Detection of Arrhythmia Using Weightage-based Supervised Learning System for COVID-19.

Yashodhan Ketkar[a], Sushopti Gawade[b]

[a]Department of Information Technology Engineering, Pillai College of Engineering, Panvel, 410206, Maharashtra, India
[b]Department of Computer Engineering, Pillai College of Engineering, Panvel, 410206, Maharashtra, India

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ABSTRACT

COVID-19 disease became a global pandemic in the last few years. This disease was highly contagious, and it quickly spread throughout several countries. Its infection can lead to severe implications in its victims, including cardiovascular issues. This complication develops in some people with a history of cardiovascular illness, whereas it emerges in others after COVID-19 infection. Cardiovascular problems are the primary cause of mortality in COVID-19 patients and are used to predict disease prognosis. Identifying arrhythmia from abnormalities in patient ECG signals is one approach to the detection of cardiovascular disorders. This is a laborious and time-consuming procedure that can be automated. The proposed method selects the most suitable model for this task. The selection is done through the weightage generated from the user's requirements. The proposed method uses supervised learning to identify abnormalities in ECG waves. The models provided by the selection system during tests were able to meet user requirements. The models achieved up to 97% accuracy and 97% precision in predictive tasks.

1. Introduction

COVID-19 has been widespread in recent years. It targets the human respiratory system, causing severe respiratory issues. Depending on a person's condition and the prevalence of comorbidities, this disease can be fatal. COVID-19 disease frequently causes cardiovascular comorbidities. Cardiovascular comorbidities are also problematic to diagnose in the absence of suitable equipment. Checking for arrhythmia in patients is one approach to detection. Arrhythmia is the irregular beating of the heart. Arrhythmia is detected by examining ECG signals. Because COVID-19 has put a strain on the medical personnel, detection takes longer than usual. Increased Internet connectivity has led to the use of machine learning and artificial intelligence (AI) for service in a variety of sectors. This increases research in the field of machine learning and has an impact on machine learning in a variety of domains. One of them is the medical and healthcare industries. Machine learning is used to detect and categorize viruses and other microorganisms in patients. In medical applications, machine learning algorithms have already been shown to be quite useful.

The machine learning system may be used to scan these ECG signals and detect them. These signs may be detected considerably faster and more efficiently using supervised learning techniques. In such exact classification problems, supervised algorithms have previously been demonstrated to be quicker than unsupervised techniques. Once taught, this algorithm may also be utilized to make future predictions.

There are several supervised algorithms available, allowing us to select the best method for our purposes. This phase can be automated in the case of the general population. A few methods may be pre-programmed into the system, and the computer can then train and pick the best model for the supplied dataset. This will free up medical personnel to focus on patient care and problem-solving.

ketkaryapr19me@student.mes.ac.in (Y. Ketkar); sgawade@mes.ac.in (S. Gawade)

2. Literature Review

Babapoor-Farrokhran, Rasekhi, Gill, Babapoor and Amanullah (2020) suggest that arrhythmia is one of the most common symptoms in patients with COVID19. Arrhythmia was found in 7% of all 19 Wuhan COVID cases and 14.8% of patients with poor outcomes. Mulia, Maghfirah, Rachmi and Julario (2021) state that 17% of patients hospitalized in China were diagnosed with arrhythmia. Mulia et al. conducted a review of 10 eligible studies (5,193 patients) for analysis and found that atrial arrhythmia was present in 9.2% of cases. A review by Liu, Chen and Zeng (2020a) of 17 studies with 5,815 patients showed that arrhythmia was detected in 9.3% of COVID-19 cases. Yarmohammadi, Morrow, Dizon, Biviano, Ehlert, Saluja, Waase, Elias, Poterucha, Berman et al. (2021) suggest that only 8% of patients with arrhythmia had prior cardiovascular conditions. Yarmohammadi et al. also mentioned that 56% of patients showed symptoms after the COVID-19 infection.

Sun, Wang, Zhao and Yan (2020) used an ensemble classifier to detect the anomalies in the ECG signal. This approach, which combines multiple classifiers for prediction, has proven effective because the accuracy of the ensemble classifier is significantly higher than that of a single classifier. A few authors used this approach to improve the prediction accuracy of supervised learning models. Huang, Chen, Zeng, Cao and Li (2020) used the maximal overlap wavelet packet transform ensemble with a neural network and achieved satisfactory results. Rajak, Shrivastava and Vidushi (2020) used the ensemble approach to predict the results of the students. Rajak et al. state the model was able to predict the correct results even with a small amount of training data. Liu, Lou and Huang (2020b) compared the FLINK-based iForest ensembled algorithms against the sklearn-iForset and other algorithms. Liu et al. concluded that the Flink-iForest algorithm showed better performance than off-the-shelf algorithms. Imbrea (2021) used the AutoML algorithm and tools on data streams. Imbrea concluded that the default classifiers can be used with AutoML tools for accurate prediction. With AutoML tools, prediction systems can be automated.

Chopade, Chopade and Gawade (2022) used machine learning for the prediction of end-of-semester results. Chopade, Chopade and Gawade (2022) used SVM, KNN, and DT models. Chopade, Chopade and Gawade (2022) concluded that the machine learning system performed satisfactorily, with SVM achieving up to 78% accuracy.

Siddiqui, Morales-Menendez, Huang and Hussain (2020) extracted appropriate features for the detection of epileptic seizures. Siddiqui et al. preprocessed data and used ML algorithms on the data. Siddiqui et al. concluded that the supervised learning models showed more effectiveness than the unsupervised learning models. Jha and Kolekar (2020) used a commercial classifier for the detection of arrhythmia. Jha and Kolekar used ECG signals from patients and applied a custom SVM classifier. Jha and Kolekar concluded that the algorithm was a successful and efficient detector of arrhythmia.

Marathe, Gawade and Kanekar (2021) used supervised learning algorithms for the early detection of heart disease and diabetes disease. Marathe, Gawade and Kanekar (2021) concluded that the model performed satisfactorily.

Hannun, Rajpurkar, Haghpanahi, Tison, Bourn, Turakhia and Ng (2019) used neural networks to process raw ECG signals and make predictions. While Sannino and De Pietro (2018) used small neural networks for efficient recognition processes, both studies concluded that artificial neural networks are extremely efficient and accurate in the prediction of anomalies.

Chen, Mazomenos, Maharatna, Dasmahapatra and Niranjan (2013) showed that the LDA classifier can outperform the SVM classifier in low-performance environments and lightweight systems. The self-learning algorithm makes the system more dynamic and adaptable to incoming signals. Lei, Li, Dong and Vai (2007) used adaptive fuzzy algorithms to classify ECG signals. Lei et al. stated that the algorithm showed satisfactory results, but it requires prior classification patterns results. Ketkar and Gawade (2021) suggest that the RPA system can be used in these systems for easier integration of machine learning with dynamic data. Rehmat, Hassan, Khalid and Dilawar (2022) used ECG signals of COVID-19 patients for patient monitoring. Rehmat et al. used LSTM, SVM, and MLP algorithms to monitor data. Rehmat et al. suggest that machine learning with robotics can provide better results.

Dev, Wang, Nwosu, Jain, Veeravalli and John (2022) used a multi perceptron neural network for stroke predictions. The neural network showed high accuracy. Dev et al. were able to achieve up to 78% accuracy. Dev et al. suggest that the model can produce better results with a larger training dataset. Chang, Bhavani, Xu and Hossain (2022) used artificial intelligence to detect heart disease. Chang et al. concluded that the algorithms achieved up to 83% accuracy. Chang et al. also concluded that the system was able to comply with the HIPAA regulations.

Verma and Gawade (2021) used machine learning algorithms to predict crop growth rates. Verma and Gawade were able to get good insights into the field. Verma and Gawade concluded that the use of machine learning will result in minimizing complexity and increasing yield in farming.

Atanasova, Todorovski, Džeroski and Kompare (2008) used a two-year dataset collected by Glumo Lake and used their expertise to train and select models. A mixed approach of data-driven and knowledge-driven modeling is used for the success of the application. Lee and Lin (2000) used loo rate and stop criteria for model selection. Lee and Lin investigated eight different issues and found that a larger loo rate was more desirable. Lee and Lin also suggested that modeling difficulties can only be found by careful numerical calculations.

Malkomes, Schaff and Garnett (2016) used a novel kernel to get the dataset description. Malkomes et al. concluded that this approach led to the discovery of invisible models. Malkomes et al. also state that this approach reduces the amount of human interaction. Calcagno and de Mazancourt (2010) created a new model using the glmulti package. These models are unique and flexible. The model is automatically optimized to provide a multi-model interface. This approach allows you to quickly explore a large set of models for selection purposes. Garcia and Lôndero (2021) optimized parameters with a genetic algorithm. Garcia and Lôndero successfully used a genetic algorithm to reduce uncertainty in the prediction results. These methods can be used for the automated model selection system.

3. Dataset and Method

3.1. Mathematical Model

Figure 1 shows the approach toward the selection of a suitable model. With this system, we can handle up to N models. Equation (1) shows the mathematical formula used to calculate the V scores of the models. These V scores will allow the system to select the appropriate model.

$$V_{score} = \left(\sum_{x=1}^{5} w_x P_x \right) - w_6^2 P6 \tag{1}$$

3.2. Performance Metrics

The following performance metrics are used in the system for evaluation of the models:

3.2.1. Accuracy Score

The accuracy score is a fraction of the correct prediction by model with respect to total predictions by model. It can

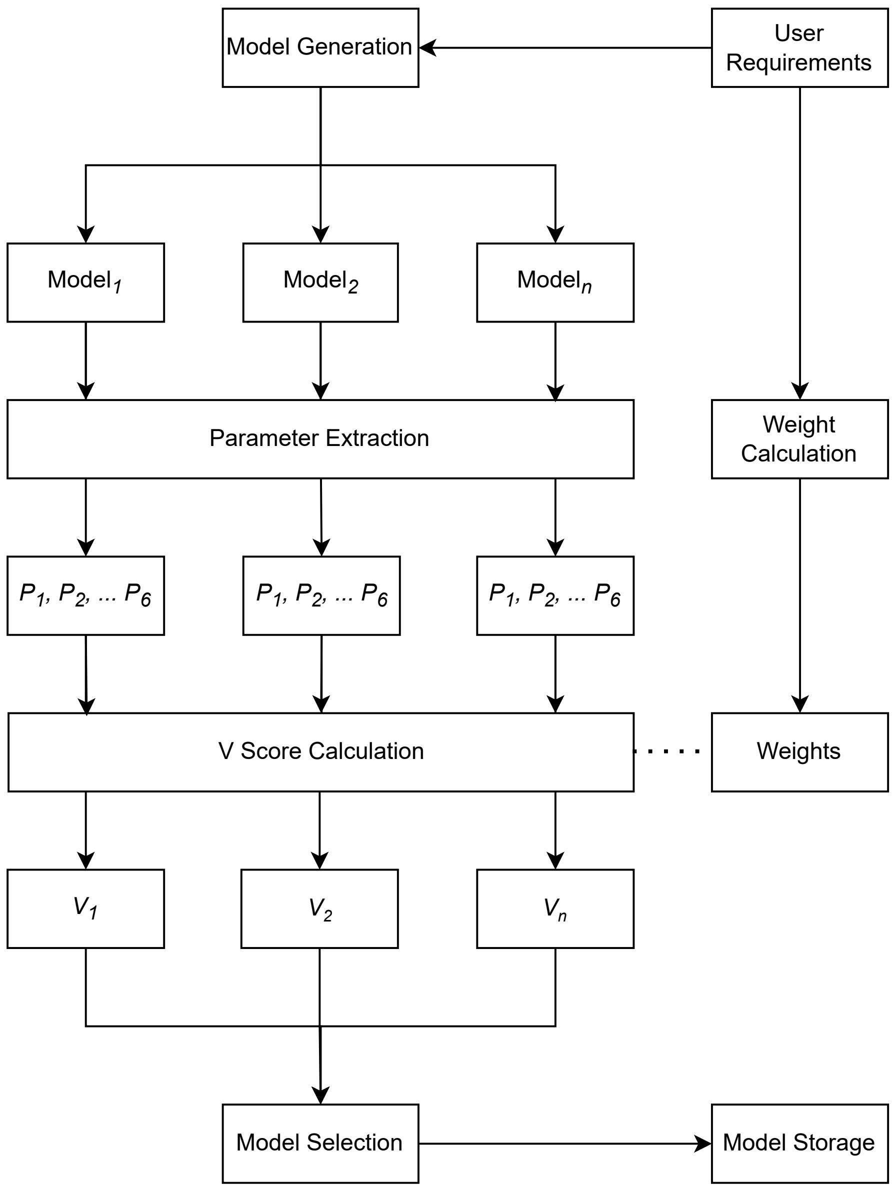

Figure 1: Model Selection Approach

be represented by following formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

3.2.2. Precision score

The precision score is a fraction of the correct positive predictions with respect to all positive predictions of the model. Higher precision scores result in fewer false positive predictions. It can be represented by following formula:

$$Precision = \frac{TP}{TP + FP}$$

3.2.3. Recall score

The recall score is the fraction of correct positive predictions with respect to all predictions of the class. It can be represented by following formula:

$$Recall = \frac{TP}{TP + FN}$$

3.2.4. F1 Score

The F1 score is the weighted average of the recall score and precision score of the model. F1 scores are more reliable than accuracy scores in case of biased or uneven dataset. It can be represented by following formula:

$$F1 = 2 \cdot \frac{Recall \cdot Precision}{Recall + Precision}$$

or

$$F1 = \frac{TP}{TP + \frac{1}{2}(FP + FN)}$$

3.2.5. ROC Score

The ROC is a classifier's predictive quality that compares and visualizes the trade-off between the model's sensitivity and specificity. In graphical format, the area under it gives a relationship between false positives and true positives. The higher these areas are, the better the predictive quality of the model.

3.2.6. Prediction Time

Prediction times are nothing but the amount of time required by the classifier to make predictions for certain testing datasets. A model with a lower prediction time is desirable.

3.3. Methodology

The system accepts the data and parameter preferences from the user. The parameter preferences are used to generate weightage. This weightage is stored in memory for future use. The dataset from the user is split into an 80-20 ratio to generate a training and evaluation dataset. These datasets are stored on a drive for future use.

The training dataset is loaded into the system simultaneously. The model generated is used to generate the pre made models. These models are trained with a training dataset and stored on disk for the evaluation process.

In the evaluation process, the evaluation dataset is used on the trained models along with weightage generated from user parameter preferences. The evaluation process produces the Vscore. The model with the highest Vscore is selected as the most suited model.

3.4. Dataset

The ECG readings in this paper are obtained from the MIT-BIH arrhythmia database [8]. This database is used for automated training and evaluation. This dataset was published in 1999 by MIT-BIH as an open-source database; it consists of training and testing datasets. This database is further divided into four equal parts for analysis. Each training set contains 21888 signals, and the testing set contains 5473 signals.

4. Results And Testing

During the automated training and selection process, the SVM classifier is selected as the best-suited model for dataset 1, dataset 2, and dataset 4. Whereas the RF classifier is selected as the best-suited model for dataset 3.

Performance metrics used for evaluation were accuracy, F1, precision, recall, area under the ROC Curve, and total prediction time. The weightage assigned to these metrics for ranking was 1.0, 0.8, 0.4, 0.4, 0.4, and 0.25, respectively. Where higher value means higher priority.

4.1. Performance Evaluation

The models are tested with a testing dataset obtained from the MIT-BIH database. The testing dataset consists of 5473 signals. Figures 2 to 5 show that models trained with an automated system produced satisfactory results. A few models, like KNN, RF, and SVM, performed better than other models (DT) at the cost of higher prediction time. Whereas MLP models produced good overall results with lower prediction times. Tables 1 to 4 show the performance of the models on their respective datasets in detail.

4.2. Performance Error Calculation

For error calculation, the best models are tested against the training datasets of other models. Figures 6 to 10 show the average error introduced when models are tested against training datasets of other models. This chart shows that KNN, MLP, and SVM models introduced minimum errors, whereas DT and RF models introduced large amounts of error. Figure 10 also shows that the SVM model produced similar errors across all datasets. This smaller difference in error suggests that the SVM classifier can be used for classification tasks of similar nature. **??–??** show the performance of the models when tested on other datasets in detail.

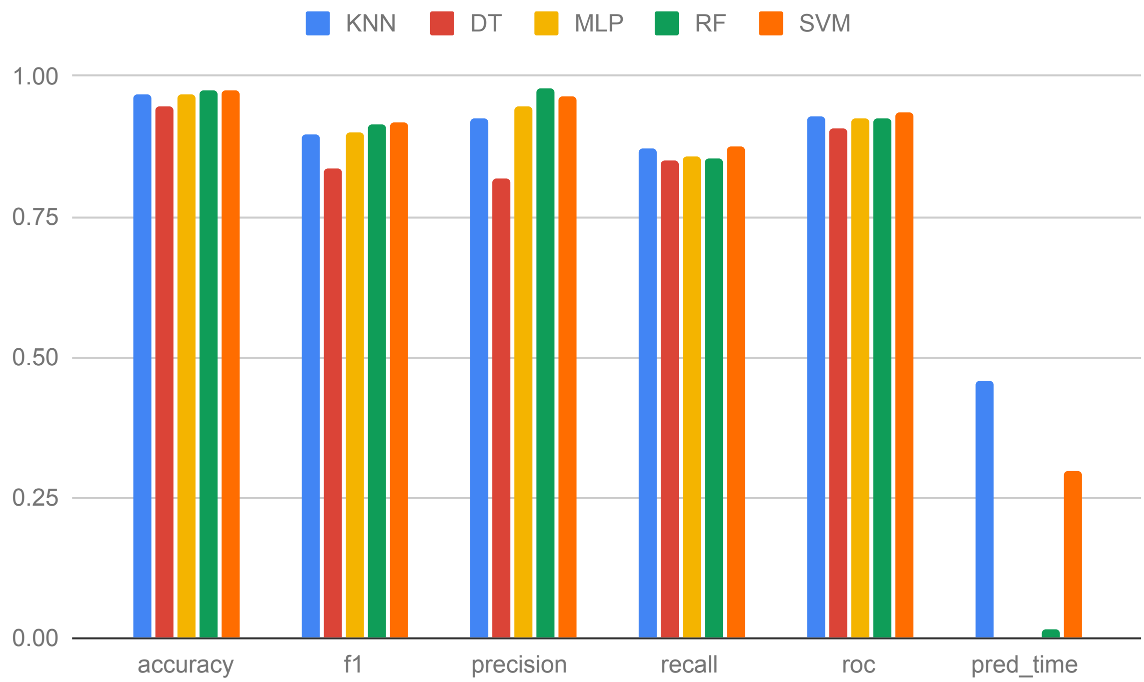

Figure 2: Performance Results Dataset 1

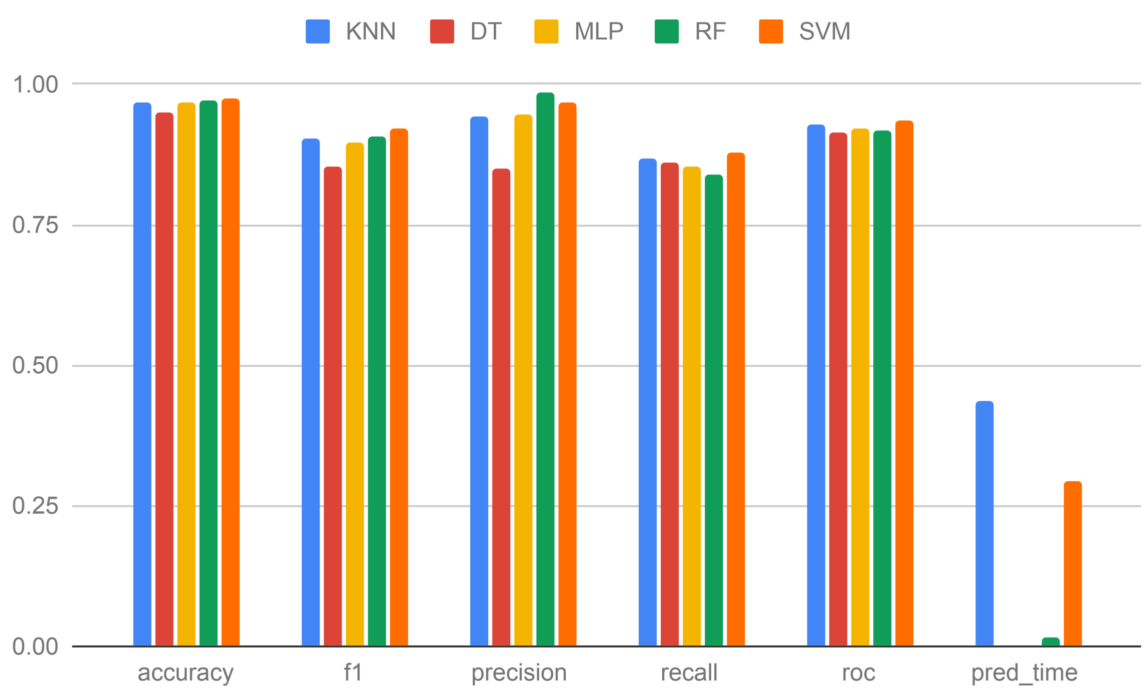

Figure 3: Performance Results Dataset 2

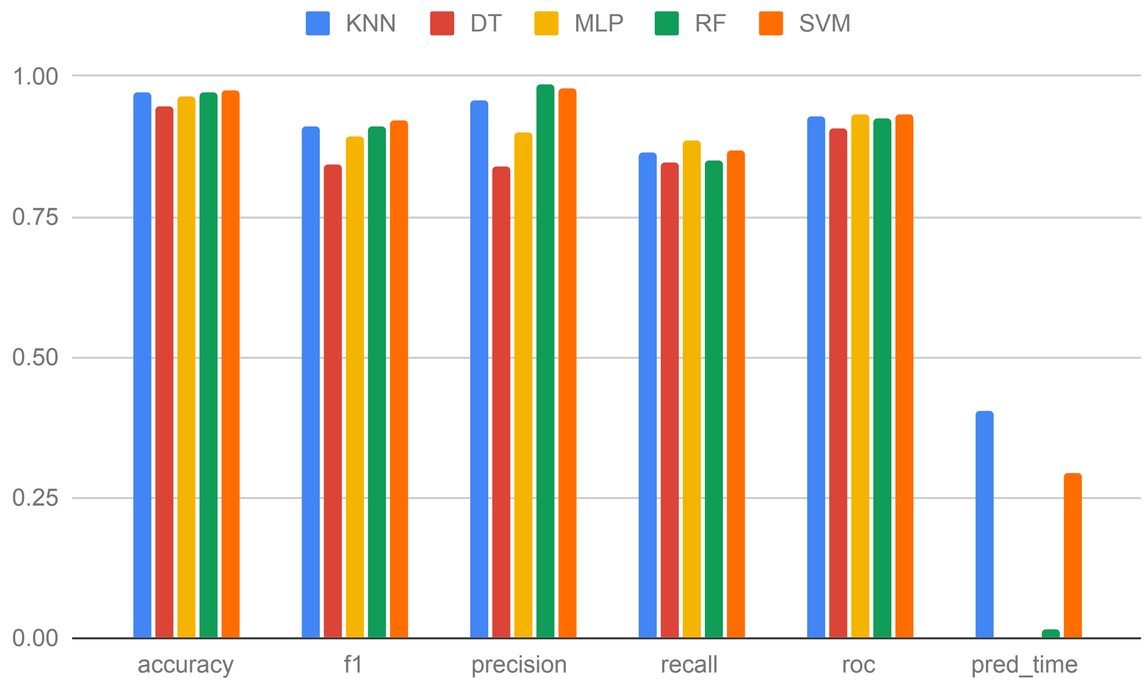

Figure 4: Performance Results Dataset 3

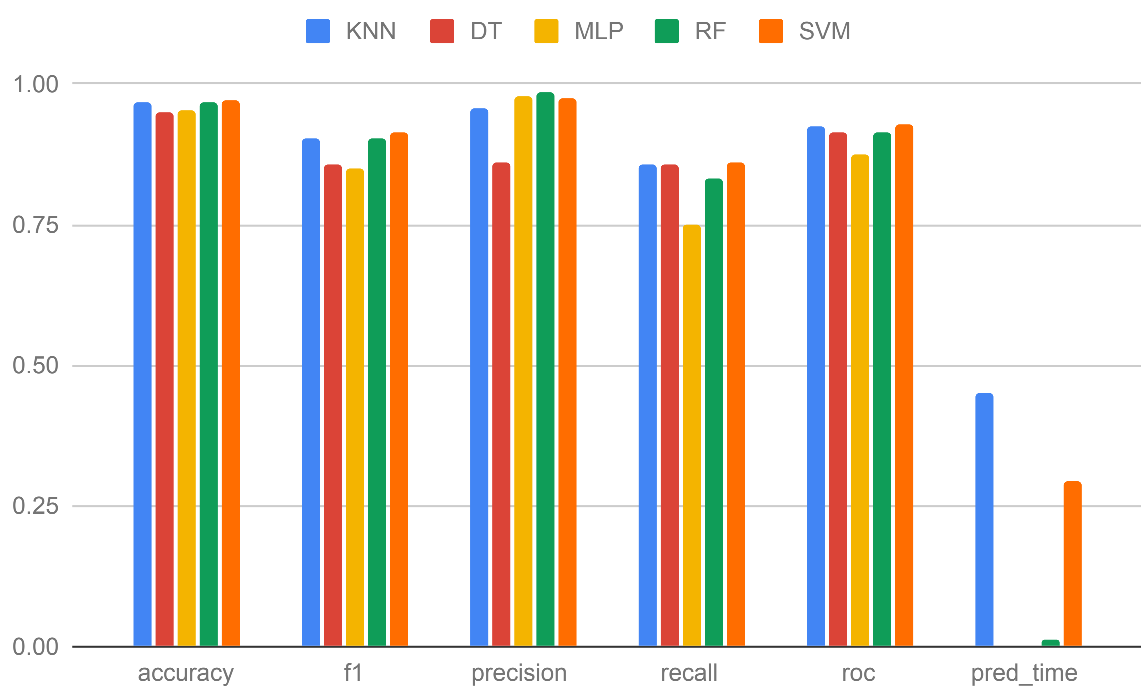

Figure 5: Performance Results Dataset 4

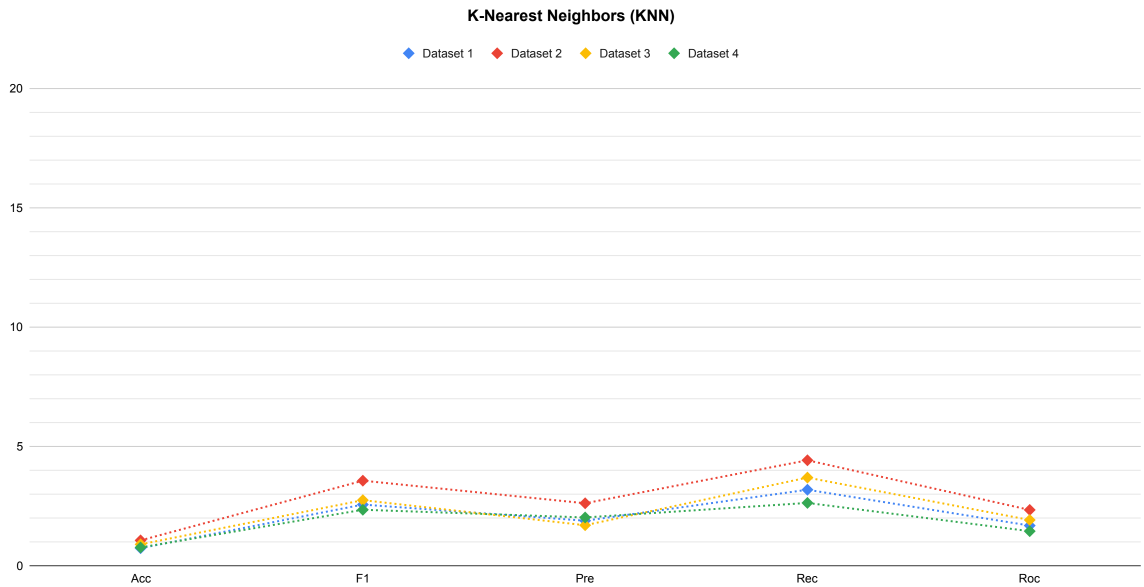

Figure 6: Average Error for K-Nearest Neighbors (KNN) model

Figure 7: Average Error for Decision Tree (DT) model

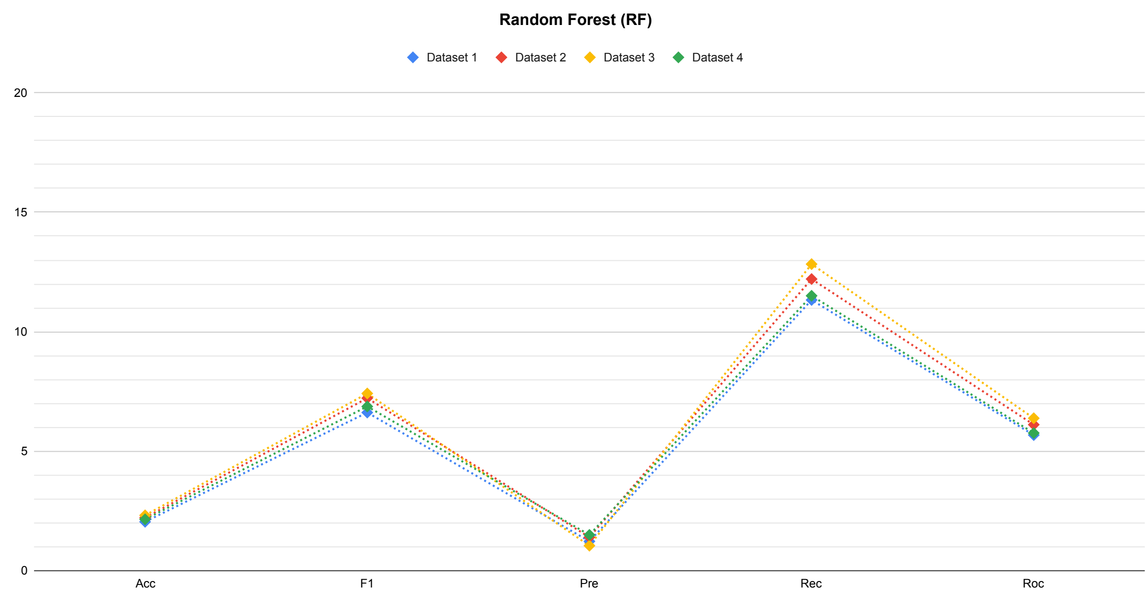

Figure 8: Average Error for Random Forest (RF) model

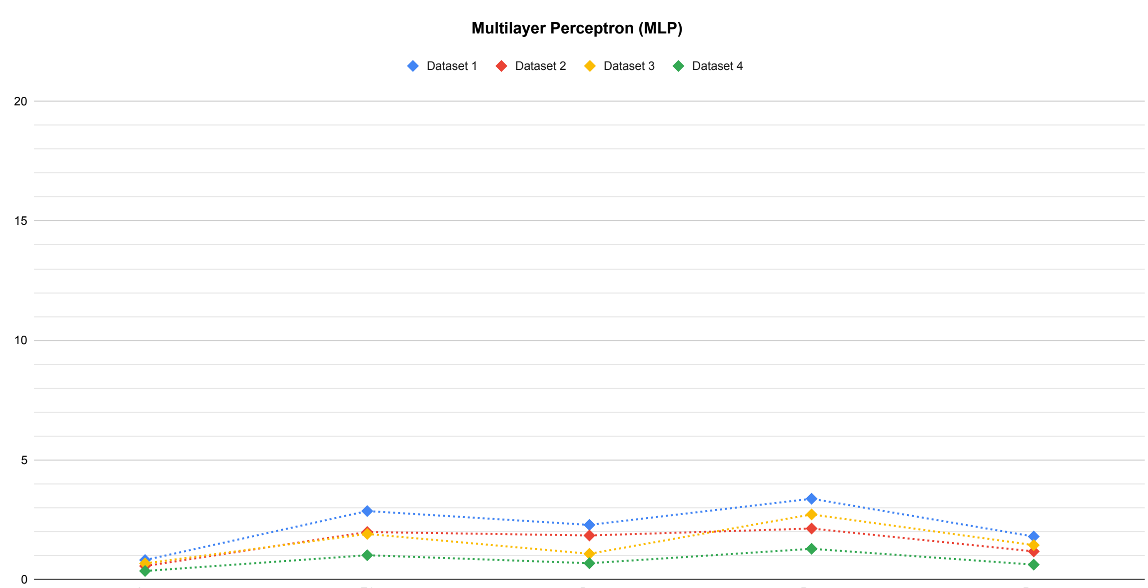

Figure 9: Average Error for Multilayer Perceptron (MLP) model

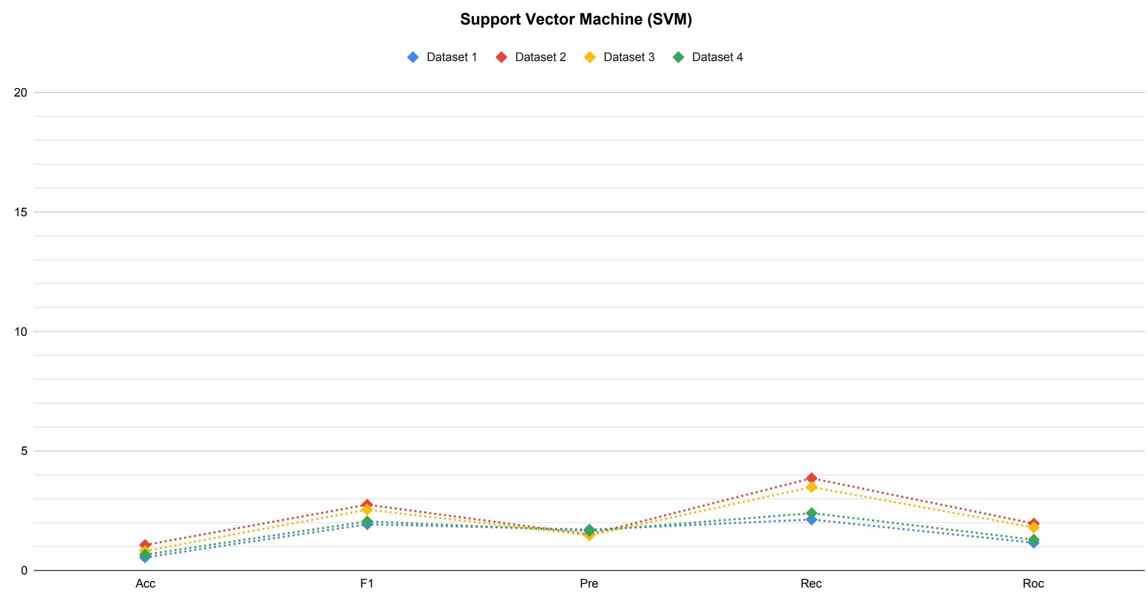

Figure 10: Average Error for Support Vector Machine (SVM) model

Table 1
Performance of models trained on dataset 1

Metric	KNN_1	DT_1	MLP_1	RF_1	SVM_1
Accuracy	96.72	94.46	96.89	**97.33**	97.40
F1	89.71	83.43	90.05	**91.30**	91.69
Precision	92.53	81.86	94.71	**97.95**	96.43
Recall	87.06	85.06	85.84	**85.50**	87.40
ROC	92.84	90.68	92.45	**92.57**	93.38
Time(s)	0.457	0.001	0.002	**0.015**	0.297
V_{score}	2.747	2.643	2.782	**2.807**	2.482

Table 2
Performance of models trained on dataset 2

Metric	KNN_2	DT_2	MLP_2	RF_2	SVM_2
Accuracy	96.83	95.04	96.69	97.09	**97.46**
F1	90.28	85.50	89.73	90.75	**92.15**
Precision	94.25	84.90	94.73	98.60	**96.79**
Recall	86.63	86.09	85.23	84.05	**87.93**
ROC	92.77	91.48	92.13	91.90	**93.66**
Time(s)	0.435	0.001	0.003	0.014	**0.295**
V_{score}	2.758	2.684	2.772	2.795	**2.808**

Table 3
Performance of models trained on dataset 3

Metric	KNN_3	DT_3	MLP_3	RF_3	SVM_3
Accuracy	97.07	94.64	96.41	97.22	**97.44**
F1	90.93	84.30	89.34	91.21	**92.00**
Precision	95.82	83.81	90.13	98.37	**97.81**
Recall	86.53	84.80	88.57	85.02	**86.85**
ROC	92.87	90.73	93.29	92.36	**93.22**
Time(s)	0.404	0.001	0.002	0.017	**0.293**
V_{score}	2.774	2.658	2.766	2.803	**2.803**

Table 4
Performance of models trained on dataset 4

Metric	KNN_4	DT_4	MLP_4	RF_4	SVM_4
Accuracy	96.84	94.99	95.34	96.88	**97.15**
F1	90.52	85.73	85.01	90.37	**91.39**
Precision	95.71	85.91	97.83	98.65	**97.41**
Recall	85.86	85.55	75.15	83.37	**86.07**
ROC	92.52	91.28	87.40	91.56	**92.79**
Time(s)	0.452	0.001	0.002	0.014	**0.294**
V_{score}	2.760	2.687	2.674	2.786	**2.790**

Table 5: Performance of K Nearest Neighbors Models

Metric	Dataset 1				Dataset 2				Dataset 3				Dataset 4			
	KNN_1	KNN_2	KNN_3	KNN_4	KNN_1	KNN_2	KNN_3	KNN_4	KNN_1	KNN_2	KNN_3	KNN_4	KNN_1	KNN_2	KNN_3	KNN_4
Accuracy	0.97	0.96	0.96	0.96	0.97	0.97	0.96	0.96	0.97	0.96	0.97	0.96	0.96	0.96	0.96	0.97
F1	0.93	0.90	0.90	0.90	0.91	0.93	0.90	0.90	0.90	0.90	0.93	0.90	0.90	0.89	0.90	0.92
Precision	0.96	0.94	0.95	0.94	0.95	0.96	0.95	0.95	0.94	0.94	0.96	0.94	0.94	0.94	0.94	0.96
Recall	0.90	0.86	0.86	0.86	0.87	0.90	0.86	0.86	0.87	0.86	0.89	0.87	0.87	0.85	0.86	0.89
ROC	0.94	0.92	0.92	0.92	0.93	0.94	0.92	0.92	0.93	0.92	0.94	0.93	0.93	0.92	0.92	0.94

Table 6: Performance of Decision Tree Models

Metric	Dataset 1				Dataset 2				Dataset 3				Dataset 4			
	DT_1	DT_2	DT_3	DT_4	DT_1	DT_2	DT_3	DT_4	DT_1	DT_2	DT_3	DT_4	DT_1	DT_2	DT_3	DT_4
Accuracy	0.98	0.94	0.94	0.94	0.94	0.98	0.94	0.94	0.94	0.94	0.98	0.95	0.94	0.94	0.94	0.98
F1	0.98	0.94	0.94	0.94	0.94	0.98	0.94	0.94	0.94	0.94	0.98	0.95	0.94	0.94	0.94	0.98
Precision	0.95	0.85	0.84	0.85	0.83	0.96	0.83	0.85	0.84	0.85	0.95	0.85	0.83	0.85	0.83	0.96
Recall	0.96	0.82	0.84	0.85	0.86	0.96	0.85	0.84	0.85	0.84	0.96	0.85	0.85	0.84	0.84	0.96
ROC	0.97	0.89	0.90	0.91	0.91	0.97	0.90	0.90	0.91	0.90	0.97	0.91	0.90	0.90	0.90	0.97

Table 7: Performance of Multilayer Perceptron Models

Metric	Dataset 1				Dataset 2				Dataset 3				Dataset 4			
	MLP_1	MLP_2	MLP_3	MLP_4	MLP_1	MLP_2	MLP_3	MLP_4	MLP_1	MLP_2	MLP_3	MLP_4	MLP_1	MLP_2	MLP_3	MLP_4
Accuracy	0.97	0.96	0.96	0.95	0.96	0.97	0.96	0.95	0.96	0.96	0.96	0.95	0.96	0.96	0.96	0.95
F1	0.92	0.90	0.89	0.85	0.89	0.91	0.89	0.85	0.89	0.90	0.90	0.85	0.89	0.90	0.88	0.86
Precision	0.97	0.95	0.89	0.97	0.95	0.97	0.89	0.97	0.94	0.94	0.90	0.97	0.95	0.95	0.89	0.98
Recall	0.88	0.85	0.88	0.75	0.85	0.87	0.88	0.75	0.85	0.85	0.91	0.75	0.85	0.85	0.88	0.76
ROC	0.93	0.92	0.93	0.87	0.92	0.93	0.93	0.87	0.92	0.92	0.94	0.87	0.92	0.92	0.93	0.88

Table 8: Performance of Random Forest Models

Metric	Dataset 1				Dataset 2				Dataset 3				Dataset 4			
	RF_1	RF_2	RF_3	RF_4	RF_1	RF_2	RF_3	RF_4	RF_1	RF_2	RF_3	RF_4	RF_1	RF_2	RF_3	RF_4
Accuracy	0.99	0.96	0.96	0.96	0.97	0.99	0.97	0.97	0.97	0.97	0.99	0.97	0.97	0.97	0.97	0.99
F1	0.98	0.9	0.9	0.9	0.91	0.97	0.9	0.91	0.91	0.91	0.97	0.9	0.91	0.9	0.9	0.97
Precision	0.99	0.98	0.98	0.98	0.98	0.99	0.98	0.98	0.97	0.97	0.99	0.97	0.98	0.98	0.98	0.99
Recall	0.96	0.83	0.83	0.84	0.85	0.96	0.84	0.84	0.85	0.85	0.96	0.85	0.85	0.84	0.83	0.95
ROC	0.98	0.91	0.91	0.91	0.92	0.98	0.91	0.92	0.92	0.92	0.98	0.92	0.92	0.91	0.91	0.97

Table 9: Performance of Support Vector Machine Models

Metric	Dataset 1				Dataset 2				Dataset 3				Dataset 4			
	SVM_1	SVM_2	SVM_3	SVM_4	SVM_1	SVM_2	SVM_3	SVM_4	SVM_1	SVM_2	SVM_3	SVM_4	SVM_1	SVM_2	SVM_3	SVM_4
Accuracy	0.97	0.97	0.97	0.97	0.97	0.98	0.97	0.97	0.97	0.97	0.98	0.97	0.97	0.97	0.97	0.97
F1	0.93	0.91	0.91	0.91	0.92	0.94	0.92	0.91	0.91	0.91	0.94	0.91	0.91	0.91	0.91	0.93
Precision	0.98	0.97	0.97	0.97	0.97	0.98	0.97	0.96	0.96	0.96	0.98	0.96	0.96	0.96	0.97	0.98
Recall	0.89	0.86	0.85	0.85	0.87	0.89	0.87	0.86	0.87	0.86	0.89	0.86	0.87	0.86	0.87	0.88
ROC	0.94	0.92	0.92	0.92	0.93	0.94	0.93	0.93	0.93	0.93	0.94	0.93	0.93	0.92	0.93	0.94

5. Conclusion and Future work

In this paper, we present a novel system. The system provides the end user the ability to train the best-suited model for the problem. With the current COVID-19 pandemic, this system can be employed by healthcare professionals for the detection of anomalies such as arrhythmia in patients. The system is tested with the ECG MIT-BIH arrhythmia database. The models trained and selected by the system showed good classification performance. These models also performed satisfactorily against training datasets of other models, suggesting good general classification performance.

Future work will involve the use of other freely available datasets to test the general classification performance of the system as well as testing the current system in a real-time environment. Future work will also focus on modifying the system to work with non-labeled databases by employing unsupervised learning methods.

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