The selection of the most efficacious SVM kernel was governed by stringent adherence to industry standards and best practices, ensuring optimal integration into health diagnostic systems. The chosen model was tested using new datasets obtained from wireless non-invasive healthcare devices and the pre-existing AHD application. Hyperparameter tuning was meticulously executed to maximize accuracy, ensuring the effectiveness of the evaluation process.
Results: The results demonstrate that the Polynomial kernel was selected as the body health diagnostic model instead of the Linear, RBF, and Sigmoid kernels. This kernel has a training time of 0.8 seconds, a testing time of 0.1 seconds, accuracy scores of 97%, precision of 97%, recall of 97%, F-1 score of 97% for training metrics, and accuracy scores of 99%, precision of 99%, recall of 99%, and F-1 score of 99% for testing metrics. The accuracy of the polynomial kernel model decreased to 0.88 on new datasets; adjusting the hyperparameter C to C = 100 resulted in the highest accuracy of 0.945.
Novelty: This study introduces a pioneering approach by rigorously optimizing Support Vector Machine (SVM) algorithms, notably the innovative application of the Polynomial kernel in general health diagnosis. Unlike traditional kernels, the Polynomial kernel exhibited exceptional accuracy (up to 99%) and precision. Furthermore, the study’s unique methodology, combining industry standards and meticulous hyperparameter tuning, ensures seamless integration into real-world healthcare systems. The deployment of this optimized model in wireless non-invasive healthcare devices signifies a groundbreaking advancement, highlighting a novel synthesis of theoretical innovation and practical implementation in machine learning for healthcare.

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INTRODUCTION

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Machine learning is the subfield of AI research [1]. A good machine learning model should generalize well from training to test data, referring to the capacity of the model to adapt its learnings to new data [2] that can be determined through specific performance evaluation [3]. Machine learning with high performance on the system can be used as rapid, low-cost, and on a large scale [1]. The problem of medical practitioner shortages and increased national health expenditure can be resolved by integrating healthcare with machine learning (ML), yielding an intelligent healthcare system [1].

The algorithms for machine learning include unsupervised, supervised, and reinforced learning [4]–[6]. Supervised learning methods encompass a range of models, such as Support Vector Machine (SVM), Linear Regression, K-Nearest Neighbor (KNN), Decision Tree, Naive Bayes, and Artificial Neural Network [1]. A popular algorithm for data classification is a support vector machine [7]. Support Vector Machine has been introduced as an effective instrument in data mining, specifically classification and regression [8]. High-dimensional data is one of the issues that plague the field of clarification [9]. In general, the data is commonly depicted in a space with many dimensions, often consisting of hundreds of thousands of words. It is important to note that a particular data point may only occupy a subset of the overall dimensions [10]. Support vector machines (SVMs) have demonstrated successful applications in the classification of high-dimensional problems across various domains, including remote sensing, web page classification, microarray analysis, etc. [11]. It has also been demonstrated that this algorithm is more effective at obtaining high accuracy. SVMs gain strength by identifying the optimal classifier with the most significant margin between instances of distinct classes [10]. It does not require additional calculations from feature selection or dimension reduction methods [11]. This is possible because SVM employs its own kernel [12].

One of the major challenges users experience when using SVM is selecting the proper kernel function based on the dataset's attributes to be analyzed [8]. In SVM classifiers, Linear, Polynomial, RBF, and Sigmoid kernels are frequently employed [8], [13]. Each of these options possesses both advantages and cons [14]. In relation to the quantity of data in the employed datasets, the Linear kernel's attributes showed the best performance [13]. Kernel Polynomials were efficient for high-resolution data prediction and time complexity. For intermediate-resolution kernels, RBF predicted better [15]. In this case, kernel performance depends on characteristics, instances, classes, missing values, and dataset type [8].

Health is crucial for humans to carry out daily activities [16]. SVM algorithms are utilized in numerous healthcare applications. This work centers on medical data, and it has been demonstrated that Support Vector Machines (SVM) exhibit satisfactory performance in classifying various disease types. According to Ray et al. [1], the SVM algorithm has the highest accuracy of 92.51% in diagnosing chronic kidney disease. On the Indian Pima population model, Kaur et al. [17] employed different algorithms for diabetes prediction, including SVM-Linear, RBF-SVM, KNN, ANN, and MDR. Compared to other models, the SVM-Linear model has the highest accuracy of 0.89 and precision of 0.88. Using the algorithms Decision Tree, Random Forest, SVM-LR, and Naive Bayes, Bashir et al. [18] developed a model for predicting cardiac disease. The results show that the SVM-LR algorithm has a maximum accuracy of 84.85 percent. Uddin et al. [19] used supervised machine learning methods, such as SVM, decision trees, random forests, and naïve Bayes, KNN, and ANN, with SVM obtaining the second-highest accuracy beneath the random forest. Ayon et al. [20] conducted a comparative analysis of various artificial intelligence techniques to forecast the occurrence of coronary artery heart disease. This analysis was performed on two distinct datasets. In the context of the Cleveland dataset, the Support Vector Machine (SVM) algorithm demonstrated a notable accuracy rate of 97.36%, surpassing the performance of alternative methods.

Despite the numerous smart healthcare innovations, machine learning applications exist in two areas of disease management: fatal diseases (cardiovascular diseases) and chronic diseases (chronic kidney diseases and diabetes) [1]. Clinical data and vital signs are pivotal in establishing continuous communication between doctors and patients, enabling the early detection of chronic disease and facilitating predictive data analysis [21]. Understanding the patient's general health status empowers healthcare providers to identify potential health issues promptly, allowing for early interventions and disease prevention [22]. The focus on general health in clinical data takes into account all factors influencing patient well-being, facilitating the development of holistic and personalized care plans. With the WHO projecting an increase in individuals experiencing better health and well-being in 2023, emphasizing general health within clinical data becomes paramount. This approach ensures that healthcare addresses existing chronic diseases and supports the overall well-being of patients, paving the way for a healthier future.

In this study, the primary research objective centers on the domain of general body health diagnosis. Notably, it aims to establish that Support Vector Machine (SVM) algorithms exhibit superior performance compared to other algorithms, as discussed in prior studies. It is crucial to emphasize that while SVM algorithms have demonstrated exceptional performance in detecting chronic illnesses, their application has historically been confined to such cases. Recognizing the potential for enhanced versatility and applicability across diverse domains beyond the healthcare sector, the research endeavors to push the boundaries of SVM kernel performance. Specifically, within the context of general health diagnosis, the aspiration is to determine the suitability of SVM kernels for achieving precision in predictive modeling under real conditions, subject to rigorous evaluation and comparative analysis. The research aims to implement the chosen robust SVM kernel model for predictive modeling in healthcare, specifically comprising wireless non-invasive healthcare device information and clinical data input from the developed AHD application.

METHODS

This research used Python version 3.7 as the programming language for implementing the diagnostic general body health prediction model. The study leveraged several essential libraries and frameworks, including Pandas, Matplotlib, Seaborn, and Scikit-Learn, to facilitate data manipulation, visualization, and machine learning model development. These tools were thoughtfully selected to ensure compatibility and efficiency in the data analysis pipeline. The dataset for this evaluation, gathered from Kaggle, a reputable public web-based source, comprised 35394 data points and was meticulously partitioned into training and testing subsets at an 80:20 ratio. This partitioning resulted in 27895 data points allocated for training, used to measure training performance metrics, and 6974 for testing, employed to assess testing performance metrics. The evaluation of these SVM algorithms involved a thorough analysis using a diverse range of performance metrics. These metrics included training and testing times, accuracy, precision, recall, F1-score, Area Under the Curve (AUC), Receiver Operating Characteristic (ROC), and cross-validation. It is worth emphasizing that throughout the testing process, the parameter configurations for each kernel remained at their default settings.

Ashmore [23] states that constructing machine learning involves four cycles: data processing, model learning, model verification, and model deployment. The methodology employed in this study is as follows:

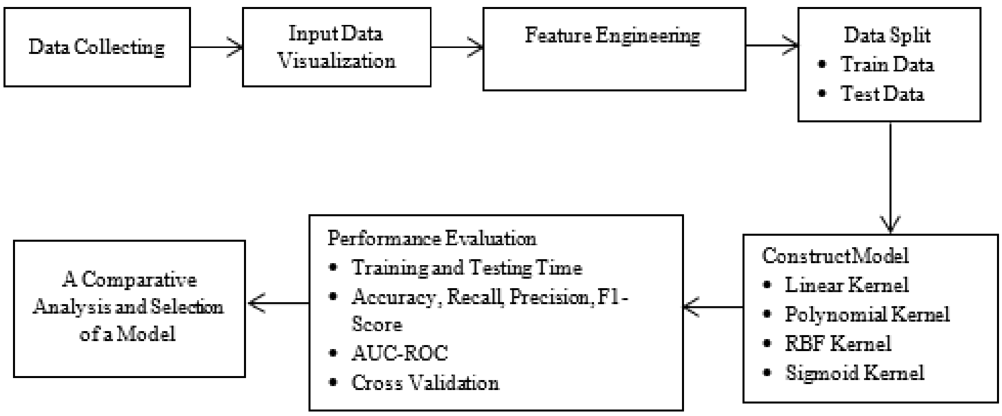

Figure 1. Research framework

Data Collecting

In the initial phase of the research framework, data collection served as a foundational step. In this stage, a comprehensive dataset was gathered from Kaggle, a reputable public web-based source. This dataset comprised a rich array of clinical data and vital signs records. Table 1 provides data set information:

Table 1. Dataset description

No. of Instances	67376
Number of Input Features	18
Number of Output Classes	2
Class Label	1-Healthy 2-Not Healthy

Feature Engineering
The dataset underwent feature engineering, involving the removal of unnecessary instances. Table 2 presents the description of the dataset after the feature engineering process.

Table 2. Description of dataset features and labels

	Feature	Type	Values
(i)	Gender	Integer	Male (M) = 1; Female (F) = 0
(ii)	Sex	Integer	[17-65]
(iii)	Body height	Integer	[140-194]
(iv)	Body weight	Integer	[35-178]
(v)	Body temperature	Integer	[10-41]
(vi)	Systole	Integer	[15-179]
(vii)	Diastole	Integer	[40-109]
(viii)	Heart rate	Integer	[6-200]
(ix)	SPO2	Integer	[8-100]
(x)	Blood sugar	Integer	[20-100]
(ix)	Body Health Diagnose	Integer	True (Healthy) = 1; False (Not Healthy) = 0

This rigorous data collection phase laid the groundwork for subsequent analyses and the development of the diagnostic health prediction model, aligning with the principles of sound scientific investigation within the context of health research.

Data Split
After passing through this stage, the data was separated into training and testing data in an 8:2 ratio. This is due to the fact that the algorithm utilized is supervised learning. This means that the data is first taught to recognize patterns in the input data so that a classifier model for future predictions can be developed. In order to mitigate the issue of overfitting the training data, it is partitioned into distinct sets [24]. 27895 training data and 6974 testing data were retrieved from the partition results. Furthermore, the parameter settings for each kernel employed in this testing were kept at their default configurations.

Construct Model
The learning algorithm utilizes the input data during the process of automated model building in order to identify and analyze patterns and relationships pertinent to achieving the desired learning objective. As previously elucidated, support vector machines (SVM) endeavor to construct a discriminative hyperplane that distinguishes between data points belonging to different classes. This often involves mapping the input data into a feature space of larger dimensions, which enhances the ability to separate the data points. The construct model is implemented in the environment. It is justifiable to compare alternative models with varying levels of complexity. This encompasses the competing model classes and alternate variants within the same model class to select a suitable prediction model for a specific task [25]. The SVM technique was used alongside several different kinds of kernels in this research [12]:

Linear Kernel
Linear kernels have identity mappings, meaning the input and feature spaces are equivalent. Linear SVMs are SVMs with Linear kernels. Mathematically, the Linear kernel is represented by equation (1) [26]:

$$K(x1, x2) = x\ T\ 1\ x2 \Rightarrow \varphi(x) = x \qquad (1)$$

RBF Kernel
The Gaussian RBF kernel calculates the Euclidean distance between two landmarks with a free parameter using the Gaussian function [27]. The RBF-Kernel equation is as follows (Equation 2) [12]:

$$K(x, x') = \exp(-\gamma\|x - x'\|2) \qquad (2)$$

Polynomial Kernel

The kernel's non-stationary characteristic renders it suitable for issues in which all training data is standardized, setting it apart from the Polynomial kernels [28]. The Polynomial-Kernel equation is represented by equation (3) [12]:

$$K(x,y)- (xy + C) \tag{3}$$

Sigmoid Kernel

The kernel makes use of the Sigmoid function. The provided system, known as the hyperbolic tangent kernel technique, can be analogized to a two-layer neural network, namely a perceptron network [28]. Sigmoid kernels are less effective than RBF kernels. Still, they can be modified to behave like Gaussian RBF kernels, especially in two-dimensional problems with high-dimensional feature vectors or non-linear decision boundaries. The Sigmoid-Kernel equation is represented by the following equation(4)[12]:

$$K(x, y) = \tanh(\propto x\ T\ y + c) \tag{4}$$

Performance Evaluation

There are numerous criteria that can be used to evaluate the quality of a model. These characteristics include its performance, processing requirements, and interpretability. Performance-based metrics are used to evaluate a model based on how well it achieves the learning task's specified objective. A number of various ratios of correct to incorrect predictions can be used to evaluate classification algorithms. Among these ratios are precision, accuracy, recall, and the F1-score [25], [29], training and testing time [30], AUC [24], ROC [29], and cross-validation [31].

RESULTS AND DISCUSSIONS

The study comprehensively evaluated various Support Vector Machine (SVM) methods, including Linear, Radial Basis Function (RBF), Polynomial, and Sigmoid kernels. The dataset utilized for this evaluation comprised 35394 data points, meticulously partitioned into training and testing subsets at an 8:2 ratio. This partitioning resulted in 27895 data points allocated for training, used to measure training performance metrics, and 6974 for testing, employed to assess testing performance metrics. The evaluation of these SVM algorithms involved a thorough analysis using a diverse range of performance metrics. These metrics included training and testing times, accuracy, precision, recall, F1-score, Area Under the Curve (AUC), Receiver Operating Characteristic (ROC), and cross-validation. It is worth emphasizing that throughout the testing process, the parameter configurations for each kernel remained at their default settings.

Within the realm of performance measurement activities, the study involved the assessment of training and testing times for algorithms. This was achieved through five iterative measurements to ensure a comprehensive evaluation of algorithmic efficiency. Notably, the research was conducted on a system powered by an Intel® Xeon® CPU@2.30GHz. The findings are presented in Table 3.

Table 3. Measurement of training and testing time

Support Vector Machine	Training Time (second)	Testing Time (second)
Linear Kernel	159.4	0.2
Polynomial Kernel	0.8	0.1
RBF Kernel	1.6	0.3
Sigmoid Kernel	14.8	3.6

Table 3 shows that the Linear kernel exhibits an anomaly at this time. This could be due to a number of factors, such as the scale of big data, which can lengthen the training period due to the increased number of matrix aggregation operations. In addition, the resource platform utilized by Google Colab has limitations. Compared to Polynomial kernels and RBF in the process of testing, the Sigmoid kernel requires the most effort. It is essential to underline that there is a significant difference between the Sigmoid kernel and other kernels. On the SVM kernel, Sigmoid functions entail more complicated mathematical operations, such as exponential functions and proliferation operations. Based on the time measurement results, it can be concluded that the Polynomial kernel has a similar time to the RBF due to the similar complexity of their tendencies.

Table 4. Training evaluation metrics

Kernel	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Linear Kernel	95	95	95	95
RBF Kernel	96	96	96	96
Polynomial Kernel	97	97	97	97
Sigmoid Kernel	74	74	74	74

The average result for the Polynomial kernel is 97%, which signifies the model's near-perfect classification of all samples within the entire dataset. The precision score of 0.97 demonstrates the model's accurate identification of nearly all positive predictions. The recall score of 0.97 indicates minimal oversight of positive cases by the model, showcasing its exceptional ability to detect positive instances and recognize true positives. Furthermore, the F1-score of 0.97 provides a balanced representation of the model's proficiency in accurately classifying positive cases (precision) and identifying genuine positive instances (recall). This superior accuracy aligns with SVM theory, emphasizing optimal classification through distinct class margin [10]. This could be due to a more complex model than the Linear or Sigmoid kernels. Polynomial kernel offers adjustable parameters to control mapping complexity, while the RBF kernel demonstrates the ability to handle highly complex data and excels in managing intricate and unstructured pattern [32]. Models with increasing levels of complexity can respond better to patterns and variability in training data. This can result in outstanding data training results and ideal numbers on the confusion matrix.

Due to the limited weakness of models coping with complex non-linear relationships in data sets, the result of training evaluation metrics on the Linear kernel is smaller than the RBF and Polynomial kernels. The availability of additional features resulting from the transformation that the Linear kernel lacks can also activate the kernel's inability to handle complex non-linear relationships. The score of 95% for all metric outcomes of the Linear kernel indicates that approximately 95% of all predictions made by the model are accurate. High consistency in accuracy, precision, and recall, as well as the F1-score equal to 95%, may indicate the classification model's proficient overall performance.

The score of 74% for accuracy, precision, recall, and F1-score indicates that the model has low accuracy and generates numerous classification errors. In this case, only about 74 percent of the model's predictions are accurate. There is a significant difference between the Sigmoid kernel and the other three kernels in the training matrix training outcome. This is in accordance with Ghosh [12], observing that the Sigmoid kernel is comparatively less effective than RBF kernels. This is possible due to the "saturation" property of the Sigmoid kernel used by this kernel's decision function at extreme values. A minor change in the input close to extreme values will produce very small changes in the output of the Sigmoid function, making it less sensitive to the extreme value. This means that models tend to make extremely accurate predictions. In addition, it may be more challenging to differentiate between classes in the case of classification.

Table 5. Testing evaluation metrics

Kernel	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Linear Kernel	99	99	99	99
RBF Kernel	99	99	99	99
Polynomial Kernel	99	99	99	99
Sigmoid Kernel	72	72	72	72

Table 5 shows that RBF and Polynomial kernels produced a fixed value of 99%, as the Linear kernel did. This demonstrates that the model can consistently distinguish between the classes present in the data. The Sigmoid kernel's accuracy, precision, recall, and F1-score of 72% indicate that the model has a low level of precision and generates many classification errors. In other words, approximately 72% of model forecasts are accurate. This indicates that the model has trouble differentiating between the classes in, the data and, therefore, cannot make accurate predictions.

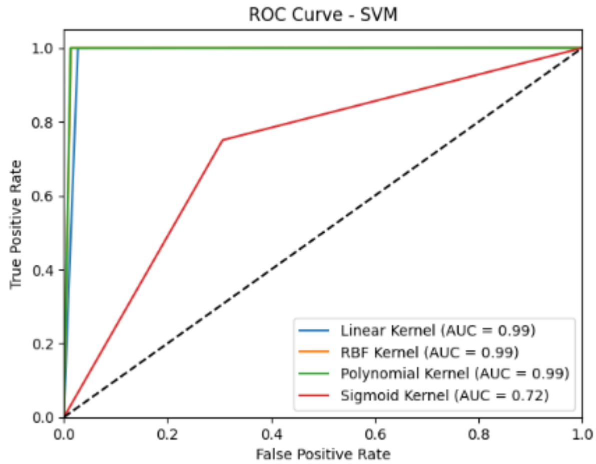

Figure 2. Comparison of AUC and curve ROC kernel SVM

Due to their shared ROC and AUC values, both the blue, green, and dwarf curves accumulate. The ROC curve has a little deviation from the diagonal and an AUC of 0.99, which is identical. This demonstrates that Linear, RBF, and Polynomial models can accurately predict positive and negative classes. The model's success in this regard illustrates its superiority over blue and green curves and dwarfs in predicting positive classes while avoiding errors in identifying negative ones. The red curve, also known as the Sigmoid kernel, tends to shift to the left until it reaches the diagonal (y=x). Even AUC values over the curve's 0.5 influence, at 0.72. This indicates the model could be making incorrect predictions between the positive and negative categories. The RBF kernel's cross-validation score of 0.991 is superior to that of the Linear kernel. This is because of the RBF kernel's capacity to manage complex or non-linear data patterns. The maximum score for the Polynomial kernel is 0.992. This is because the model employs a Polynomial transformation, which allows it to capture non-linear relationships between features. This kernel has high stability and is resistant to change and variation. In line with the theoretical understanding that the sigmoid kernel is considered the least effective [33], the research findings corroborate this notion by revealing the smallest value achieved with the sigmoid kernel, i.e., 0.443. These kernels performed poorly when coping with intricate data patterns. The tendency of the Sigmoid function to "saturate" at extreme levels can impede the model's ability to distinguish between positive and negative classes. Consequently, performance and robustness values may decline.

Based on the comprehensive comparison of overall performance, the significant differences observed between the Sigmoid kernel and the other three kernels, as indicated by Ghosh [12], underscore the importance of these variations. The inherent 'saturation' property in the Sigmoid kernel's decision function at extreme values reduces its sensitivity, resulting in highly accurate predictions yet potentially challenging class differentiations during classification. This observation emphasizes the necessity of understanding these subtle differences, providing valuable insights for kernel selection in SVM models.

Implementation Model in Healthcare Devices

In this study, the polynomial kernel SVM algorithm, which exhibited the best performance among the three kernels based on the aforementioned evaluation parameters, was tested for its accuracy using a new dataset. This dataset comprised wireless non-invasive healthcare device information and clinical data inputted from the AHD application developed [34]. For this experiment, the model was tested with a dataset containing 200 records and six different values of the parameter C, which serves as a hyperparameter in the polynomial kernel. The following presents the comparative results:

Table 7. Accuracy comparison based on variations of parameter C

No.	C Parameter	Model Accuracy (%)	New Dataset Accuracy (%)
1.	Not Found	96.5	88
2.	0.01	94	86
3.	0.1	95	86
4.	1	96.5	88
5.	10	97	92
6.	100	97	94.5

Based on these results, the higher the value of parameter C, the better the accuracy of the model and the new data. This indicates that the polynomial kernel with a parameter setting of C=100 achieved the highest accuracy for new data, with a value of 0.945, while the model accuracy remained at 0.97. This model is the one implemented in the system.

CONCLUSION

Aligning with the outlined dual objectives, this study meticulously examined various SVM kernels for general body health diagnosis. In addition, it successfully implemented the chosen model in wireless non-invasive healthcare devices by utilizing clinical data sourced from the developed AHD application. Among the kernels scrutinized, the Polynomial kernel emerged as the optimal choice, displaying consistently outstanding performance metrics, including a training time of 0.8 seconds, a testing time of 0.1 seconds, and exceptional accuracy, precision, recall, and F-1 scores of 97% for training metrics and 99% for testing metrics. The model's robustness was further affirmed through a cross-validation score of 0.992, solidifying its reliability for future diagnostic applications. Despite encountering a minor accuracy decrease on new datasets, fine-tuning the hyperparameter C to C = 100 significantly enhanced accuracy to 0.945, facilitating its seamless integration into the body health diagnosis system. These results mark a significant stride in optimizing SVM algorithms and extending their applicability, aligning perfectly with the study's overarching purpose. Moreover, these findings hold promising implications for healthcare practices and patient outcomes, exemplifying the study's commitment to refining machine learning methodologies and advancing diagnostic systems. Looking ahead, further exploration of the Polynomial kernel's adaptability across diverse healthcare datasets could unlock new possibilities, ensuring continued innovation and fulfilling the comprehensive purpose of this research endeavor.

REFERENCES

[1] A. Ray and A. K. Chaudhuri, "Smart healthcare disease diagnosis and patient management: Innovation, improvement and skill development," *Mach. Learn. with Appl.*, vol. 3, p. 100011, Mar. 2021, doi: 10.1016/J.MLWA.2020.100011.

[2] J. Vamathevan *et al.*, "Applications of machine learning in drug discovery and development," *Nat. Rev. Drug Discov.*, vol. 18, no. 6, pp. 463–477, 2019, doi: 10.1038/s41573-019-0024-5.

[3] J. R. Cano, P. A. Gutiérrez, B. Krawczyk, M. Woźniak, and S. García, "Monotonic classification: An overview on algorithms, performance measures and data sets," *Neurocomputing*, vol. 341, pp. 168–182, 2019, doi: 10.1016/j.neucom.2019.02.024.

[4] A. Singh and R. Kumar, "Heart Disease Prediction Using Machine Learning Algorithms," *Int. Conf. Electr. Electron. Eng. ICE3 2020*, pp. 452–457, Feb. 2020, doi: 10.1109/ICE348803.2020.9122958.

[5] E. Retnoningsih and R. Pramudita, "Mengenal Machine Learning Dengan Teknik Supervised Dan Unsupervised Learning Menggunakan Python," *Bina Insa. Ict J.*, vol. 7, no. 2, p. 156, 2020, doi: 10.51211/biict.v7i2.1422.

[6] H. Abijono, P. Santoso, and N. L. Anggreini, "Algoritma Supervised Learning Dan Unsupervised Learning Dalam Pengolahan Data," *J. Teknol. Terap. G-Tech*, vol. 4, no. 2, pp. 315–318, Apr. 2021, doi: 10.33379/gtech.v4i2.635.

[7] D. Aprilianto, "SVM Optimization with Correlation Feature Selection Based Binary Particle Swarm Optimization for Diagnosis of Chronic Kidney Disease," *J. Soft Comput. Explor.*, vol. 1, no. 1, Sep. 2020, doi: 10.52465/joscex.v1i1.1.

[8] I. S. Al-Mejibli, D. H. Abd, J. K. Alwan, and A. J. Rabash, "Performance evaluation of kernels in support vector machine," *Proc. - 2018 1st Annu. Int. Conf. Inf. Sci. AiCIS 2018*, pp. 96–101, 2019, doi: 10.1109/AiCIS.2018.00029.

[9] C. Zhang, Y. Zhou, J. Guo, G. Wang, and X. Wang, "Research on classification method of high-dimensional class-imbalanced datasets based on SVM," *Int. J. Mach. Learn. Cybern.*, vol. 10, no. 7, pp. 1765–1778, 2019, doi: 10.1007/s13042-018-0853-2.

[10] S. F. Hussain, "A novel robust kernel for classifying high-dimensional data using Support Vector Machines," *Expert Syst. Appl.*, vol. 131, pp. 116–131, 2019, doi: 10.1016/j.eswa.2019.04.037.

[11] V. Pappu and P. M. Pardalos, *High-Dimensional Data Classification*. doi: 10.1007/978-1-4939-0742-7.

[12] S. Ghosh, A. Dasgupta, and A. Swetapadma, "A study on support vector machine based linear and non-linear pattern classification," *Proc. Int. Conf. Intell. Sustain. Syst. ICISS 2019*, no. Iciss, pp. 24–28, 2019, doi: 10.1109/ISS1.2019.8908018.

[13] A. Goel and S. K. Srivastava, "Role of kernel parameters in performance evaluation of SVM,"

Proc. - 2016 2nd Int. Conf. Comput. Intell. Commun. Technol. CICT 2016, pp. 166–169, 2016, doi: 10.1109/CICT.2016.40.

[14] N. L. Husni, M. Al Muhaajir, E. Prihatini, A. Silvia, S. Nurmaini, and I. Yani, "Optimal Kernel Classifier in Mobile Robots for Determining Gases Type," *Proc. 2018 Int. Conf. Electr. Eng. Comput. Sci. ICECOS 2018*, vol. 17, pp. 107–110, 2019, doi: 10.1109/ICECOS.2018.8605252.

[15] V. Sharma, D. Baruah, D. Chutia, P. Raju, and D. K. Bhattacharya, "An assessment of support vector machine kernel parameters using remotely sensed satellite data," *2016 IEEE Int. Conf. Recent Trends Electron. Inf. Commun. Technol. RTEICT 2016 - Proc.*, pp. 1567–1570, 2017, doi: 10.1109/RTEICT.2016.7808096.

[16] N. Reska and K. Tsabita, "Comparison of KNN, naive bayes, and decision tree methods in predicting the accuracy of classification of immunotherapy dataset," *J. Student Res. Explor.*, vol. 1, no. 2, pp. 104–121, Jul. 2023, doi: 10.52465/josre.v1i2.170.

[17] H. Kaur and V. Kumari, "Predictive modelling and analytics for diabetes using a machine learning approach," *Appl. Comput. Informatics*, vol. 18, no. 1–2, pp. 90–100, 2022, doi: 10.1016/j.aci.2018.12.004.

[18] S. Bashir, Z. S. Khan, F. Hassan Khan, A. Anjum, and K. Bashir, "Improving Heart Disease Prediction Using Feature Selection Approaches," *Proc. 2019 16th Int. Bhurban Conf. Appl. Sci. Technol. IBCAST 2019*, pp. 619–623, 2019, doi: 10.1109/IBCAST.2019.8667106.

[19] S. Uddin, A. Khan, M. E. Hossain, and M. A. Moni, "Comparing different supervised machine learning algorithms for disease prediction," *BMC Med. Inform. Decis. Mak.*, vol. 19, no. 1, pp. 1–16, 2019, doi: 10.1186/s12911-019-1004-8.

[20] S. I. Ayon, M. M. Islam, and M. R. Hossain, "Coronary Artery Heart Disease Prediction: A Comparative Study of Computational Intelligence Techniques," *IETE J. Res.*, vol. 68, no. 4, pp. 2488–2507, 2022, doi: 10.1080/03772063.2020.1713916.

[21] "View of Electronic Medical Record Analysis To Determine Medical Diagnosis In Chapter Icd 10 Category Using Machine Learning."

[22] Y. Khan, A. E. Ostfeld, C. M. Lochner, A. Pierre, and A. C. Arias, "Monitoring of Vital Signs with Flexible and Wearable Medical Devices," *Adv. Mater.*, vol. 28, no. 22, pp. 4373–4395, 2016, doi: 10.1002/adma.201504366.

[23] R. Ashmore, R. Calinescu, and C. Paterson, "Assuring the Machine Learning Lifecycle: Desiderata, Methods, and Challenges," *ACM Comput. Surv.*, vol. 54, no. 5, 2021, doi: 10.1145/3453444.

[24] D. Rafique and L. Velasco, "Machine learning for network automation: Overview, architecture, and applications [Invited Tutorial]," *J. Opt. Commun. Netw.*, vol. 10, no. 10, pp. D126–D143, 2018, doi: 10.1364/JOCN.10.00D126.

[25] D. P. F. Möller, "Machine Learning and Deep Learning," *Adv. Inf. Secur.*, vol. 103, pp. 347–384, 2023, doi: 10.1007/978-3-031-26845-8_8.

[26] V. K. Chauhan, K. Dahiya, and A. Sharma, "Problem formulations and solvers in linear SVM: a review," *Artif. Intell. Rev.*, vol. 52, no. 2, pp. 803–855, 2019, doi: 10.1007/s10462-018-9614-6.

[27] J. Qezelbash-Chamak, S. Badamchizadeh, K. Eshghi, and Y. Asadi, "A survey of machine learning in kidney disease diagnosis," *Mach. Learn. with Appl.*, vol. 10, p. 100418, Dec. 2022, doi: 10.1016/j.mlwa.2022.100418.

[28] S. Chidambaram and K. G. Srinivasagan, "Performance evaluation of support vector machine classification approaches in data mining," *Cluster Comput.*, vol. 22, pp. 189–196, 2019, doi: 10.1007/s10586-018-2036-z.

[29] S. Nandhini and D. J. Marseline, "Performance Evaluation of Machine Learning Algorithms for Email Spam Detection," *Int. Conf. Emerg. Trends Inf. Technol. Eng. ic-ETITE 2020*, pp. 1–4, 2020, doi: 10.1109/ic-ETITE47903.2020.312.

[30] M. Mohammadi *et al.*, "A comprehensive survey and taxonomy of the SVM-based intrusion detection systems," *J. Netw. Comput. Appl.*, vol. 178, no. January, p. 102983, 2021, doi: 10.1016/j.jnca.2021.102983.

[31] O. Karal, "Performance comparison of different kernel functions in SVM for different k value in k-fold cross-validation," *Proc. - 2020 Innov. Intell. Syst. Appl. Conf. ASYU 2020*, pp. 0–4, 2020, doi: 10.1109/ASYU50717.2020.9259880.

[32] H. Talabani and E. Avci, "Performance Comparison of SVM Kernel Types on Child Autism Disease Database," *2018 Int. Conf. Artif. Intell. Data Process. IDAP 2018*, pp. 1–5, 2019, doi: 10.1109/IDAP.2018.8620924.

[33] M. A. Almaiah *et al.*, "Machine Kernels," 2022.

[34] A. S. Handayani *et al.*, "Design of Android and IoS Applications for Mobile Health Monitoring

Devices," *Adv. Sustain. Sci. Eng. Technol.*, vol. 5, no. 2, p. 0230206, 2023, doi: 10.26877/asset.v5i2.16508.