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Heart Disease Prediction using NAFS and Image Processing

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Abstract*:* The detection of Heart Disease (HDD) is becoming increasingly important as it is recognised as a leading cause of death worldwide, especially in high-income countries. About 7 million people each year lose their lives to HDD, with men being affected more than women (12%). As a result, several different approaches to disease element analysis have been developed, all with the same goal in mind: to reduce the variation in doctors' clinical practises, as well as clinical costs and mistakes.Developing a robust and clever data-mining-based clinical decision-support system is the primary goal of this study. In order to efficiently detect and identify cardiac illness, the method developed consists of pre-processing, de-noising, clustering, filtering, segmentation, feature extraction, and classification. Other methods such as the Bilateral filter, Gaussian filtering, the average filter, and the notch filter for filtering linked factors, and the Sobel edge detection for locating specific illnesses, are also available. Background and foreground segmentation of identified disease-affected regions is accomplished with the help of ROI segmentation. Extraction of DWT characteristics typically yields a high-quality, relevant image. The New adaptive neuro-fuzzy system (NAFS) algorithm, which is performance-growing when compared to various existing methodologies, was developed in response to this ongoing need for a more sophisticated kind of algorithm. When used to the estimation of the bushy or fuzzy rule sets method in a neural network, this new adaptive neuro-fuzzy system algorithm is a part of the machine learning methodology that is being used to boost the system's overall performance.

Keywords: *Heart Disease(HDD), Digital Image Processing(DIP), MATLAB, Machine learning (ML).*

1. Introduction

About 35 percent of all fatalities in the United States are attributable to heart disease (HDD) [1], and this number is expected to rise to 20.3 million by 2020. Monitoring healthcare is essential for determining the need for preventative and emergency care, as well as for conserving or increasing pleasurable experiences to improve quality of life. When caught early, heart disease can often be treated successfully. Adopting better practises, for instance, may or may not result in up to an 80% decreased relative risk of myocardial infarction [2], according to the findings of a large-scale case-control investigation rather. The difficulty of early intervention is exacerbated by the fact that the development of heart disease may still go unnoticed for significant periods of time. Symptoms, including fatigue or shortness of breath, that patients report to their doctors are central to the standard acute care approach in the United States and Canada [3, 4]. By 2020, the prevalence of HDD is estimated to have multiplied by four, and by 2050, one new case would be diagnosed every 30 seconds [7]. An abundance of studies and treatments are being developed to slow HDD's progression [8] [9]. This chapter provides a comprehensive look at the disease and the relevant medical results related to the computational algorithms.

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1.1. A Survey Of Heart Disease

Humans' lifestyle choices affect both the prevalence and presentation of cardiac disease. Conditions like chest discomfort, jaw pain, neck pain, back pain, stomach difficulties, pain in the fingers and shoulders, and difficulty breathing are all included [10]. [11]. The heart diseases that coronary artery disease, heart failure, and stroke all belong to are caused by heart problems. The highest prevalence of any chronic illness worldwide is heart disease, however this is entirely avoidable. Primary prevention consists on adopting a healthy lifestyle and regular exercise, whereas secondary prevention relies on timely diagnosis and treatment. The analysis and early prevention of heart disease complications [12] are greatly aided by the practise of routine testing (secondary prevention). Diagnostic procedures such as X-rays, MRI, CT, ECG, HD, and the exercise tolerance test all play a role. To this matter of paramount importance. This testing, however, can be costly and requires the right clinical equipment.

1.2. Symptoms

Angina, or chest pain, is the most prominent symptom of a problem with the blood vessels. One's chest may feel tight or uncomfortable, or they may experience a tightness, heaviness, pressure, ache, burning, fullness, squeezing, or discomfort from angina. It might be taken for heartburn or indigestion without proper context. Angina can also be experienced as a dull discomfort in the back or shoulders, fingers, neck, throat, jaw, or teeth.

1.3. Motivation

Based on data gathered from online medical records, approximately 4.45 million people seek medical attention each year. Individuals of advanced years, such as those with heart disease or other illnesses, are among those who make unnecessary trips to medical facilities. Diagnostic strategies for people with heart disease can be unconventional. But a doctor must see the patient in person to do tests like a physical, blood work, and a heart scan. Due to this, people with HDD end up needlessly making multiple trips to the clinic.

Having more people in need of medical attention means more work for doctors and nurses, longer wait times for patients, and higher overall costs for healthcare systems and individuals. The ever-expanding patient roster is kept in a massive database for research and analysis purposes. The most common application of these massive datasets is in referencing patients' medical records. Using the extensive feature and scientific history data, system learning generates all other potential solutions for cardiac disease diagnosis. For accurate prediction and analysis of a wide range of diseases, medical decision support systems have increasingly turned to data mining techniques. Because of the sheer volume of data generated in the scientific community, it is important to ensure that this information is being put to good use. Data and statistics abound throughout the healthcare system. Health care statistics may benefit from data mining methods because there is a dearth of effective evaluation procedures for identifying connections and patterns in this area. There are restrictions on data analysis in terms of precision, velocity, error rate, etc., which are consistent with the findings of the literature review.

Massive amounts of information are produced daily in the healthcare sector. Many of these data collections, however, are underutilised. However, there is a lack of widely available, high-quality machinery for mining this data for insights that can be used to detect Heart Disease in the lab or clinic, among other applications.

2. Literature Survey

This section offers a thorough summary of the many studies that have been conducted on the specified issue. In order to evaluate ML algorithms for the purpose of Alzheimer's disease prognosis, a number of medical and computer science research papers were analysed.

To better understand cardiac disease, [15] explored k-Nearest-Neighbors' (k-NN) potential in analysing patient data. In this study, we show that k-NN outperforms collaborative NN in terms of accuracy. In contrast to the increased accuracy shown by the use of tree classifiers according to the voting, the application of integrated vote casting fails in improving k-NN accuracy while diagnosing patients with heart condition. To aggregate the results from several classifiers into a single set, a technique known as "vote casting" is defined. The highest accuracy (97.4%) was achieved by using K-NN without voting. Fork-accuracy NN's dropped to 92.7% with voting, though.

In order to combine a learning algorithm and a function choosing strategy, [16] devised a hybrid approach. UCI's repository was mined for a dataset, and from its 76 properties, k-nearest neighbour methods were employed to narrow the field down to 14. Data mining and an Adaptive Neuro-Fuzzy Inference System were also employed in this method (ANFIS). Artificial Neural Fuzzy Inference System (ANFIS) combines the best features of traditional neural networks and fuzzy inference systems. The proposed method achieved an accuracy of 98.24% when information gain was utilised to select the most relevant qualities.

By using DNFS, [17] provided an overview of current research (Decision tree-based Neural Fuzzy System). Decision trees, Naive Bayes classifiers, K-Nearest Neighbor classification (KNN), Support Vector Machine (SVM), and synthetic neural networks methodologies were employed as part of the data mining process to improve heart disease analysis and prediction. By combining the malleability of fuzzy inputs with the predictive power of a neural network, the technique was designed to speed up the learning process of neuro-fuzzy devices and systems. Classification was carried out with the aid of C4.5 decision tree algorithms and ripper RIPPER (Repeated Incremental Pruning to Produce Error Reduction). Compared to other data mining techniques for prediction, such as support vector machine and neural networks, the C4.5 classifier achieved higher results. Naive Bayes classifier was a strong contender, but there were other option. They came to the conclusion that, for cardiovascular disease prognosis, Decision trees and Naive Bayes classifiers are distinguishable to an accuracy of more than 95%.

Using the WEKA (Waikato Environment for Knowledge Analysis) software, [18] tested different Decision tree classification algorithms to improve the accuracy of diagnosing cardiac disease. Understanding the relative performance of the J48 method, the logistic model tree, and the random forest algorithms was the goal of this study. The datasets used for the evaluations were obtained from the UCI repository and consisted of 303 occurrences and 76 attributes. WEKA includes J48, a dependable open-source Java version of the C4.5 algorithm. The J48 algorithm builds the tree using a divide-and-conquer strategy. Each node's properties were hand-picked to ensure that the element may be reliably categorised into samples using only those attributes.

There is a clear drawback due to the data size, which grows linearly with the number of examples. The leaves of a decision tree are replaced by the logistic regression function in a tree-shaped logistic model. Parallel and multi-class target variables, numerical and nominal qualities, and missing features are all within the purview of the rules or algorithms. [24][25]. However, the time required to express data using Logistic Model Tree (LMT) is more. An ensemble classifier, a random forest is a collection of several individual decision trees. The classes' results are shown as individual trees. It builds decision trees that can be easily updated to reflect new information.

Sharan Current methods for data mining with J48, NB (Naive Bayesian) Tree, and simple CART were surveyed by [19]. (Classification And Regression Trees). Using a narrower set of parameters from the WEKA software, it correctly diagnosed heart illness. In order to make judgements based on information acquired, C4.5 was implemented in Java as J48. Models with predictive abilities were produced via the Naive Bayes classifier, which performed best with continuous data. Rapidly and clearly, CART revealed key correlations in the data. There were three different decision tree algorithms used in WEKA. At 0.08 seconds, J48's development time was the quickest, but CART's 92.2% accuracy rate was the highest.

Specific data mining strategies for cardiac disease forecasting were investigated by [20]. When compared to using a single classification method, hybrid approaches were found to be more accurate by the majority of the studies. Conclusion: the neural network contributed significantly to the accuracy of the forecast. While results from the machine trained in tandem with genetic algorithms were encouraging, they were not conclusive.

The unique classification procedures of J48 Decision, k-Nearest Neighbors (k-NN), Naive Bayes (NB), and SMO (Sequential Multi-Objective) were analysed and rated by [21]. Optimizing as little as possible. The class algorithms were implemented in WEKA software, and the vital functions were extracted using the gain ratio assessment method. The mining techniques were validated 10 times to ensure their reliability. The maximum precision was achieved by J48, which was 83.732%.

Artificial neural networks (ANNs), according to [22], have shown enormous promise for diagnosing heart disease. The number of nodes (neurons) and connections (links) between them in a neural network is determined by its architecture. A layer is a logical partition between several levels of processing. The intricacy of the system determines how many layers and how many neurons are used. Unsupervised learning, in which the learner is given inputs relating to the unknown objectives, makes heavy use of artificial neural networks, which are widely employed in synthetic neural networks. The Cleveland team provided the dataset utilised, which had 14 attributes and 303 instances. Synthetic neural networks, also known as artificial neural networks, are trained by applying a returned propagation learning algorithm to historical data. Sixty percent of the input and output samples became the training set, twenty percent became the validation set, and twenty percent became the test set. For the inferred layers, the activation functions are tangent sigmoid, and for the output layer, they are linear transfer performance. The accuracy of our classification system for heart disease was assessed at 88%, and the Mean Square Error (MSE) was calculated to be equal to 0.1071.

Using the Support vector machine and Nave Bayes Classification methods, [26] made liver disease predictions. There were a total of 560 cases and 10 attributes in the ILPD (Indian Liver Patient dataset) that we got from UCI. Evaluations were based on how well and how quickly tasks were completed. In 1670.00 ms, naive Bayes showed a 61.28% accuracy rate. Using SVM, we were able to improve accuracy to 79.66% in just 3210.00 ms. The programme was written in MATLAB. In terms of predicting liver illness, SVM outperformed Naive Bayes. Naive Bayes was faster to run than SVM in terms of raw execution time.

[27] examined the available options for identifying liver patients. Five practical techniques (J48, MLP, Random forest, SVM, and Bayesian Network classifiers) were tested using data from a dataset hosted by UCI and mined using the WEKA facts mining tool. First, the original dataset was used to fully implement the algorithms, ensuring an accurate percentage. Second, the entire dataset of liver patients was subjected to a feature selection technique. The third stage is locating the comparative consequences of making choices before and after selecting features. After doing an FS (Full Search), the most accurate algorithms were found to be SVM (71.3551%), MLP (70.6805%), and J48 (70.669%), Random forest predicted with 71..8696% accuracy whereas Bayesian Network only managed 69.1252%.

3. Methodology

The large volume of medical data requires a standardised format for the data that may be used for many aspects of disease prediction. Machine learning algorithms play a clear role in the classification of patients' medical records, which leads to efficient disease diagnosis, as do various levels of predefining processes. This section provides an overview of the many techniques used for disease detection and prognosis by analysing medical records. The significance of various machine learning methods for medical data mining is also highlighted.

Data mining uses categorization approaches to manage the ordered processing, as seen in Figure 1. Classification consists of two sub-processes: instruction and evaluation and diagnostic procedures for cardiac illness. A classification is a structured hierarchy of classes used to organise data by shared characteristics. It comprises of a set of codes and descriptions that help organise survey responses into understandable buckets for analysis. To classify an image is to extract specific types of data from a raster image that spans multiple colour channels. The raster produced by picture categorization is then utilised to generate thematic maps.

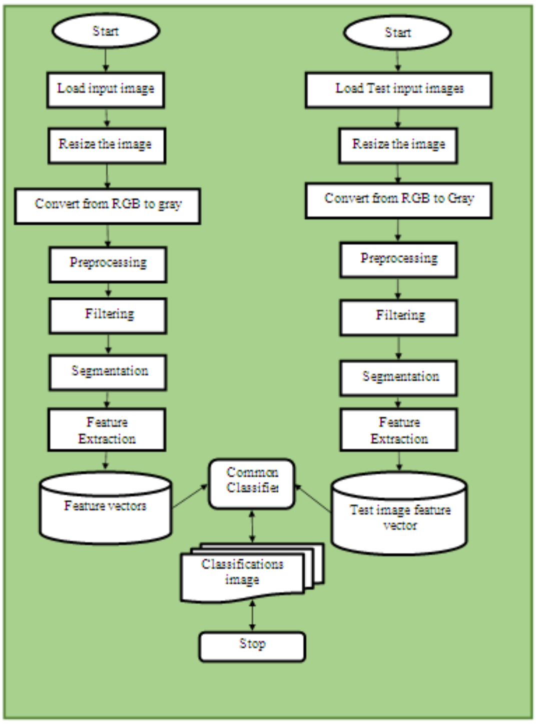

Fig.1. Classification of Training and Assessment Levels

3.1. Implementation

The heart's own sounds become a fundamental and indispensable instrument for assessing and diagnosing cardiac pathology. Due to the cost-effective, time-saving, and life-enhancing possibilities, automatic HDD-diagnosis using data mining and machine learning algorithms is strongly suggested. This method uses non-invasive information to automatically diagnose HDDs by identifying and classifying them. Some studies use clinical criteria like BP (blood pressure), age, and smoking habit to classify HDD patients, while others use signal recording methods like ECG (electrocardiograph) and HD (phonocardiography) to diagnose HDD symptoms. Pattern recognition is commonly used as a model for the method used to diagnose heart disease. There are primarily four approaches.

- Data collection;
- Noise reduction Division into Subgroups
- Feature extraction
- 5 different types of classifications (i.e., subject identification).

Fuzzification, Accumulation, Aggregation, Activation, and Defuzzification are the NAFS phases ingested by classification. The fuzzification interface maps each exact input variable to a membership quality according to the membership functions defined. An appropriate de-fuzzification technique is employed by the de-fuzzification interface to transform the obtained fuzzy result into a crisp output, and the inference engine then runs the process of fuzzy reasoning to recover the fuzzy set that has been gathered in the output variable.

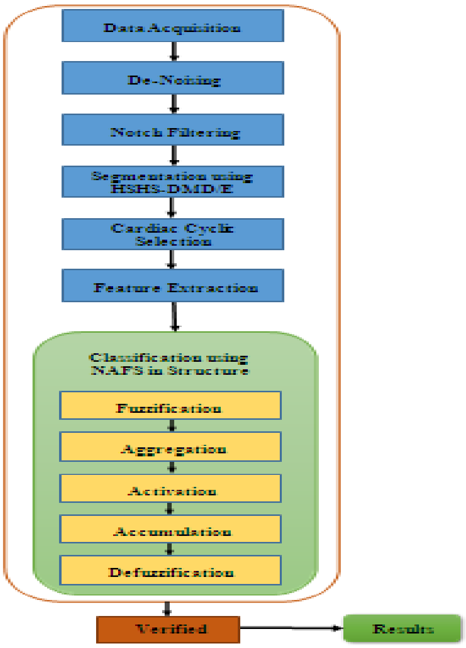

Fig.2. The method for identifying Heart Diseases

3.1.1. Image Recognition and Prediction Stages

The major goal of this study is to detect and forecast cardiovascular disease from clinical records. Below, we'll go over the numerous procedures that were employed to analyse the accessible patient medical records.

Phase 1 (Pre-Processing) : Identification of photographs is the first and most important stage. The next stage is to standardise the registered medical data as images into a predefined format. In addition, the datasets are combed for any relevant medical images, which are then analysed and separated as needed. Clearing a medical image requires locating it, and then reappearing pre-processing splits it into relevant parts that characterise the structures in an MRI, such as long, uniform areas of darkness and light. Pre-processing aims to improve image quality before it is used in the main processing step. To do this, the original image's background is stripped of all unnecessary elements.

Phase 2 (Filtering) : In this step, medical images are filtered so that they can be quickly and accurately identified and predicted. The filtering process makes use of a wide variety of filters, some of which are listed below. In order to soften the image's edges without sacrificing detail, a bilateral filter can combine their values nonlinearly. It connects shades of grey according to colour similarity and geometric closeness. A value is assigned to each pixel in the image that is the weighted average of the values of the surrounding pixels. The bilateral filter is the product of combining the variety and spatial Gaussian filters. More importance is given to nearby pixels by the spatial Gaussian, whereas pixels further away receive less importance.

The basic idea is to give more weights to pixels that are physically closer to the current crucial pixel but are further away from it in the range region. With this option, you can easily preserve boundaries and crucial information while also taming areas of progressive colour difference. With the help of a Gaussian filter, we may refine the photos until they are only grayscale snapshots. The process of honing is used to pick up on minute details of the highlighted image. It's also useful for determining out the borders. These filters improve the photographs by creating a high-quality intersection that emphasises structural boundaries within the images. It goes on to say that better photos are produced as a result of the incorporation of pilot pictures and the accelerated model of the line structure with image edges. To preserve the frequency information in the image, a Gaussian filter is also used. Phonocardiogram noise can be reduced by notch filtering if the recording environment was not appropriately handled (HD). De-noised image are obtained by eliminating the unpredictability of the noise's effects. Reserved HD Notch-filtered indications for delaying unwanted low-frequency information.

- **White de-noising:** This is a random sign, which comprises all feasible frequencies in equal quantity and indicators of HD, which are filtered for removing the white noise with the aid of utilising wavelet packet.

HD indicators are normalised at this stage so that the expected amplitude of the signal is not impacted by the normalisation process.

Filtering and de-noising the HD statistics serve to mitigate distracting background noise. Electromagnetic interference from power frequency disruption and electric sign interference with human lung and body sounds are common sources of noise that degrade HD image. HD data analysis or diagnosis is frequently and sometimes impossible due to this unique aspect of noise. Due to its incorporation of windowing and multi-decision procedures, filtering has been shown to be an advanced way of signal de-noising. To get rid of the sounds in the HD indicators, the authors employ a de-noising family, the De-noising wavelet family of order ten (Db 10).

3.1.2. Segmentation

In this talk, we'll go into detail about how the images' complex features are uncovered through a technique called segmentation. One of the most important steps in segmentation is defining the necessary image region. In addition, the most challenging parts of an image isolate into a large number of neurons with subtle distinctions during study and practise. Auxiliary terminating is used to refine the localization process by capturing geographically related neurons in the vicinity.

Digital image processing relies heavily on segmentation of pictures as a primary methodology. Magnetic resonance imaging (MRI) image sectioning for heart disease has become a hot topic in medical imaging research in recent years. Radiologists use MRI to look inside of bodies and extrapolate the desired phase with ease. Thresholding is a straightforward picture segmentation method that has found widespread application in diagnosing cardiac conditions. However, this method may not accurately determine out all heart diseases, so region developing is an additional methodology that offers seed point technique to the sectioned Regions of Interest (ROI) location so that the heart diseases is easily spotted and extensively used once again for the categorization purpose.

3.1.3. Extracting Features

In this article, we'll discuss the crucial function that feature extraction serves in the overall image classification procedure.

A new collection of capabilities, the Discrete Wavelet Transformation (DWT), is derived from the original set of characteristics. The functions are in a changed state during feature extraction. The most crucial task in picture categorization is the separation of visual components. Image characterizations may be based on a variety of different types of information, each of which is important in its own way: shading and shape highlights; pixel facts; and change coefficient highlights. Furthermore, some experts have used logarithmic information for recognition and categorization of images.

Images can be converted from the spatial domain to the frequency domain using DWT. Technology for managing images, which is in high demand in business, is within reach. DWT is an efficient method for decomposing an image into its constituent parts, each of which has a unique set of coefficients. The DWT is finished with the help of cascading filter banks, with certain needs being supplied by the low-pass and high-pass filters.

- Extraction of DWT Features Algorithm Check out the image first.
- Second, you should resize the full image in the database.

- Deconstruct a shade image with first-level Haar DWT to obtain the desired coefficients.
- In this Step, we'll distribute 0.003 weights based on the estimated coefficients.
- In this Step, we will convert the expected coefficient image to the Hue Saturation Value (HSV) colour space.
- Execute colour quantization with a colour histogram, allocating 18 bins to hue, 3 bins to saturation, and 4 bins to value; this will yield a quantized HSV region with a total of 25 histogram bins.
- Perform Steps 1–6 on all of the photographs already stored in the database.
- Determine the database's image-to-image correspondence matrix (Step 8).
- Repetition of Steps 7 and 8 for All Database Images
- Get a hold of the pictures.

3.1.4. Classification

To get started with classification, read this section. The purpose of this investigation is to evaluate the consistency and general effectiveness of algorithms used to forecast the health of individuals or patients based on historical data. The employed classifiers are the Support vector machine classifier, the Polynomial Sigmoid Support vector machine classifier, the Artificial neural network classifier, the Doppler effect classifier, and the New adaptive neuro-fuzzy system classifier.

4. Case Study Results

The MRI data came from BENCHMARK, and all the work is done in a MATLAB environment. All input data is stored in MS-Access, and the resulting data is also stored there.

Using a variety of machine learning methods, this study aspires to develop a system for the early diagnosis and prediction of cardiovascular illness, as well as to enhance the quality of the results acquired from such systems. Simulation results are used to assess the efficacy and scale of current approaches for detecting and forecasting cardiovascular disease. This allows for the identification of the possibility of disease detection at an early stage, which was not achievable before. Here are some screenshots of the simulation results demonstrating the precision of the proposed NAFS method for HDD identification and prediction. A-H of Figure 3 depict the HDD identifying procedure.

Fig. 3(A). Initial magnetic resonance imaging data

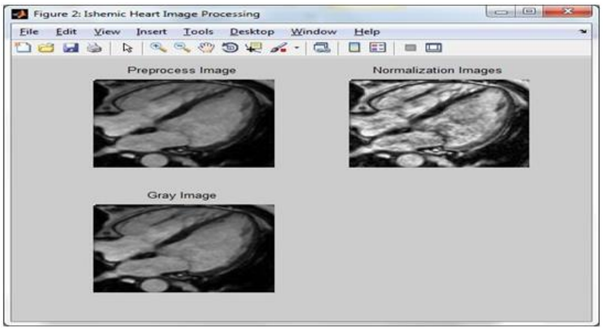

Fig. 3(B). Previewing, or Preprocessing

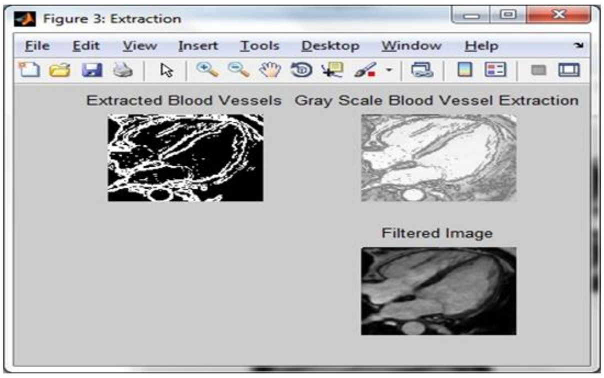

Fig. 3(C). Diagram of Filtering

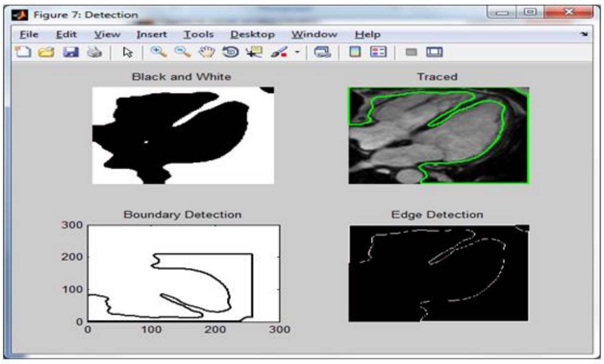

Fig. 3(D). Edge Detection

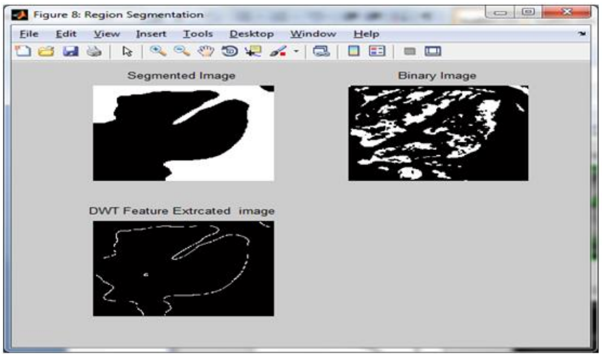

Fig. 3(E). Segmentation and Feature Extraction

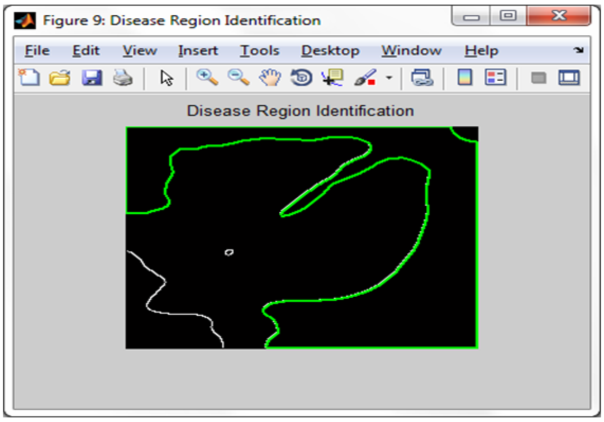

Fig. 3 (F). Identifying a Specific Area

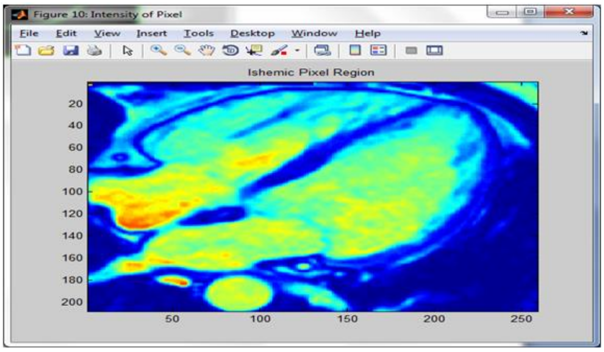

Fig. 3 (G). Classification of Affected Regions

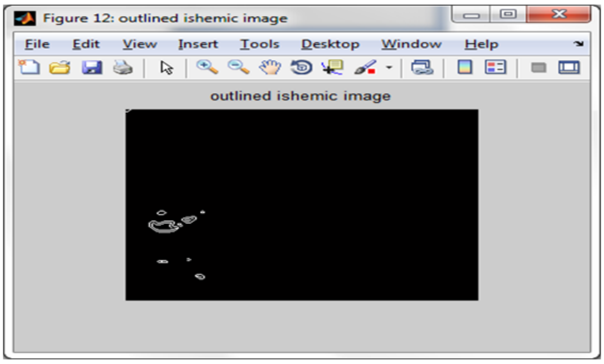

Fig. 3 (H). Final Product

5. Conclusion

In this study, we looked at how to improve the early diagnosis of heart problems by using data mining approaches that are specific to this problem. With the use of a MATLAB device, specifically, five classifiers have been developed and implemented to better simulate health-related decisions. Even further, two datasets are used to conduct an in-depth investigation. The chosen classifiers are put through one out cross validation for each dataset. All of the results demonstrated that the classification algorithms are predictive and may deliver a mostly right answer. Consequently, we may draw an important conclusion about the value of selection criteria for data categorization. Machine learning (ML) is vital in many fields, including image recognition, data mining, natural language processing, and medical diagnosis. To a large extent, ML provides workable answers in these areas. The unique ML methods developed in this study are made available for heart disease prognosis. In this study, we evolve every form of algorithm that has been shown to be effective at perceiving qualities.

The results of using the established Classification algorithms to identify cardiac disease are encouraging. The research and development outcomes of ML algorithms used in disease prediction are given in great depth. Research reveals that these algorithms significantly improve the accuracy of diagnosing heart disease. Furthermore, the developed suite of tools may prove useful to the field of AI study as a whole. These tools are invaluable for issue solving and decision making, allowing for in-depth examination and improved deliberation.

6. Future Projects

This study paves the way for the development of a more accurate prediction system that will be used to adorn healthcare in an effort to cut costs. Many avenues for future study exist, any one of which could significantly improve the state of the art's practical applications. If a patient is diagnosed with heart disease, a future intelligent machine could help them decide on the best course of treatment. If a patient is at risk for developing heart disease, advanced machine learning algorithms can determine this with high accuracy. With the help of these enhanced feature sets, doctors may come up with a plethora of techniques for treating patients who have been diagnosed with a certain type of cardiac disease.

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