Mathematical Statistician and Engineering Applications
ISSN: 2094-0343
2326-9865

Comparative Analysis of Kernel based Support Vector Machine Models for Multi Disease Prediction

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Article Info
Page Number: 23 - 37
Publication Issue:
Vol 68 No. 1 (2019)

Article History
Article Received:
09 September 2019
Revised: 16 October 2019
Accepted: 21 November 2019
Publication: 28 December 2019

Abstract
In today's digital age, data is invaluable, and massive amounts of data have been produced in every field imaginable. Reports from the healthcare sector often contain details about patients' health. By having this clinical expertise, we are better able to detect undetectable health problems and provide individualised therapy to each patient. The purpose of this study was to evaluate and contrast several kernel-based Support Vector Machine (SVM) models for use in healthcare prognostication. With the SVM-LRBF technique, we examined the models with the feature reduction set of the Renal Disorders Disease, Diabetes Mellitus, and Cardiovascular Disease datasets. Similarities and differences between the models and other machine learning systems such as Random Forest, SVM-Linear, Decision Tree, SVM-Gaussian Radial Bias Kernel, and SVM-Polynomial were also analysed. Performance of machine learning approaches was measured using a number of different metrics, including specificity, sensitivity, precision, misclassification rate, and accuracy. The experimental findings showed 98.1 percent accuracy for the Renal Disorders Disease dataset, 90.9 percent accuracy for the Diabetes mellitus dataset, and 98.1 percent accuracy for the Cardiovascular Disease dataset.

Keywords: Support Vector Machine, Laplace Radial Bias Kernel, Multi-Disease Prediction Model, Radial Bias function, Diabetesmellitus and Cardiovascular Disease, Renal Disorders.

I. INTRODUCTION

Today, we utilise Machine Learning to make predictions about almost everything. Applications include weather forecasting, stock market analysis, disease prognosis, cyber attack forecasting, battery life prediction, software quality forecasting, wireless sensor network (WSN) security threat forecasting, Internet of Things (IoT) device fraud detection, and many more. Algorithms that utilise large datasets [7, 13] can be better comprehended, generalised, and predicted with the aid of machine learning algorithms [25]. Both computational statistics and decision theory have deep roots in the field of machine learning (ML). Forecasting product sales, predicting low oxygen levels during surgery, estimating the likelihood of a certain amount of rain falling in a specific area, etc., are all examples of situations in which machine learning techniques and approaches are used.

In the field of medicine and health care today, most machine learning models are created to study only one disease. Most state-of-the-art approaches[31] focused on a single type of analysis, such as diabetes [29][36], cancer [30][32][33][34], skin diseases [35], or lung diseases [37][38]. There is currently no well-accepted method for making multiple disease predictions from a single study.In order to aid in the diagnosis and critical stages of a disease, doctors need to be able to recognise patterns in patient cases [5].Predictive analytics [27][28] for individual health care, monitoring patients' adverse signs during trials, and assisting doctors in determining the medication for patients can all benefit from the methodical study of machine learning algorithms. Here, we present a Medico-Supportive System [10] for disease prognosis that makes use of machine learning methods.The primary goal of this system is to speed up diagnosis so that treatment can begin sooner for patients. This decision support system was built on top of the SVM-LRBF for disease prediction, and its performance was compared to that of other state-of-the-art methods [6].

IIRELATED WORK

Medical data statisticians and analysts utilise a wide variety of algorithms to make illness predictions. Different algorithms[23][24] utilised for the analysis of clinical data are discussed, as well as many studies in health analytics [19], chronic renal illnesses, diabetes mellitus, cardiovascular disease, and other related topics.Numerous strategies[14], procedures[19], and methods[20][21][22] have been created for the purposes of multi-disease prediction[1][2][6], multi-disease diagnosis[16][17][20], multi-disease recommendations[10][11][15], multi-disease analysis[13], and multi-disease classification[12][16] [18]. This section will focus on a handful of them.

Using Flask API (the python pickling and unpickling files idea), Tensor Flow, and Machine Learning algorithms, Yaganteeswarudu, A. (2020) [1] predicted a variety of ailments, including diabetes, cancer, and heart disease. To study diabetic retinopathy, we gathered data from the UCI machine learning repository; to study diabetes, we used the Pima Indian Diabetes Dataset; and to study cancer, we used the Cancer Wisconsin (Diagnostic) Data Set. For diabetes, the model had a 92% success rate; for cardiovascular disease, 95%; and for cancer, 96%.

Chronic obstructive pulmonary disease, obesity, hypertension, bronchial asthma, cardiovascular disease, blood cholesterol, triglycerides, pneumonia, diabetes, and other conditions were predicted using a non-invasive diagnostic approach by Vijayalaxmi, A. et al., (2020) [2]. They looked at just one factor for each condition, such as blood pressure for hypertension, temperature for fever, pulse oximeter for lung disease, glucose for diabetes disregarding skin thickness and insulin, body mass index (BMI) for obesity, and so on. They used many machine learning models to predict diabetes based on both basic and advanced sets of characteristics, and then compared the algorithms' performance. Using Decision Tree Classifier, they got an accuracy of 74.68%, whereas using Naive Bayes, they got 78.57% for diabetes milletus.

Taking into account both diabetic retinopathy and diabetic macular edema, Tu, Z., Gao, S., et al., (2020) [3] created a model for the simultaneous prediction of retinal illnesses, which they dubbed the feature Separation and Union Network (SUNet). The model's overall accuracy is 61.16 percent. The model has a 65% success rate in identifying diabetic retinopathy and an 81.5% success rate in identifying diabetic macular edema.

Using Recurrent Neural Networks, Wang et al. (2019) [4] predicted a wide range of ailments, including acute renal failure, diabetes, heart disease, lung disease, etc. Different measures of the model's efficacy were taken into account throughout the analysis. Experiments on the MIMIC dataset, which includes information about patients hospitalised in intensive care units, yielded an exact-match score of 98.90% when using 3-digit aggregation and 96.60% when using 4-digit aggregation, while those conducted on the GenCare dataset yielded scores of 95.12% and 96.83%, respectively.

Multiple Linear Discriminant Model was suggested by Kundu, A. K. et al., (2020) [5] to predict gastrointestinal disorders such as bleeding, ulcer, and tumour. Different measures of performance, such as F1-Score, recall, precision, and accuracy, are used to assess the model's efficacy. The proposed model achieved a high F-1 score (86.27%) along with high accuracy (91.38%), precision (87.14%), recall (85.41%), and accuracy (86.27%) from independent samples.Multi-disease prediction using SVM-Radial bias kernel technique: Harimoorthy, K., et al., (2020) [6] obtained 98.3% accuracy for the Renal disorders dataset, 98.7% accuracy for the Diabetes mellitus dataset, and 89.9% accuracy for the Cardiovascular Disease dataset.

Using a k-medoid clustering algorithm and a fuzzy model, i.e. a modified adaptive neuro-fuzzy inference (M-ANFIS) system, Vidhya, K et al. (2020) [7] focused on health care big data (BD) of a healthcare organisation in the United States and analysed a number of diseases, including diabetes, malaria, dengue, etc . Precision, recall, F-measure, and accuracy were some of the metrics used to assess M-performance. ANFIS's After being pitted against Neural Networks, SVM, Deep Neural Networks, and an adaptive neuro-fuzzy inference system, M-ANFIS came out on top with 98% recall, 98% F-measure, 98% precision, and 95% accuracy (ANFIS).

Using weakly supervised image classification, Tushar, F. I. et al. (2020) [8] successfully predicted many illnesses, including lung, liver, and renal ailments, with an F1-score of 98% and an accuracy of 99% when the test set was manually verified.Using a recursive neural knowledge network (RNKN), Jiang, J. et al. (2020) [9] predicted many illnesses with a degree of accuracy of 55, 67, and 59 percent for networks of 50, 100, and 200 dimensions, respectively.

IIIMETHODOLOGY

Figure 1 shows the conceptual architecture we advocate for the recommended medically supporting system, and Figure 2 shows a data flow depiction of the system. The illness classification flowchart utilising a medically-based method is shown in Figure 3.

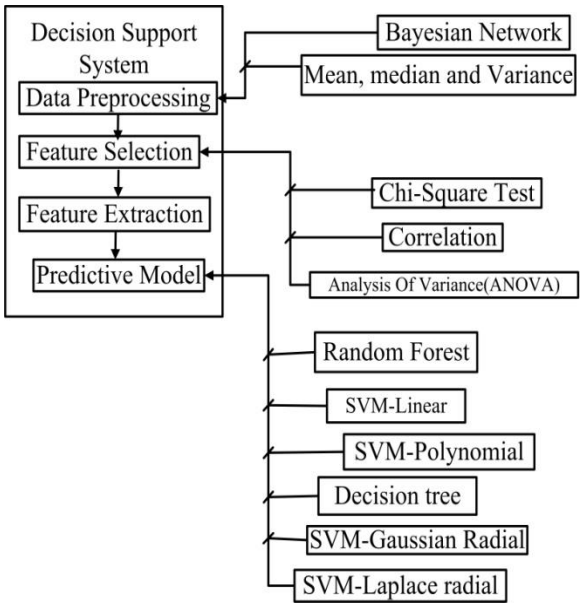

Figure 1: Health Care Sustaining Mechanisms

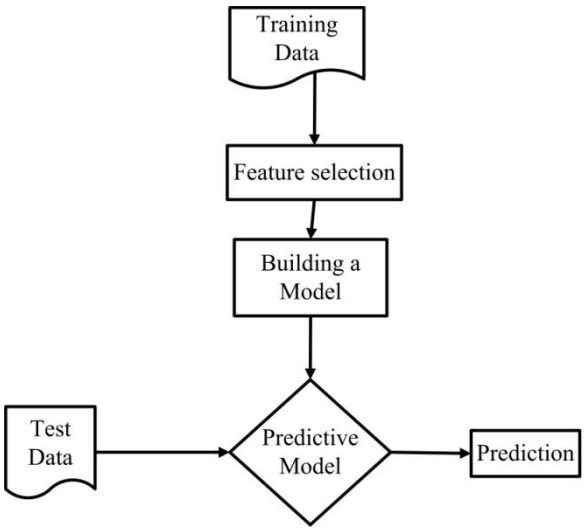

Figure 2: Illustration of a Decision Support System as a Flow of Data

Support Vector Machine

Support vector machine (SVM) is a statistical learning technique that may be used to divide the data into two groups: positive and negative. The following equations are used to classify the data along the maximum marginal hyperplane:

$$z_i \cdot v + i \geq +1 \; \forall \; y_i = +1$$

$$z_i \cdot v + i \leq -1 \; \forall \; y_i = -1$$

where z, v are vectors and i is bias.

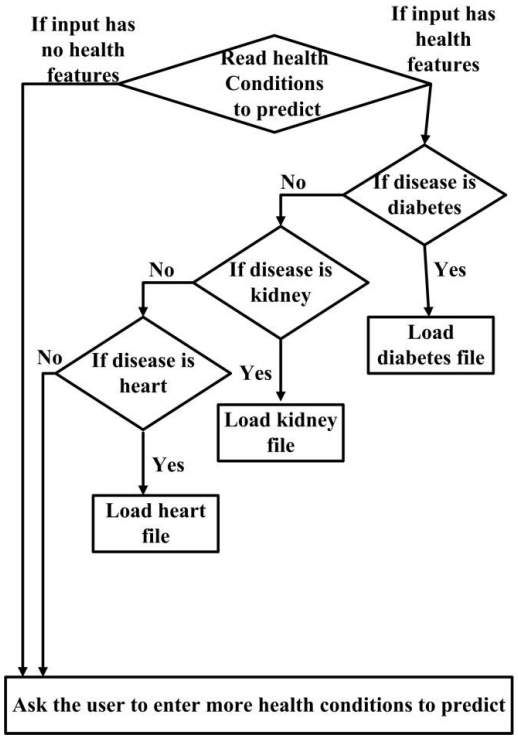

Figure 3: Disease classification flowchart based on medical decision support data.

In all, there are four different models that make up the Medico-Supportive System.

A. Data preprocessing model

Removing irrelevant, missing, incomplete, and noisy information from data sources is a crucial part of data analysis, which is why data preparation is so important. These questions will be answered during the preliminary processing of the data. Some of the following methods are used in machine learning to deal with missing information.

(i)The missing fields are ignored.

(ii) Missing values are computed with the mean value of the attributes.

(iii) Computing missing values using statistical models such as a linear regression model.

In this work, we ignored the missing fields for data preprocessing.

B. Feature selection model

In order to find the best attributes from the selected data set we used ANOVA(Analysis Of Variance) method because the classifier's accuracy doesn't rely on entire set of features{f_1, f_2, f_3, f_4,…,f_C} of the dataset 'D' where 'C' is the count of total attributes. The best attributes which are chosen from the data set 'D' is represented as {f_1, f_2, f_3, f_4,…,f_c }, where c<C.

C. Feature extraction model

When selected features are broken down further, we get a new, more manageable collection of features. It's a process that takes the richness of the raw data and distils it into a more manageable collection of characteristics.

D. Predictive model.

The quality of the data, the quantity of the data collection, and the prediction algorithm all contribute to the reliability of the predictions made by a medico-supportive framework.

There are several ways in which the SVM algorithm's precision might be enhanced. One such option is to modify the kernel's function.

The kernel function K(p, q) is defined as <f(m), f(n)>, where 'f' is function that maps from the dimensional space and p, q are the dimensional inputs.

The following are the different types of mathematical functions used in the kernel.

1. Polynomial Kernel

It is widely used in image processing. It can be formulated as follows:

$K(p_u, p_v) = (p_u * p_v + 1)^d$

Where 'd' is the degree of the polynomial.

2. Gaussian Kernel

It can be formulated as follows:

$$K(p, q) = \exp(-\frac{||p-q||^2}{2\sigma^2})$$

3. Gaussian Radial Bias function (RBF)

It can be formulated as follows:

$K(p_u, p_v) = \exp(-\gamma \| p_u - p_v \|^2)$

4. Laplace RBF Kernel

It can be formulated as follows:

$$K(p, q) = \exp(-\frac{||p-q||}{\sigma})$$

5. Hyperbolic Tangent Kernel

It can be formulated as follows:

$K(p_u, p_v) = \tanh(k(p_u * p_v) + c)$

6. Sigmoid Kernel

It can be formulated as follows:

$K(p, q) = \tanh(\alpha p^T q + c)$

7. Bessel function of first kind kernel

It can be formulated as follows:

$K(p, q) = \frac{J_{a+1}\sigma||p-q||}{||p-q||^{-n(a+1)}}$

8. Anova Radial Basis Kernel

It can be formulated as follows:

$K(p, q) = \sum_{k=1}^{n} \exp(-\sigma((p^k - q^k))^2)^d)$

9. Linear Spline Kernel in One dimension

It's helpful when working with large sparse vectors of data. Sometimes it is used in categorization of text. Even the splines kernel performs well inregression issues. It is formulated as follows:

$$\mathbf{k(p,q) = 1 + pq + pq\ min(p,q) - \frac{p+q}{2} min(p,q)^2 + \frac{1}{3} min(p,q)^3}$$

IV RESULTS AND DISCUSSION

The framework has been tested on data relating to renal illness, diabetes, and cardiovascular disease that may be found in the UCI repository. In this experiment, we split the dataset in half, using 80% for training and 20% for validation. To define the most salient features of the illness dataset, we used an ANOVA strategy.

Important characteristics of the Diabetes mellitus illness dataset are shown in Figure 4. Important characteristics of the cardiovascular disease dataset are shown in Figure 5, whereas those of the renal diseases dataset are depicted in Figure 6.

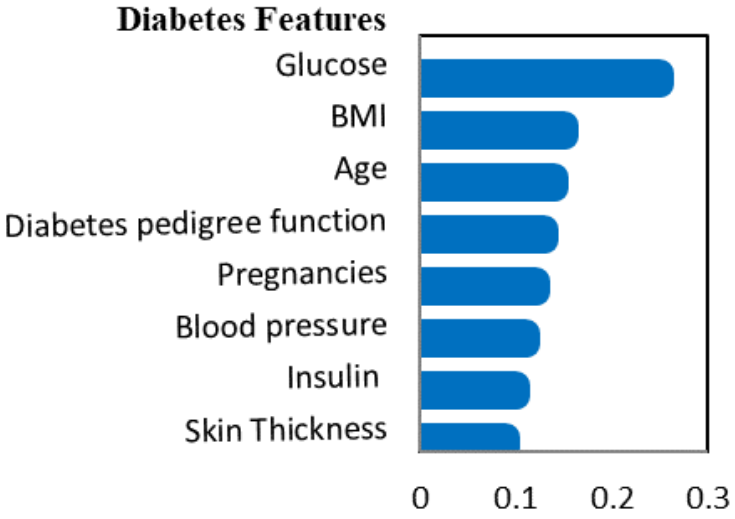

Figure 4:Significant Diabetes mellitusFeatures

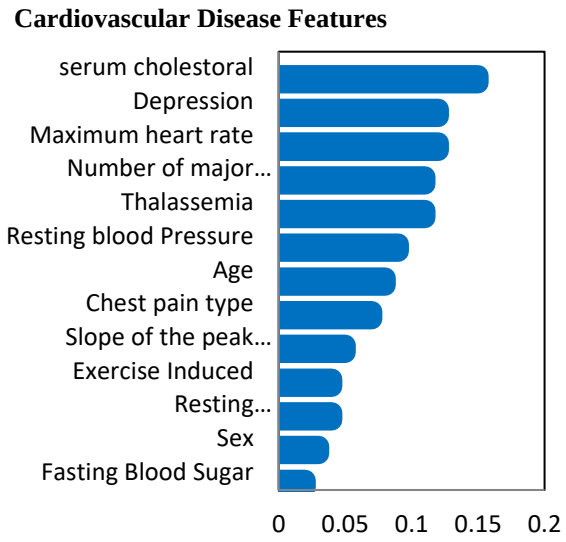

Figure 5: Significant Cardiovascular Disease Features

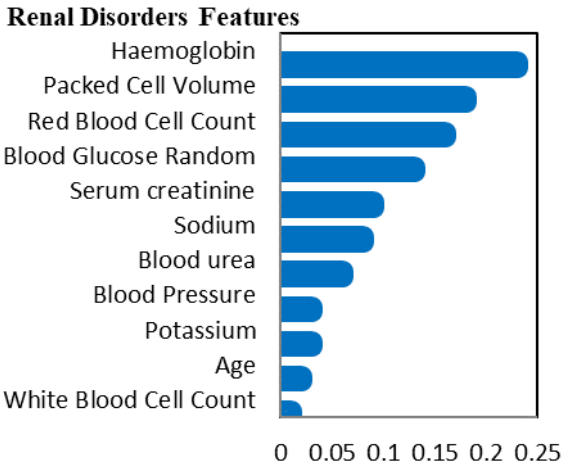

Figure 6: Significant Renal disorders Disease features

Table 1 compares the results from various machine learning algorithms, including SVM-Laplace RBF kernel, Random Forest, SVM-Linear, Decision Tree, SVM-Gaussian RBF kernel, and SVM-Polynomial, in terms of evaluation metrics like specificity, sensitivity, precision, recall, misclassification rate, and accuracy.

The accuracy, misclassification, sensitivity, Precision, and Specificity of SVM-Radial bias, as well as comparisons to other approaches, are shown graphically in Figures 7, 8, 9, 10, and 11.

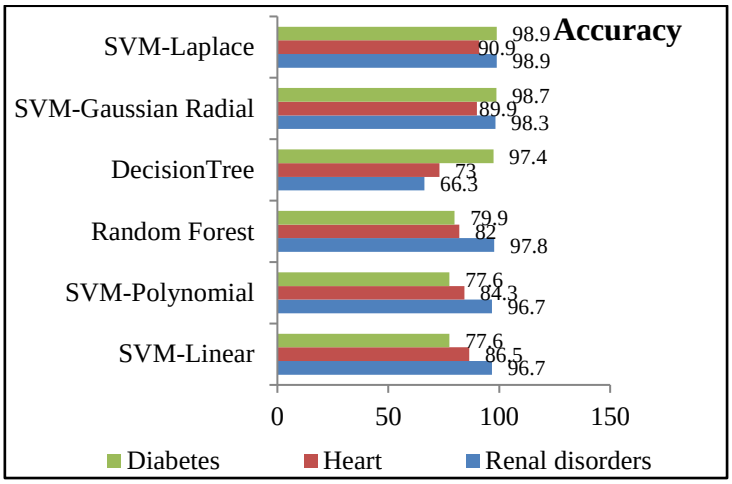

Figure 7: Graphical Illustration showing SVM-Laplace Radial Bias's accuracy compared to other Machine Learning methods'

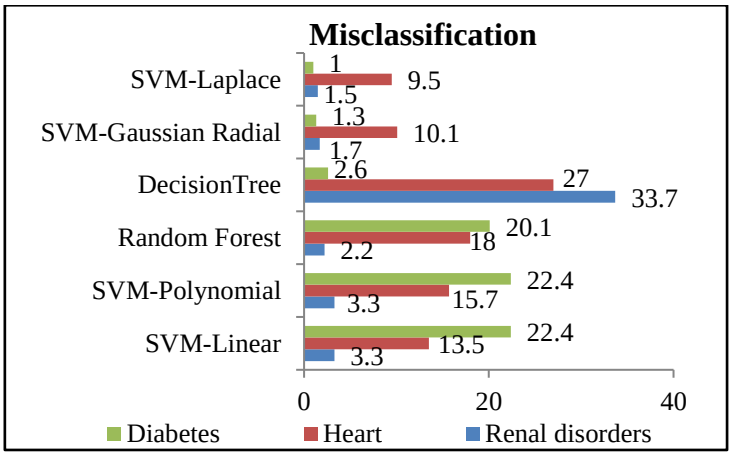

Figure 8: Graphical representation comparing the SVM-Laplace Radial Bias's misclassification rate with those of other Machine Learning methods.

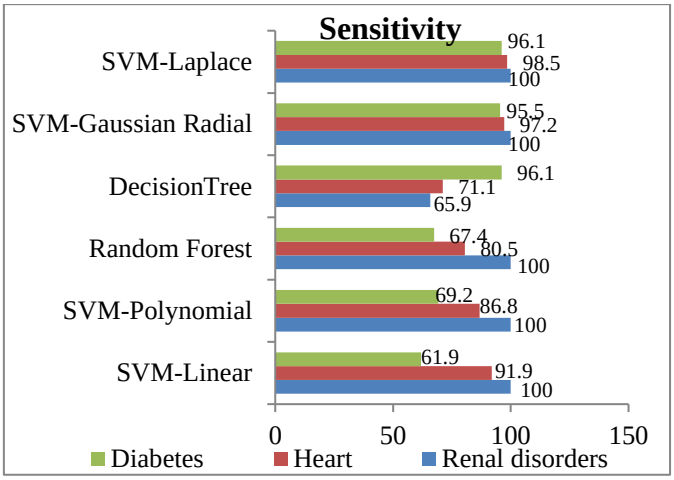

Figure 9: Graphical interpretation comparing the SVM-Laplace Radial Bias's sensitivity to those of other Machine Learning methods.

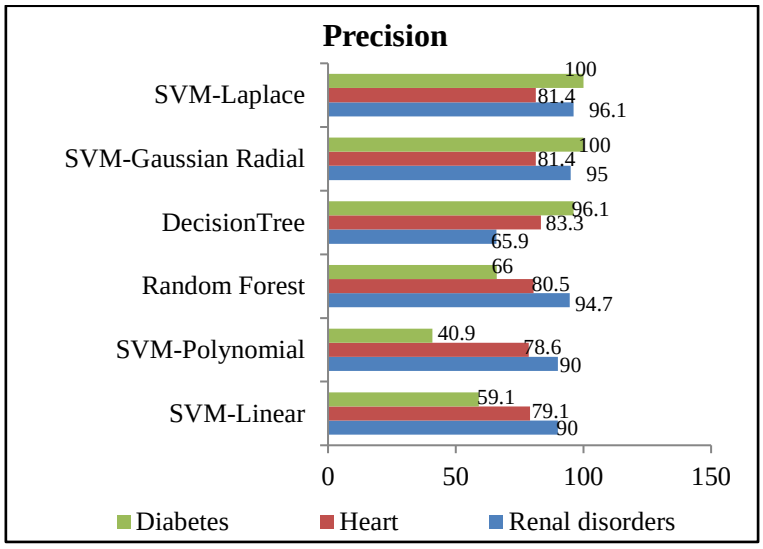

Figure 10: Precision of SVM-Laplace Radial Bias compared to other Machine Learning Methods using a Graphical Representation.

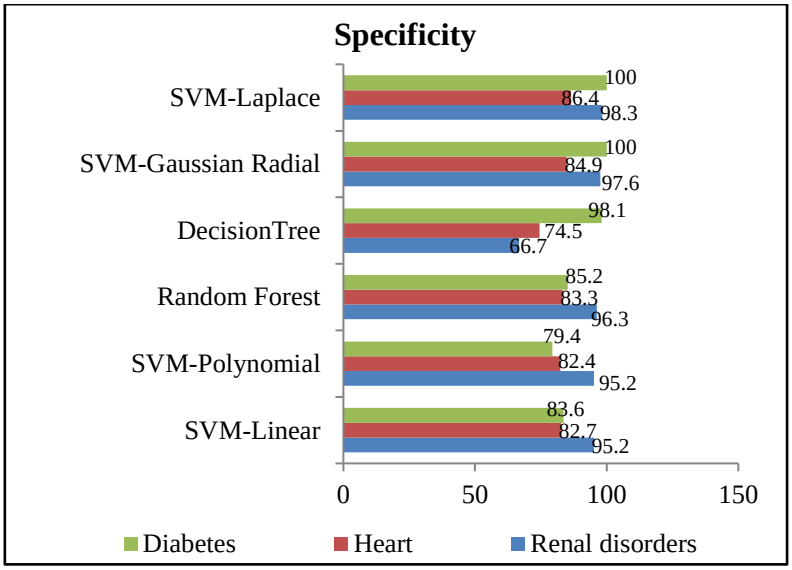

Figure 11: Specificity of SVM-Laplace Radial Bias against Other Machine Learning Methods, displayed as a Bar Chart.

Table 1: Performance Evaluation metrics for Machine learning algorithms.

Model/ Evaluation Parameters	**Disease**	**SVM - Linea**	**SVM-Polynomial**	**Random Forest**	**Decision tree**	**SVM-Gaussian Radial**	**SVM-Laplace**
Accuracy	Renal disorder	96.7	96.7	97.8	66.3	98.3	98.9
	Cardiovascular Disease	86.5	84.3	82.0	73.0	89.9	90.9
	Diabetes mellitus	77.6	77.6	79.9	97.4	98.7	98.9
Misclassification	Renal disorder	3.3	3.3	2.2	33.7	1.7	1.5
	Cardiovascular Disease	13.5	15.7	18.0	27.0	10.1	9.5
	Diabetes mellitus	22.4	22.4	20.1	2.6	1.3	1.0
Sensitivity	Renal disorder	100.0	100.0	100.0	65.9	100.0	100.0
	Cardiovascular Disease	91.9	86.8	80.5	71.1	97.2	98.5
	Diabetes Mellitus	61.9	69.2	67.4	96.1	95.5	96.1
Precision	Renal disorder	90.0	90.0	94.7	65.9	95.0	96.1
	Cardiovascular Disease	79.1	78.6	80.5	83.3	81.4	81.4
	Diabetes Mellitus	59.1	40.9	66.0	96.1	100.0	100.0
Specificity	Renal disorder	95.2	95.2	96.3	66.7	97.6	98.3
	Cardiovascular Disease	82.7	82.4	83.3	74.5	84.9	86.4
	Diabetes mellitus	83.6	79.4	85.2	98.1	100.0	100.0

According to the results of the evaluations, the SVM-LRBF kernel strategy yielded the highest degree of precision. The experimental findings demonstrated an accuracy of 98.9% in the renal diseases dataset, 90.9% in the Diabetes Mellitus dataset, and 98.9% in the cardiovascular disease dataset.

V CONCLUSION

Several medical diagnostic illnesses' prognosis may be predicted with the use of a comparative analysis we done here. Datasets for renal illnesses, cardiovascular disease, and diabetes mellitus have all been tested inside the framework, all of which were obtained from the biggest repository of the machine learning community, the UCI repository.

We have tried out many different SVM procedures, including SVM-Laplace RBF kernel, Random Forest, SVM-Linear, Decision Tree, SVM-Gaussian RBF Kernel, and SVM-Polynomial, on these datasets using the characteristics we've isolated.

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