International Journal of Future Generation Communication and Networking
Vol. 13, No. 4, (2020), pp. 2057–2071

Prediction Of Periodontal Disease Using Modified Anfis Based Classifier Model

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Abstract

The ultimate objective of this research is to predict periodontal disease and model a computer-based decision-making system based on a modified adaptive neuro-fuzzy inference system (M-ANFIS). The accuracy has computed for predicting and diagnosing periodontal disease. This work concentrates on the optimality of (M-ANFIS) algorithm. The performance of predictive accuracy, specificity, sensitivity, (Receiver Operating Characteristics) ROC, and a confusion matrix to be determined with (M-ANFIS) algorithm. The dataset validation with the collected dataset from available online sources partitioned for testing and training purposes has been performed. Evaluating and optimizing the dataset has to be performed with the M-ANFIS classifier model. The proposed decision-making process has achieved a productive and efficient method of predicting and diagnosing periodontal disease.

Keywords- *Machine learning, Support Vector Machine, Periodontal disease, prediction accuracy, sensitivity, and specificity*

I.INTRODUCTION

Periodontal disease (PD) is determined to be an acute or chronic disorder leading to extensive intra-oral pathology for some common type of inflammatory disease [1]. By the destruction of supporting tissues that include ligaments and alveolar bone over the tooth measured the constant PD disease progression. PD reported being an extensive cause of tooth loss in all the age factors [2]. Numerous experimental studies have been carried out to analyze systematic chronic inflammation. Periodontal pathogens [3] are measured as a risk factor or risk indicator for diseases like cardiovascular disease, obesity, diabetes mellitus, cancer, and osteoporosis [4].

Enhancing the treat periodontal disease and supporting structures the plenty of surgical and non-surgical techniques to be performed with various studies involved over the regeneration of

ISSN: 2233-7857 IJFGCN

periodontal tissues[5]. The advancements towards the treatment modalities were not determined adequately until now [6]. The enhancements of disease prediction are still a complicated factor [7], even with periodical radiographs and probes extensively used as a diagnostic tool for predicting PD [8]. These are all conventional disease prediction methods and clinical diagnosis and prognostic factors based on empirical evidence.

Here, a machine learning approach known as Support Vector Machine (SVM) used to predict PD and classify the factors that influence the disease in most cases. This model has been developed rapidly from later 2010 [9]. The medical data to be formulated with digital storage and gathered quantitatively with qualitatively. The SVM with a Computer-aided detection system provides a clear insight into various medical applications [10]. This faster growth in these fields may lead to impressive outcomes based on the prediction and diagnosis of pathological and radiological research. Hence, the most recently used artificial intelligence approaches have been provided based on machine learning techniques and explicitly generated for medical data classification.

An ANFIS is an integration of fuzzy logic and neural network. It has been utilized for system identification based on a given dataset. There exist some adaptive network classes that are equivalent to a fuzzy inference system. It uses a hybrid learning algorithm for learning and training Neural Network (NN) to determine undefined system parameters. ANFIS is based on a fuzzy model comprised of rules and some commands with the type of ANN-based on the Takagi-Sugeno fuzzy interface system, Merges fuzzy logic, and neural principles. The inference rule has based on a fuzzy-based IF-THEN rule that effectual for an approximation of non-linear functions.

Eventhough radiographic image analysis has extensively utilized to predict and diagnose PD. It is still determined to operate as an additional measure for clinical prediction, diagnosis, and investigations based on PD diagnosis with Modified ANFIS (M-ANFIS) and CAD are extremely limited. Henceforth, this investigation's ultimate objective is to compute the efficiency and accuracy of machine learning approaches for prediction and diagnosis of PD. For this computation, the dataset has been collected from available online sources. From this dataset, data partitioned for training and testing and to make further validation.
The remainder of the work formulated as Section II background studies related to PD disease prediction and diagnosis. Section III shows pre-processing, data collection, and classification with M-ANFIS for predicting PD, Section IV determined the numerical analysis and results related to PD prediction. Section V is the conclusion with future research directions.

II RELATED WORKS

The author in [11], examined the oral health based cognitive functionality and impairments encountered in adults. This analysis and corresponding functionality increase the complexity of daily activities. With this analysis process, data from roughly 220 patients collected that may include patients with PD without dementia details and impairment details. Data has examined

with regression-based multi-variable analysis utilized for the prediction of functionality changes and dental factors. The proposed model's competency measured with an experimental analysis, and this system attains 95% prediction accuracy while recognizing oral hygiene-based impairments.
In [12], the author recognized cognitive impairments based on dementia using diverse approaches like linear discriminated analysis, radial basis function, neural network, support vector machine, random forest, an Classification and Regression Treesc (CART) classification model. Various classifier utilized for diagnosis of dementia based features, which help reduce cognitive infections more effectually. The dementia prediction model examined via diverse metrics like accuracy, specificity, and sensitivity. A 5-fold CV used for analyzing the system efficiency that evaluated with the non-parametric test like Friedman's test during this computation. Here, prediction accuracy is about 90% accuracy.

The author in [13] modeled a dental problem associated with the dementia detection process utilizing random forest models. Some persons have affected patients' information with development approaches, and 35 regular patients' were gathered, including numerous analyses like an oral test, Stroop test, figure test, and visuospatial memory-based report. The data collected from the dataset is evaluated with an experimental study and compared with logistic regression and naïve Bayes model—Parkinson's disease based dementia disease prediction by attaining 76% accuracy. The research performed by various investigators related to oral hygiene-based brain disease requires enormous cognitive examination attention. With this process, different machine learning procedures used to evaluate dental, and brain imaging-based features more resourcefully; however, they collect vast amounts of dental data, image data that fails to handle prediction accuracy [14]. Conventional approaches are used for complete feature extraction and may consume enormous time and encounters complexity in predicting dental based brain changes more effectually. Here, system complexities reduced with intelligent approaches termed as a bacterial optimization-based associative neural network utilized to predict changes in the brain due to oral hygiene.
Some deep learning-based approaches have used with medical image investigation with resourceful utilization of computer-aided detection and prediction. While many studies concentrated on examining images from pathology, radiology, and dermatology analysis that deals with diverse dental imaging modalities. Here, various studies concentrated on plaque and caries; some analysis done with periodontal disease prediction. The author in [15] utilized intra-oral images for periodontal detection. There are various restrictions: deep NN used for training manually cropped teeth patches, the dataset is used for small, and these architectures are shallow, as shown in Fig 1 and Fig 2.

The working model of intellectual bacterial optimization is based on oral hygiene analysis. With this process, oral hygiene based disease data collected from the PubMed dataset. The data gathered from searching for oral hygiene and blood test. These may include various details like brushing time, brushing criteria, Stroop test, periodontal index score, Rey figure testing, white blood count, c - reactive protein, cholesterol, and sugar level. The data gathered from various patients by partitioning age and gender. Then, dental pocket details, dental probing, and regular blood test details were accumulated from patients [16]. Therefore, machine learning approaches considered to give better results in PD disease prediction [17].

Fig 1: Sample dental radiographs

Fig 2: Periodontal bone loss

III METHODOLOGY

The complete structural model of the anticipated approach comprises of various stages. Initially, the input image is trained with a segmentation network for extracting teeth and is used for predicting PD lesions. The segmented data provides a classification network that indicates the existence of PD. For further enhanced, M-ANFIS trained classifier model used for training the system for recognizing PD specifically for molar teeth and pre-molar teeth types. The classification methods used for complete PD prediction.

a. Dataset

The dataset acquired from the Chozhan group of dental clinics, Theni, Periyakulam, and Kodaikanal. Here, images identified with various noises and haziness that are partially available or severely distorted. Teeth with four roots may undergo root canal treatment and undergo surgery with root re-section with severe caries with complete restorative crown from typical anatomical structures. The flow diagram of the anticipated approach given in Fig 3.

b.Pre-processing

The data acquired from radiographic images are re-sized and cropped to 220*220 pixels and transformed into PNG format. The teeth vertically flipped to form mandibular teeth. The network is pre-trained and augmented and normalized for performing further segmentation process.

c.ROI Based Segmentation

There is extensive variability in frontal view and contextual information in dental radiographs based on patients and devices and based on impedes and detection of PD lesions more appropriate for teeth regions in radiographs. To determine this variability, the segmentation trained for the automatic extraction of region of interest **(**ROI).

The extraction performed with an encoder and decoder part of the predictor modelHere, the L2 regularization norm is used to determine the loss function for generating ROI segmented image in Eq. (1):

$$L_R(\hat{y}^R, y^R) = -\frac{1}{n}\sum_i [y_i^R log\hat{y}_i^R + (1-y_i^R)\log(1-\widehat{y_i^R})] + \frac{\lambda}{2n}\sum_k w_k^2 \quad (1)$$

Where 'n', specifies the number of pixels in radiography, y_i^R is binary label, $\widehat{y_i^R}$ for predicting pixel label, λ is the regularization parameter. The ROI prediction is a post-processing function with morphological filling holes with segmented mask. The segmented region is determined with the black ground region with a prediction mask in radiography by normalizing the input image.

d.ANFIS classifier model

Adaptive Neuro-Fuzzy Inference System modeled as an improved version of conventional NN combined with fuzzy logic. It gives a non-linear map among input and output using IF-THEN rules. It has two inputs and one output. ANFIS comprises of five layers with a particular task. Fig 4 depicts the general ANFIS model. The first layer receives information and evaluates the production of every node with membership functions as in Eq. (2):

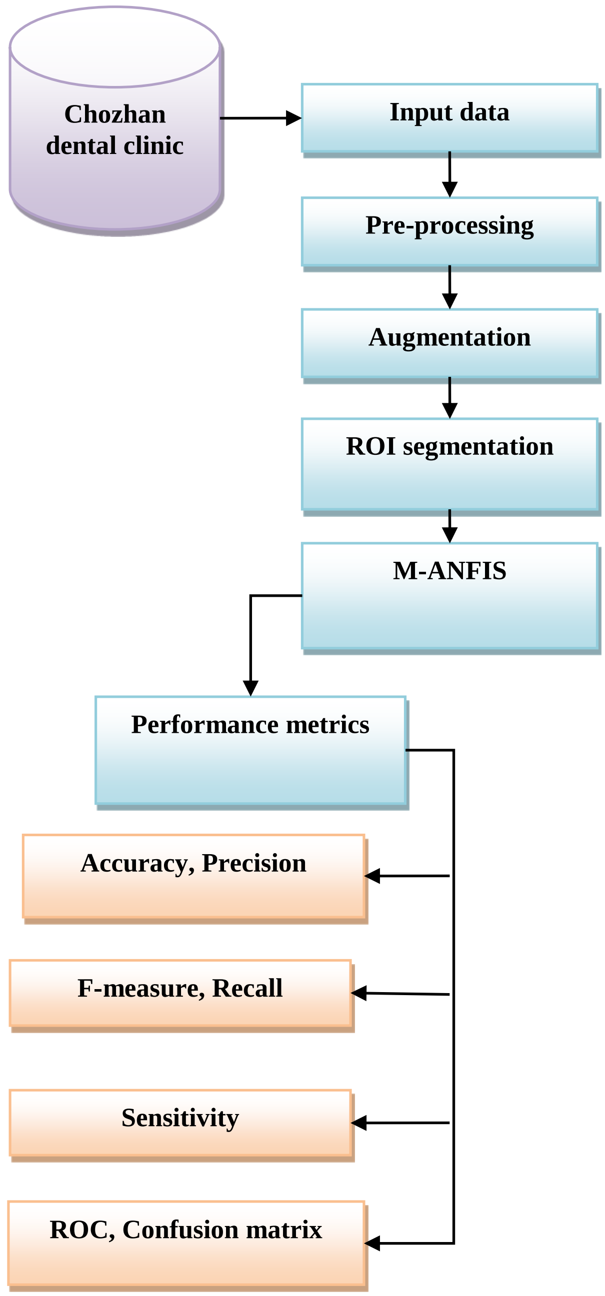

Fig 3: Flow diagram of the proposed model

$$O_{li} = \mu A_i(x)$$

Where, $i = 1{,}2, O_{li} = \mu B_{i-2}, i = 3{,}4$

$$\mu\,(x) = \; e^{\wedge} - \left(\frac{x-\rho_i}{\alpha_i}\right)^2 \qquad (2)$$

The parameters αi and are parameter sets. Ai and Bi are μ'S membership values used for computing nodes' output in the second layer.

$$O_{2i} = \; \mu_{A_i}(x) * \; \mu_{B_{i-2}}\,(y) \qquad (3)$$

A node in the third layer evaluates output using the normalizing strength of the layershown in Eq. (4):

$$O_{3i} = \; \overline{w_i} = \frac{\omega_i}{\sum_{(i=1)}^{2}\omega_i} \qquad (4)$$

An adaptive node over the fourth layer evaluates output based on O 3_i as in Eq. (5):

$$O_{4,i} = \; \overline{\omega_i} f_i = \; \overline{\omega_i}\,(p_i x + q_i y + r_i) \qquad (5)$$

The parameters of ri, qi and pi are parameters over ith node. Finally, ANFIS output computed with Eq. (6):

$$Output = \sum_i \overline{w_i} f_i \qquad (6)$$

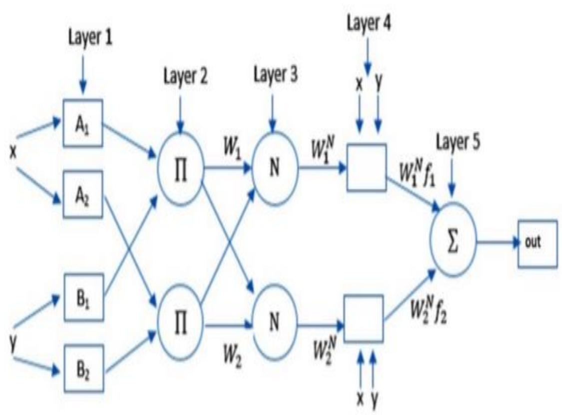

Fig 4: ANFIS model

e. k-medoid ANFIS

This algorithm commences with the arbitrary selection of k-data items to represent k-cluster. The other items comprise of a cluster that holds the medoid nearest to it. This projects better clustering. The complete dataset items provided to clusters with the closest medoid. For all iterations, the medoid may changes. It limits the sum of dissimilarity among data items and equivalent medoids. This is recurring to no variation is encountered and marks process completion. Also, final cluster results with medoids are attained. 'k' clusters are constructed with medoids, and complete data members are deployed over an appropriate cluster center. The steps are given below:

1. Consider *C={C1,C2,….,Cj,….,C8}* specifies clusters.
2. Allocate each subset to the nearest clustered values.
3. Compute Euclidean distance for measuring distance among the variables

$$D = \sqrt{(u_1 - v_1)^2 + (u_2 - v_2)^2}$$

   Here, 'u' and 'v' are co-ordinates and subset values.

4. Compute distance of subset values
5. Choose random subset values to replace the existing values over a condition of a threshold value. When the cost is higher than the average one, it will be replaced.
6. Allocate subset values to the nearest threshold value to attain an optimal value. The, Euclidean distance is used to compute total distance.
7. If sum of distance is equal to the preceding sum of THE distance, then the algorithm will be terminated
8. Else move to step 3.

Algorithm 1:

Input:number of subset

Output: clustered value

Begin

Randomly select data points from medoid m_k

Repeat

Allocate non-medoid point to nearest medoid

Compute distance between medoid and non- medoid

For all medoid do

Choose non-medoid with total distance

Compute $TD\left(e_j \rightarrow m_i\right)$

If $(TD(e_j \rightarrow m_i)$ is smaller than TD_i

ISSN: 2233-7857 IJFGCN

Swap m_i and e_j
End if
End for
Until no m_i changes
End

IV EXPERIMENTAL RESULTS

The simulation done with MATLAB environment for prediction and diagnosis of periodontal diseases. The data has been collected from Chozhan dental clinic, theni tamilnadu[17] Confusion matrix utilized for determining the performance of classification process by evaluating the performance metrics. The performance measurement utilized for determining metrics of True positive (TP),True Negative (TN),False Positive (FP) and False Negative (FN).

The classification accuracy of M-ANFIS classifier is to identify the competency of classifier algorithm to identify classes of dataset.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \qquad (9)$$

Sensitivity or recall specifies accuracy measure of target class occurrence.

$$\text{Recall} = \text{sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \qquad (10)$$

$$\text{True positive rate (TPR)} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{False positive rate (FPR)} = \frac{\text{FP}}{\text{FP} + \text{TN}}$$

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

$$\text{F} - \text{measure} = 2 * \frac{\text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}}$$

Table I: Clinical parameters

S.No	Parameters
1	Patient ID
2	GI
3	MB
4	PPD
5	AL
6	ABL

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7	Sex
8	Smoking
9	Drug
10	Genetic
11	Hormonol
12	PI
13	Age
14	BVMI

	Healthy	Moderate	Severe
Healthy	**49**	**11**	**0**
Moderate	**2**	**34**	**8**
Severe	**0**	**11**	**53**

Fig 5: Confusion matrix without normalization (Pre-molar)

	Healthy	Moderate	Severe
Healthy	**41**	**11**	**0**
Moderate	**5**	**45**	**14**
Severe	**0**	**12**	**52**

Fig 6: Confusion matrix without normalization (Molar)

Healthy	**0.81**	**0.19**	**0**
Moderate	**0.06**	**0.78**	**0.19**
Severe	**0**	**0.16**	**0.83**

Healthy Moderate Severe

Fig 7: Confusion matrix with normalization (Pre-molar)

	Healthy	**Moderate**	**Severe**
Healthy	**0.80**	**0.22**	**0**
Moderate	**0.09**	**0.71**	**0.23**
Severe	**0**	**0.20**	**0.82**

Fig 8: Confusion matrix with normalization (Molar)

Table II: Performance Metrics

Parameter	**ANFIS**	**M-ANFIS**	**NN**	**SVM**	**NB**
Sensitivity	0.6785	0.9285	0.6428	0.5357	0.3571
Specificity	0.9196	0.9821	0.9107	0.8839	0.8392
Accuracy	0.8714	0.9714	0.8571	0.8142	0.7428
Precision	0.6785	0.9285	0.6428	0.5371	0.3571
Recall	0.6785	0.9285	0.6428	0.5371	0.3571
F-measure	0.6785	0.9285	0.6428	0.5371	0.3571
NPV	0.9196	0.9821	0.9107	0.8839	0.8392
FPR	0.0803	0.01785	0.0892	0.1160	0.1607
FNR	0.3214	0.07142	0.3571	0.4642	0.6428
MC	0.59	0.91	0.553	0.41	0.19

C	82	07	5	69	64
FR R	0.32 14	0.07 142	0.357 1	0.46 42	0.64 28

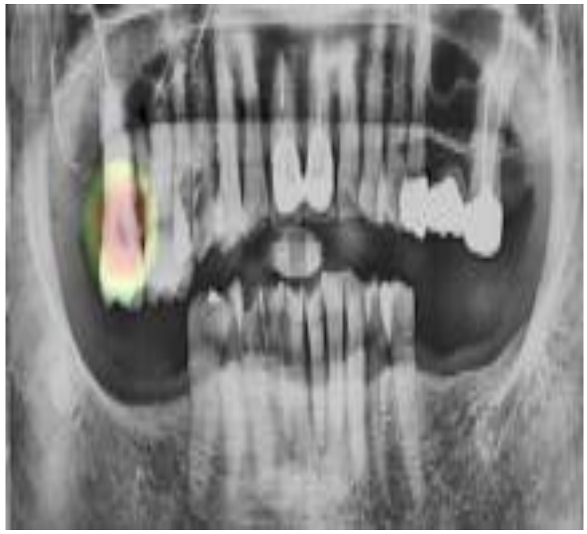

Fig 9: Severe periodontal bone loss (sample 1)

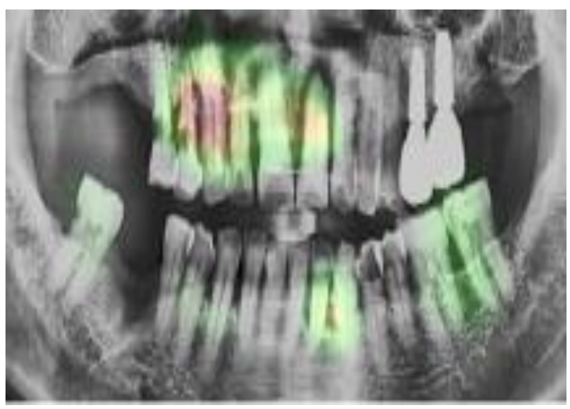

Fig 10: Severe periodontal bone loss (sample 1)

Initially, the clinical parameters considered for measuring the severity of periodontal disease. Table I depicts the clinical parameters related to disease prediction. The parameters include plaque index, gingival index, pocket depth, clinical attachment level, and gingival recession, bleeding on probing and rediographical bone loss. Figure 5- Fig 8 shows the confusion matrix that has analyzed for four different factors like normalization with molar and pre-molar and without normalization in molar and pre-molar regions.

ISSN: 2233-7857 IJFGCN

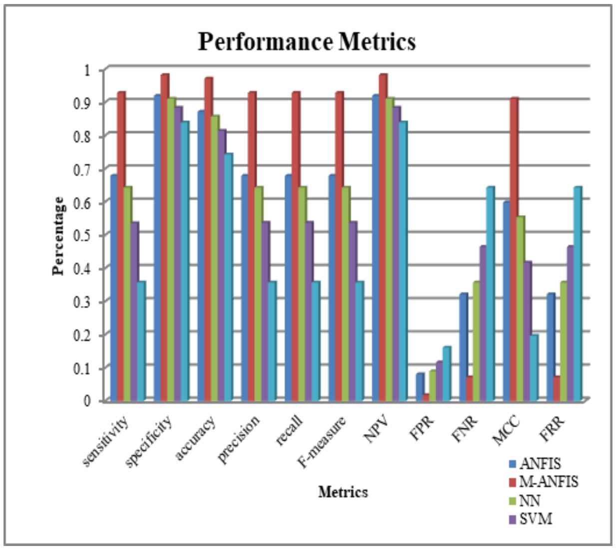

Fig 10: Performance metrics computation

The confusion matrix is designed based on three measures like Healthy, moderate and severe cases. Table II shows the performance metrics with various measures like sensitivity, specificity, accuracy, precision, recall, F-measure, NPV, FPR, FNR, MCC, FRR. The values associated with this are 0.92857, 0.98214, 0.97143, 0.92857, 0.92857, 0.92857, 0.017857, 0.071429, 0.91071 and 0.071429 respectively. The anticipated M-ANFIS classifier model shows improved prediction accuracy with 97% in molar and pre-molar conditions. However, there are some limitations while using this classifier, i.e. imbalanced dataset validation. Here, the dataset partitioned into 80:20 ratio for training and testing purposes. This work does not consider cross-validation in this work while more attention will be given in the feature. Feature selection also plays an essential in enhancing prediction accuracy. Therefore, machine learning-based feature selection models have to be designed for the periodontal disease-based predictor model. Figures 8 and 9 and 10 depict the severity of periodontal disease prediction with a dataset set horizontally. This M-ANFIS classifier assists in predicting the severity of bone loss with ROI based segmentation model. The anticipated model works effectually in contrast to prevailing approaches and provides better trade-off than other approaches.

Based on the above analysis, the severity of PD measured for the features leads to heart attack or cardiac arrest. The most influencing elements mentioned above are the primary cause of other diseases, whereas the less influencing factors have to be treated in the initial stage.

V.CONCLUSION

A modified adaptive neuro-fuzzy inference system M-ANFIS has adapted for predicting PD disease with available data sources. The prediction of PD in an earlier stage may lead to a reduction of complexity towards crucial conditions like cardio-vascular disorders. Therefore, accurate and faster forecast considered to be an essential factor in PD treatment. The performance has been measured with the metrics of predictive accuracy, specificity, sensitivity, ROC, and a confusion matrix to be determined with (M-ANFIS) algorithm. Then, optimization accuracy and speed are the major research problem. These factors lead to complications in disease prediction. The proposed model shows a prediction accuracy rate of 97%. in all the conditions. Here, data are segmented with ROI and classified using the M-ANFIS classifier. This classifier model works effectually in disease prediction and attains better performance with healthy, moderate, and severe cases. Some limitations were encountered during data collection. In the future, ensemble approaches or hybridized methods are used for the classification approach. Similarly, feature selection plays an essential role in improving prediction accuracy. Thus, feature selection is also provided with more concentration.

In the future, this work extended with the prediction of cardiac arrest. The PD factors that influence cardiac arrest will be performed as the future research direction using Machine Learning algorithms.

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