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Electro Cardio Gram Using Different Machine Learning Techniques for Early Heart Attack Prediction

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ABSTRACT

An electrocardiogram (ECG) is used to monitor the heart's electric impulses and visualize cardiac signals in order to identify issues. For the early identification of heart-related conditions, the non-invasive Electrocardiogram (ECG), which offers data on cardiac abnormalities, has become a common procedure. A variety of methods are employed to identify irregular heartbeats. To predict cardiovascular illnesses, which can lead to severe illness or even death in middle-aged and older persons, this study suggests a way to categorize ECG records. One of the largest anomalies was caused by an arrhythmia sickness.

Several deep learning approaches were utilized to predict early arrhythmias and save lives. Several ECG signal classifications have been done utilizing pre-existing databases, such as MIT-BIH arrhythmia, according to a review of the literature. In order to detect irregularities associated with arrhythmias.

This research suggests an architecture that integrates a number of heart disease classification methods with a 99.7% accuracy rate, including logistic regression, CNN, LSTM, decision trees, k-nearest neighbors, Naive Bayes, discriminant analysis, and neural networks.

Keywords: *EGC, electrocardiogram, CNN-LSTM, deep learning, machine learning*

1. INTRODUCTION

Cardiovascular diseases (CVDs) are becoming the primary cause of death, owing to a WHO study. Every year, cardiovascular diseases, one of the worst conditions, take the lives of millions of individuals. Cardiovascular problems are responsible for 17.9 million deaths each year, or about 31% of all deaths, according to a recent study. Machine learning (ML) has lately reemerged in healthcare innovation because to the massive development in electronic health records, which contain organized collections of various types of digitalized medical data as well as new methods for effectively evaluating this large quantity of data.

It should be noted that the reader might not understand why a priori feature establishment is required. Frameworks for ECG interpretation (such as rate, rhythm, axis, intervals, and ventricles) are already in place to classify and identify different heart issues. It would be foolish to rule out the possibility of additional morphologies that are invisible to the human eye, either locally or as connections between beats, given the intricacy of the cardiac conduction system and its relative stability. In signal processing and imaging, the high-fidelity automated feature engineering offered by DL may be advantageous for the many underived features present in raw waveforms and pixels. Despite not being fully proved, these mysterious patterns must explain why Attia et al. 26's optimistic predictions of paroxysmal atrial fibrillation (AF) in individuals from a benign, normal sinus rhythm ECG were successful. Over three-fourths of all deaths in countries with low and moderate incomes are caused by cardiovascular diseases. Studies have shown that cardiac arrhythmias are directly responsible for about 50% of heart disease deaths and 80% of sudden cardiac deaths.

This is an example of how poor diagnostic methods exacerbate heart problems. The majority of these deaths are caused by strokes and heart attacks. An early, accurate diagnosis, made possible by ECG analysis, can improve the chances of survival for many heart disorders. The primary cause of CVDs is the detrimental long-term effects of cardiac arrhythmias. Very slow or very fast irregular heartbeats are known as arrhythmias.

2. RELEATED WORKS

In light of their findings, Bhekumuzi et al. suggested Two-dimensional images were utilized as inputs to the CNN classifiers after the ECG time series had been divided and transformed using an RP. A two-stage categorization method is suggested in this research to increase accuracy. In the first stage, ventricular fibrillation (VF) and noise were detected using the ResNet-18 architecture.

An arrhythmia is a type of cardiac ailment that is distinguished by the heartbeat's rhythm or rate. The heartbeat may exhibit an erratic pattern, be too slow, or be faster than usual. Bradycardia is a cardiac condition linked to extremely slow heartbeats, while tachycardia happens when the heartbeat is too rapid[2]. Every 36 seconds, someone dies in the US from heart disease. In America, heart disease accounts for about 655,000 fatalities annually, or one death out of every four that are caused by cardiovascular disease [3].

The ECG signal can be obtained in a number of ways and is generally available. Many signal processing-based automatic ECG classification methods have been proposed over time. These include neural networks (ANNs) [5,6], decision trees [7], Bayesian classifiers [4], wavelet transform [4,5], frequency analysis [6], support vector machines (SVMs) [8,9], and linear discriminant analysis [5]. The most popular method in the last few years was the application of DL algorithms [8]. A Random Forest (bagged decision tree) based classifier was trained using 380 features in total. Weights based on the distribution of classes were applied since the classes in the Challenge were seriously out of balance [9].

The study made use of the Reverse Time Attention model (RETAIN), which is based on a combination of Recurrent Neural Networks (RNNs) and includes an attention mechanism [13]. Predicting cardiac disease effectively and consistently is challenging, despite the fact that machine learning and deep learning approaches are currently transforming the healthcare industry [11].

Heart disease has been predicted using a variety of classification techniques; one ensemble learning method, Random Forest (RF), has demonstrated some promising outcomes in this regard [12]. This makes it possible for the experts and healthcare providers to understand which variables or time periods are most crucial for the model's forecasts. The state-of-the-art DL algorithms' inability to extract features in complex and noisy contexts hinders the development of precise and dependable object differentiation [14]. One study used numerous machine learning algorithms to predict CVD using clinical data. The researchers made use of DTs, RFs, and K-nearest neighbor (KNN) models. Using these models, the authors demonstrated a high degree of accuracy in CVD prediction [15].

The capacity of various machine learning algorithms to forecast heart illness was examined in another study. The scientists reported that the models accurately predicted heart issues [17]. Using closed-loop, one-dimensional/zero-dimensional cardiovascular models, the impact of hepatic vein exclusion or fenestration on extracardiac Fontan hemodynamics will be examined in this study. To model challenges in the splanchnic circulation, we modify mesenteric vascular resistance and consider fenestration conduits of different widths [18].

However, Ventricular Fibrillation, a severe form of arrhythmia, is thought to be a contributing factor to heart attacks and has the potential to be lethal. While lifestyle choices or other heart conditions might cause certain arrhythmias, some can be inherited. Arrhythmias can be treated in the majority of instances that are detected early. Prompt, comprehensive diagnosis and medical therapy reduce the risk of unexpected death for patients with these illnesses [19,20]. In the medical sector, machine learning is essential. A wide range of diseases can be identified and predicted thanks to machine learning [21]. The application of data mining and machine learning techniques to forecast the risk of contracting specific diseases has grown recently [22]. Data mining techniques for disease prediction have been applied in the published literature [23]. While some studies have tried to forecast the likelihood of the disease's future course, they have not yet produced reliable findings [24].

3. PROPOSED METHOD

3.1 Methodological ECG Interpretation

The reader will quickly see that the use of an algorithm greatly facilitates the interpretation of ECGs, since it speeds up the process and lowers the possibility of overlooking critical abnormalities. The following algorithm is easy to understand and anyone may use it. It is always necessary to read the ECG methodically; otherwise, it could be harmful.

3.2 EVALUATION

The normal rhythm, or sinus rhythm, has the following traits. The heart rate ranges from 50 to 100 beats per minute, the P-wave arises before each QRS complex, the PR interval is continuous, and the P-wave is positive in lead II.

Lead II's P-wave needs to be positive for the rhythm to be sinus.V1 may have a biphasic (diphasic) P-wave, and the negative deflection should be smaller than 1 mm.A noticeable second hump may be present in the leads of the inferior limbs, especially lead II. Pmitrale: longer P-wave, longer second hump in lead II, and longer negative deflection in V1.Increased P-wave amplitudes in lead II and V1 are indicative of P pulmonale.P-waves that are retrograde, or reversed, can be found anywhere from the J point to the terminal part of the T-wave.if the P-wave is not easily visible. PR interval >0.22 s: AV block in the first degree.PR interval <0,12 s: WPW syndrome or pre-excitation.Blocks of the left and right bundle branches make up the wide QRS complex (QRS length ≥0.12 s). aberration of intraventricular conduction that is not specified. elevated potassium levels. Antiarrhythmic drugs of class I. tricyclic drugs for depression. heart rhythms and cardiovascular extra systoles, often known as premature complexes. The ventricle contracts due to an artificial pacemaker. unusual conduct (aberrancy).Pre-excitation, also known as Wolff-Parkinson-White syndrome. The population has a high prevalence of innocent ST segment elevation, especially in the precordial leads (V2–V6).. The male/female pattern refers to the fact that up to 90% (in certain age ranges) of healthy men and women exhibit concave ST-segment elevations in V2–V6. Elevations of the ST-segment that are not benign or caused by ischemia are relatively frequent. In healthy people, ST-segment depression is unusual. The presence of ST-segment depression in the chest leads is very concerning. According to guidelines, all leads should have a ST segment dip of less than 0.5 mm.ST-segment elevation causes include: Ischemia. Myocardial infarction with ST elevation (STEMI/STE-AKS). Coronary vasospasm, also known as Prinzmetal's angina. Pattern of men and women. Repolarization early on. Perimyocarditis.bundle branch block on the left. Disruption of intraventricular conduction that is not specific. Left ventricular enlargement. Heart disease caused by Takotsubo.elevated potassium levels. After cardioversion. The figure 1 illustrated that ECG diagram of Heart attack prediction in different level P,Q,S value.

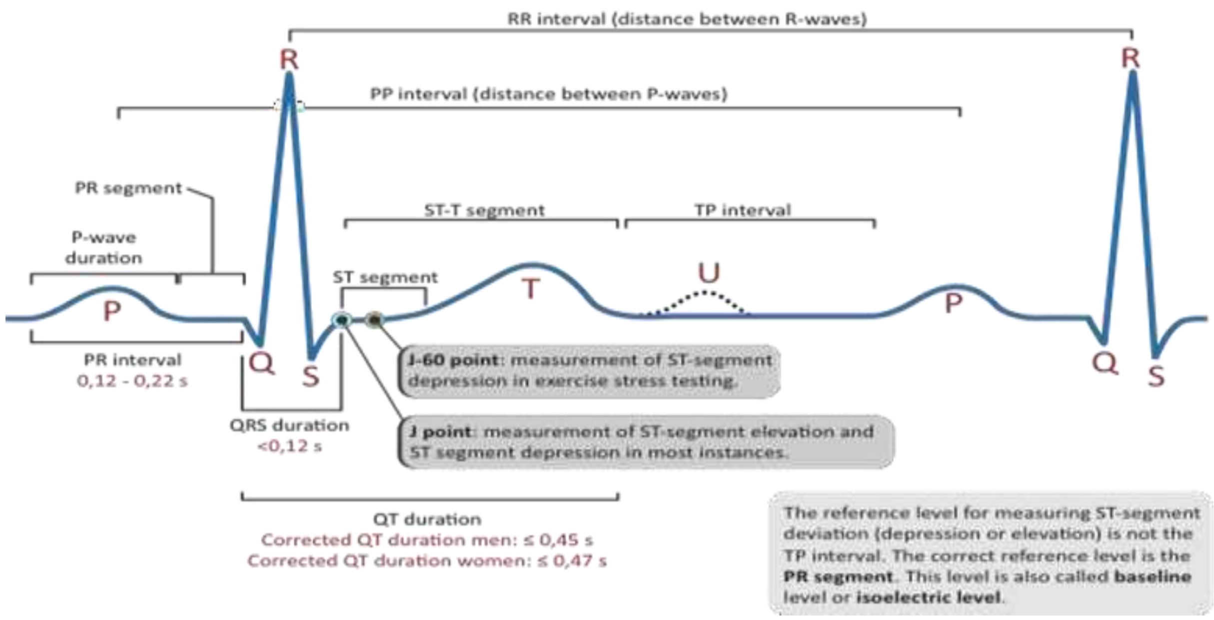

Fig. 1 :ECG diagram of heart Attack Prediction in different level P,Q,S value.

A. Input Data

This approach makes advantage of information from an online database, such as the MIT-BIH dataset, that offers precise details regarding cardiac abnormalities. Over 8,000 ambulatory ECG readings were obtained from patients at Beth Israel Hospital in Boston, comprising approximately 40% outpatients and 60% inpatients. The initial dividing is on the basis of patient samples from the database. Consequently, the division is carried out according to individual patients rather than samples. Eighty percent of the data is made up of training and testing datasets. Examples of pre-processing techniques include data cleansing and standardization. The neural network was trained using the training dataset, and its accuracy and loss percentages were evaluated using the validation dataset. The testing set was ultimately employed.This method uses data from an online database that provides accurate information about cardiac anomalies, like the MIT-BIH dataset. More than 8,000 ambulatory ECG readings were obtained from patients at Boston's Beth Israel Hospital, 40% of whom were outpatients and 60% of whom were inpatients. The first separation is based on patient samples from the database. As a result, the splitting is done based on individual patients rather than samples. Eighty percent of the entire data is made up of training and testing datasets. Pre-processing techniques include things like data cleansing and standardization. After the neural network was trained using the training dataset, its accuracy and loss percentages were evaluated using the validation dataset. The testing set was ultimately employed.

B. Performance Factors:

Based on performance criteria, ECG signal data input online or in real time is categorized as normal or abnormal. The traits include sensitivity, specificity, false positive and true positive values, and false and true negative values. The accuracy of the models is assessed. The figure 2 illustrated that flow diagram of the data in MIT-BIH dataset.

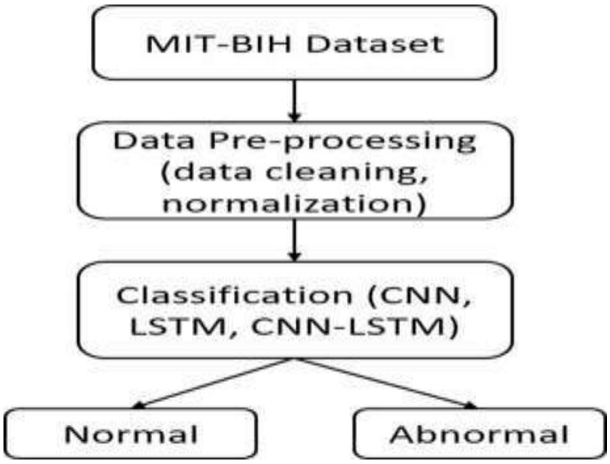

Figure 2: Flow diagram of the data in MIT-BIH dataset

4. RESULTS AND DISCUSSIONS

This study trains and evaluates the MIT-BIH arrhythmia dataset using decision trees, k-nearest neighbors, Naive Bayes, logistic regression, discriminant analysis, neural networks, LSTM, CNN-LSTM, and CNN deep learning models—all heavily used due to their uniqueness in ECG signal data [25]. The lowest frequency at which data is recorded is 360 Hz. In order to distinguish between aberrant and normal ECG signal data, the online database's input signals are used to load the signals and annotations of a particular patient. The remaining 80% of the input dataset was divided into training groups, while 20% was divided into testing groups [26]. The CNN-train model training loss and validation loss during the various epochs and data network loss were depicted in figure 3.

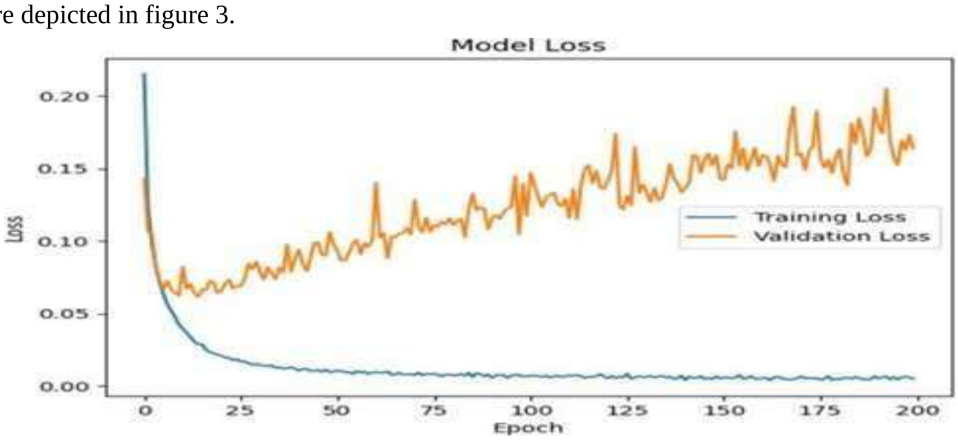

Fig. 3. CNN: lack of validation and training

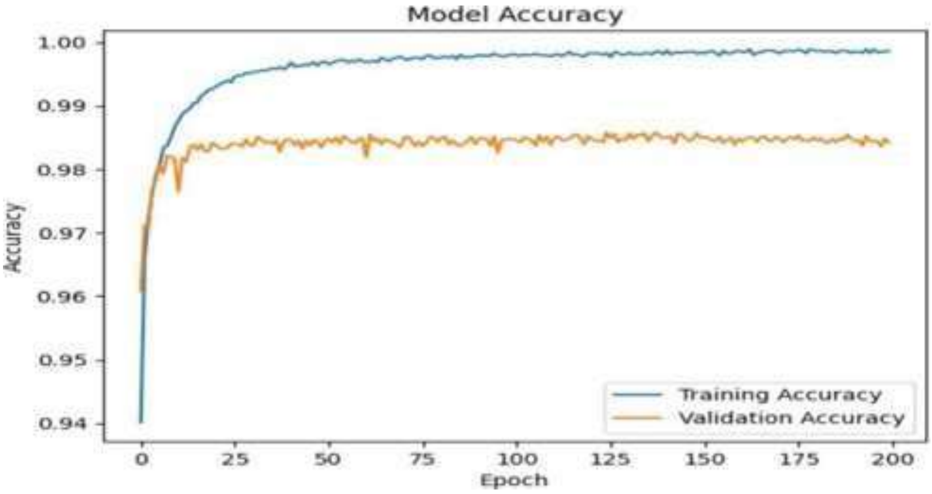

Fig. 4. CNN-LSTM – train and validation accuracy

The figure 5 illustrated that testing and training of data in heart attack dataset in cholesterol versus age in different age in India.

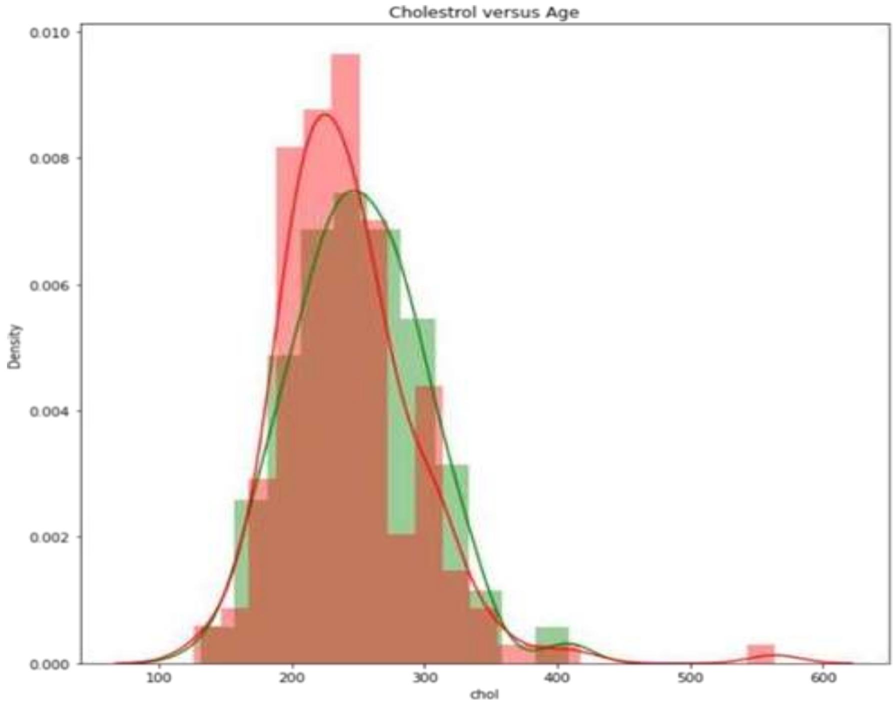

Fig 5. Testing and training of data in heart attack dataset in cholesterol

The figure 6 illustrated that ECG image for heart attack prediction in the patients.

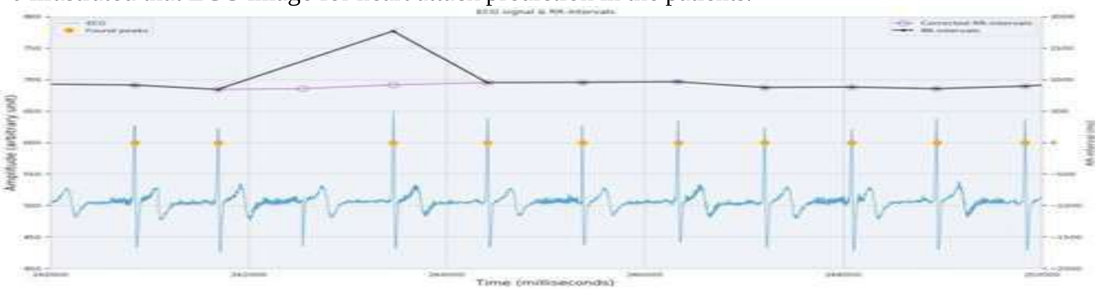

Fig 6. ECG image for heart attack prediction in the patients

The figure 7 illustrated that confusion matrix of different types of algorithm of heart attack prediction.

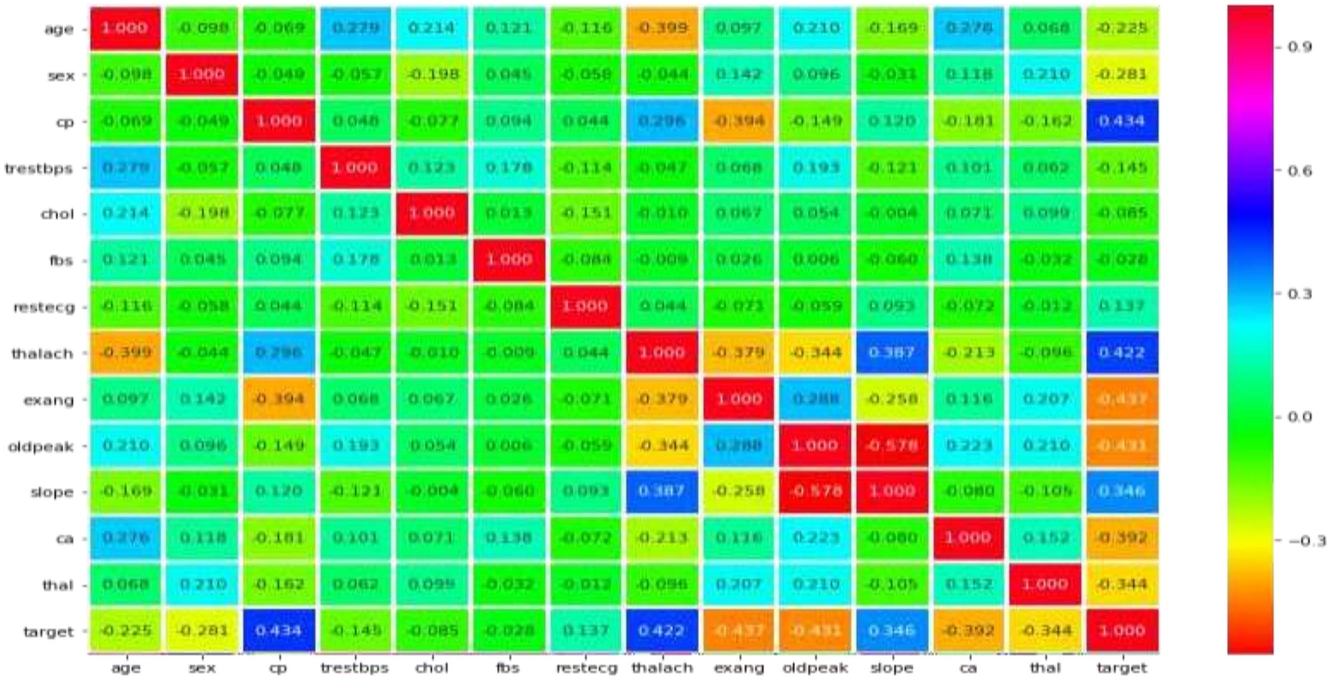

Fig 7. Confusion Matrix of different types of algorithm

The figure 8 illustrated that target data set for the male and female in heart attack in different time interval.

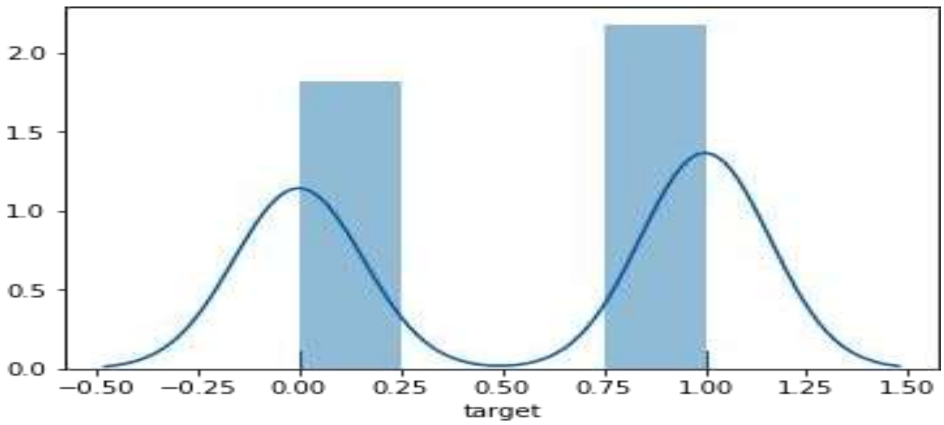

Fig 9. Male and female in target data in different time interval

The figure 10 illustrated that error rate and K value in different time interval.

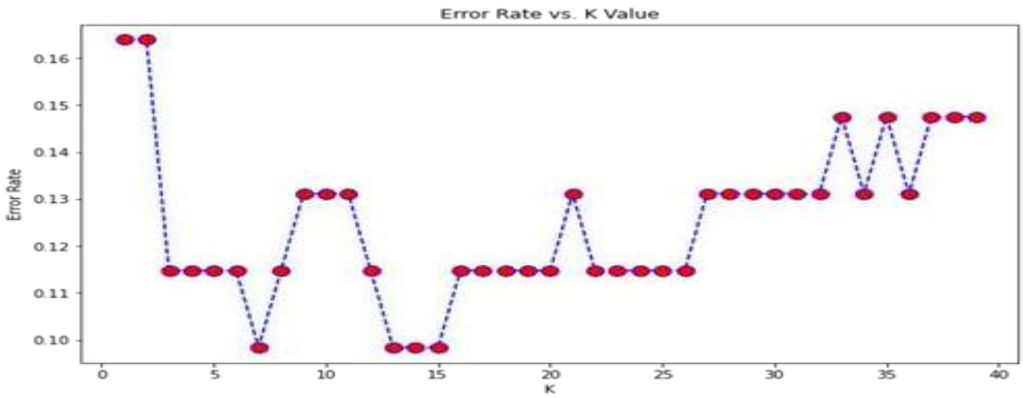

Fig 10. Error rate and K value in different time interval.

The figure 11 illustrated that sensitivity. specificity, accuracy and AUC in different types algorithm such as ANN, Decision tree, AdaBoost and support vector machine.

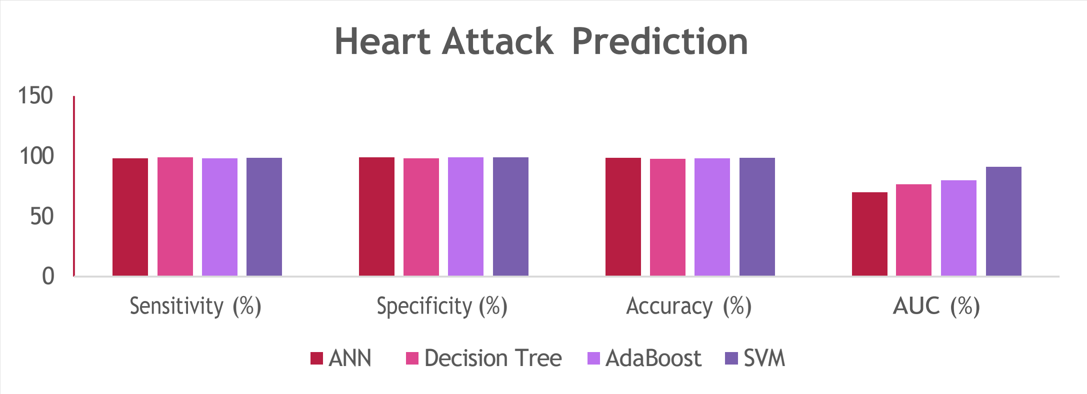

Fig 11: Sensitivity. Specificity, Accuracy and AUC

The figure 12 indicate that accuracy in different types of machine learning algorithm in the MIT-BIH data base.

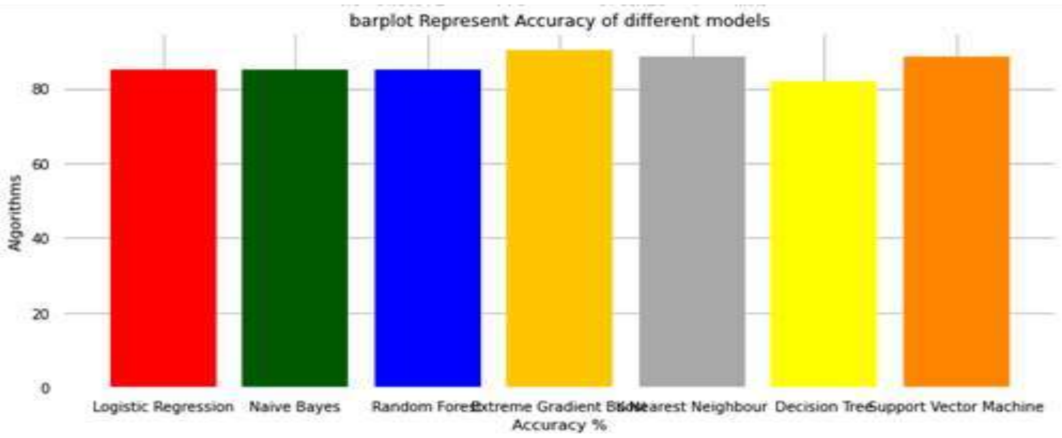

Fig 12. Accuracy in different types of machine learning algorithm in the MIT-BIH data base

REFERENCES

[1] Bhekumuzi M. Mathunjwa, Yin-Tsong Lin, Chien-Hung Lin, ECG recurrence plot based arrhythmia classification using two-dimensional deep residual CNN features, Sensors 22 (2022).

[2] Centers for Disease Control and Prevention. Underlying Cause of Death, 1999–2018. CDC WONDER Online Database; Centers for Disease Control and Prevention: Atlanta, GA, USA, 2018.

[3] Virani, S.S.; Alonso, A.; Benjamin, E.J.; Bittencourt, M.S.; Callaway, C.W.; Carson, A.P.; Chamberlain, A.M.; Chang, A.R.; Cheng, S.;Delling, F.N.; et al. Heart disease and stroke statistics—2020 update: A report from the American Heart Association. Circulation 2020, 141, e139–e596.

[4] Martis, R.J.; Acharya, U.R.; Min, L.C. ECG beat classification using PCA, LDA, ICA and discrete wavelet transform. Biomed. Signal Process. Control 2013, 8, 437–448.

[5] Banerjee, S.; Mitra, M. Application of cross wavelet transform for ECG pattern analysis and classification. IEEE Trans. Instrum.Meas. 2013, 63, 326–333.

[6] Odinaka, I.; Lai, P.H.; Kaplan, A.D.; O'Sullivan, J.A.; Sirevaag, E.J.; Kristjansson, S.D.; Sheffield, A.K.; Rohrbaugh, J.W. ECG biometrics: A robust short-time frequency analysis. In Proceedings of the 2010 IEEE International Workshop on Information Forensics and Security, Seattle, WA, USA, 12–15 December 2010; pp. 1–6.

[7] Raj, S.; Ray, K.C. ECG signal analysis using DCT-based DOST and PSO optimized SVM. IEEE Trans. Instrum. Meas. 2017, 66,470–478.

[8] Moavenian, M.; Khorrami, H. A qualitative comparison of artificial neural networks and support vector

machines in ECG arrhythmias classification. Expert Syst. Appl. 2010, 37, 3088–3093.

[9] Kropf, M.; Hayn, D.; Schreier, G. ECG classification based on time and frequency domain features using random forests. In Proceedings of the 2017 Computing in Cardiology (CinC), Rennes, France, 24–27 September 2017; pp. 1–4.

[10] Acharya, U.R.; Fujita, H.; Oh, S.L.; Hagiwara, Y.; Tan, J.H.; Adam, M. Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals. Inf. Sci. 2017, 415 –416, 190–198.

[11] Nouman, A. & Muneer, S. A systematic literature review on heart disease prediction using blockchain and machine learning techniques. Int. J. Comput. Innov. Sci. 1(4), 1–6 (2022).

[12] Khan, A. et al. A novel study on machine learning algorithm-based cardiovascular disease prediction. Health Social Care Commun. 23, 1–10 (2023).

[13] Choi, E., Schuetz, A., Stewart, W. F. & Sun, J. Using recurrent neural network models for early detection of heart failure onset. J. Am. Med. Inform. Assoc. 24(2), 361–370 (2017).

[14] Roy, A. M. & Bhaduri, J. Densesph-yolov5: An automated damage detection model based on densenet and swin-transformer prediction head-enabled yolov5 with attention mechanism. Adv. Eng. Inform. 56, 102007 (2023).

[15] Yang, M., Wang, X., Li, F. & Wu, J. A machine learning approach to identify risk factors for coronary heart disease: a big data analysis. Comput. Methods Programs Biomed. 127, 262–270 (2016).

[16] Ngufor, C., Hossain, A., Ali, S. & Alqudah, A. Machine learning algorithms for heart disease prediction: a survey. Int. J. Comput. Sci. Inform. Secur. 14 (2), 7–29 (2016).

[17] Shoukat, A., Arshad, S., Ali, N. & Murtaza, G. Prediction of Cardiovascular diseases using machine learning: a systematic review. J. Med. Syst. 44 (8), 162.

[18] A. Van De Bruaene et al.Effect of respiration on cardiac filling at rest and during exercise in Fontan patients: a clinical and computational modeling study IJC Heart Vasc.(2015).

[19] Ternacle J., Côté N., Krapf L., Nguyen A., Clavel M.-A., Pibarot P. Chronic kidney disease and the pathophysiology of valvular heart disease. Can. J. Cardiol. 2019;35:1195–1207. doi: 10.1016/j.cjca.2019.05.028.

[20] House A.A., Wanner C., Sarnak M.J., Piña I.L., McIntyre C.W., Komenda P., Kasiske B.L., Deswal A., DeFilippi C.R., Cleland J.G.F. Heart failure in chronic kidney disease: Conclusions from a Kidney Disease: Improving Global Outcomes (KDIGO) Controversies Conference. Kidney Int. 2019;95:1304–1317. doi: 10.1016/j.kint.2019.02.022.

[21] Ahmad G.N., Fatima H., Abbas M., Rahman O., Alqahtani M.S. Mixed machine learning approach for efficient prediction of human heart disease by identifying the numerical and categorical features. Appl. Sci. 2022;12:7449. doi: 10.3390/app12157449.

[22] Khdair H. Exploring Machine Learning Techniques for Coronary Heart Disease Prediction. 2021. [(accessed on 12 April 2023)]. Available online: https://thesai.org/Publications/ViewPaper?Volume=12&Issue=5&Code=IJACSA&SerialNo=5.

[23] Bohnert AS, Guy Jr GP, Losby JL (2018) Opioid prescribing in the united states before and after the centers for disease control and prevention's 2016 opioid guideline. Ann Intern Med 169(6):367–75.

[24] Waigi, R.; Choudhary, S.; Fulzele, P.; Mishra, G. Predicting the risk of heart disease using advanced machine learning approach. Eur. J. Mol. Clin. Med. 2020, 7, 1638–1645.

[25] Amit Gupta, Meeravali Shaikh, G. Jithender Reddy, Arun Singh Chouhan," Detection of Cardiac Failure using the Convolutional neural network (ConvNets CNN's) Technique", DOI: 10.1109/AISP57993.2023.10134963, Electronic ISBN:979-8-3503-2074-9, ISBN:979-8-3503- 2075- 6. https://ieeexplore.ieee.org/document/10134963.

[26] Amit Gupta, Arun Singh Chouhan, Kanagaraj Jyothi,Abha Dargar, Shashi Kant Dargar,"An Effective Investigation on Implementation of Different Learning Technique Used For Heart Disease Prediction", 2024 11th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future ons)(ICRITO),https://ieeexplore.ieee.org/document/10522150.