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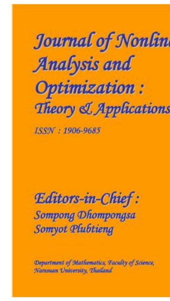

EARLY IDENTIFICATION OF CARDIAC ARREST IN NEWBORN INFANTS IN THE CARDIAC INTENSIVE CARE UNIT THROUGH MACHINE LEARNING USING STATISTICAL MODELS

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ABSTRACT

Newborn cardiac arrest is a frightening yet common medical emergency. The optimal care and treatment for these newborns depends on early identification. The development of precise and effective diagnostic instruments for early detection has been the focus of recent research, along with the identification of possible biomarkers and signs of cardiac arrest in neonates. A variety of imaging modalities, including computed tomography and echocardiography, may aid in the early identification of cardiac arrest. The goal of this study is to create a Cardiac Machine Learning Model (CMLM) for the early diagnosis of cardiac arrest in neonates in the Cardiac Intensive Care Unit (CICU) by applying statistical models. The neonate's physiological data were combined to identify the cardiac arrest occurrences. Predictive models for cardiac arrest were built using statistical modeling approaches including logistic regression and support vector machines. The suggested methodology will be used in the CICU to facilitate the prompt identification of cardiac arrest in neonates. The suggested CMLA achieved 0.912 delta-p, 0.894 False discovery rate (FDR), 0.076 False omission rate (FOR), 0.859 prevalence threshold, and 0.842 CSI value in a training (Tr) comparative zone. The suggested CMLA achieved 0.896 delta-p values, 0.878 FDR value, 0.061 FOR value, 0.844 prevalence threshold values, and 0.827 CSI value in a testing (Ts) comparison zone. It will assist in lowering the CICU-related neonatal cardiac arrest death and morbidity rates.

I. INTRODUCTION

1.1 About the project

Cardiac arrest in newborn babies is a devastating event that can lead to severe complications and death. Early detection of this condition is critical to provide the best care for these infants and ensure their long-term health. In order to ensure the early detection of cardiac arrest in newborn babies, it is essential to understand the signs and symptoms associated with this condition and the risk factors that may put a baby at an increased risk of cardiac arrest. The most common signs and symptoms of cardiac arrest in newborn babies are a rapid heart rate and difficulty breathing. Other signs that may indicate a baby is in cardiac arrest include a bluish tinge to the baby's skin, unresponsiveness, or decreased movement. If any of these signs are present, it is essential to seek medical attention immediately. Risk factors that may increase the likelihood of cardiac arrest in newborn babies include low birth weight, a family history of cardiac arrest, preterm birth, a difficult delivery, or a mother with a history of high blood pressure during pregnancy. A baby's medical history should also be evaluated for any potential risks. In order to ensure early detection of cardiac arrest in newborn babies, regular monitoring of the baby's heart rate and respiratory rate is essential. It can be done through pulse oximetry, a non-invasive, painless procedure that measures the amount of oxygen in the baby's blood. Additionally, auscultation, or listening to the baby's heart rate and breathing with a stethoscope, can also help to detect any irregularities in the baby's heart rate or breathing. Early detection of cardiac arrest in newborn babies is vital to provide the best care for these infants and ensure their long-term health. By understanding the signs and symptoms of this condition and being aware of the risk factors that may put a baby at an increased risk of cardiac arrest, parents and medical professionals can work together to ensure the best possible outcomes for these babies. The early detection of cardiac arrest in newborn babies can be achieved using Statistical Models. Statistical models are mathematical techniques used to analyze and draw conclusions from data. These models are powerful tools in the medical field, as they can help predict, diagnose, and treat certain diseases and conditions. One example of a statistical model used for the early detection of cardiac arrest in newborn babies is the Logistic Regression model. This model uses data collected from the baby's medical history, such as birth weight, gestational age, and gender, to create a predictive model to determine the likelihood of cardiac arrest. This model can help doctors identify those babies at risk and can help them decide whether to treat the baby with medication or perform surgery to correct the issue. Another model used for the early detection of cardiac arrest in newborn babies is the Naive Bayes model. This model uses a probabilistic approach to analyze data and identify patterns to make predictions. The model can identify high-risk babies and help doctors determine the best course of action to take [8]. The Support Vector Machine model is another statistical model used for the early detection of cardiac arrest in newborn babies. This model uses data collected from the baby's medical history and other sources to create a predictive model that can determine the likelihood of cardiac arrest. This model can identify those babies at risk and help doctors decide on the best course of treatment. Statistical models are powerful tools that can be used for the early detection of cardiac arrest in newborn babies. These models can help doctors identify those at risk so that they can provide the best possible treatment for the baby. Furthermore, these models can help doctors determine the best course of action to take in order to prevent or reduce the likelihood of cardiac arrest.

Cardiac arrest in newborns is a life-threatening medical condition that requires immediate medical attention. Early detection and intervention can improve the outcomes of these infants and reduce mortality rates. Statistical models are powerful tools that can be used to identify risk factors and predict the likelihood of cardiac arrest. Logistic regression is one of the best statistical models for the early detection of cardiac arrest in newborns. This model allows researchers to quantify the relationship between risk factors and the probability of experiencing an arrest. It can be used to identify the most critical factors associated with cardiac arrests, such as gender, gestational age, and birth weight. Logistic regression can also be used to calculate the odds ratio for each risk factor, which indicates how much more likely an infant is to experience an arrest if they have a particular risk factor. Another effective model for the early detection of cardiac arrest in newborns is a support vector machine (SVM). This model type is well-suited for binary classification tasks, such as classifying an infant as either healthy or having experienced a cardiac arrest. It can also be used to identify important risk factors associated with cardiac arrest and predict the likelihood of an infant experiencing an arrest. Finally, artificial neural networks (ANNs) can also detect cardiac arrest in newborns. ANNs are powerful machine learning models that can learn complex patterns from data. These models can be used to identify risk factors associated with cardiac arrest and predict the likelihood of an infant experiencing an arrest. Logistic regression, support vector machines, and artificial neural networks are all effective models for the early detection of cardiac arrest in newborns. These models can be used to identify the most critical risk factors associated with the condition and predict the likelihood of an infant experiencing an arrest. Therefore, these statistical models should be used to improve newborns' early detection and intervention of cardiac arrest. Machine learning is increasingly used to predict and detect cardiac arrest in newborn babies. Cardiac arrest is a life-threatening condition in which the heart suddenly stops beating, and blood flow to the brain and other organs stops. It can lead to permanent brain damage or death. Due to the complexity of the condition, early detection of cardiac arrest in newborns has been difficult. However, machine learning is changing that. Machine learning algorithms analyze large amounts of complex data, such as patient medical histories, vital signs, and other physiological data. The algorithms can detect patterns in the data indicative of cardiac arrest and alert medical personnel. For example, one study used machine learning to detect signs of cardiac arrest in newborns by analyzing their heart rates, breathing patterns, and other vital signs. The algorithm detected signs of cardiac arrest up to eight hours before conventional methods. It could significantly improve the chances of survival for newborns and reduce the damage caused by the condition. In addition, machine learning is used to predict newborns' risk of cardiac arrest. By analyzing large amounts of patient data, machine learning algorithms can identify risk factors associated with the condition. It can help medical personnel identify newborns at an increased risk of cardiac arrest to receive the care they need. The machine learning is revolutionizing the early detection of cardiac arrest in newborns. By analyzing large amounts of complex data, machine learning algorithms can detect signs of cardiac arrest and identify newborns at an increased risk of the condition. This technology could save lives and reduce the damage caused by cardiac arrest in newborns. The critical contribution of machine learning models used for the Early Detection of Cardiac Arrest in Newborn Babies is that these models can detect subtle changes in vital signs such as heart rate, respiratory rate, and oxygen saturation that are difficult to detect with the naked eye. This early detection can help to identify newborns at risk of cardiac arrest and allow for timely intervention and treatment. Additionally, machine learning models can be used to analyze patient data to provide personalized advice and care to patients, enabling better longterm management of their condition. The following are the critical contribution of the proposed research works.

- Automated and accurately detected critical signs associated with cardiac arrest in newborn babies.
- Ability to recognize subtle changes in the baby's vital signs that can indicate potential cardiac arrest.
- Ability to identify high-risk babies likely to suffer from cardiac arrest.
- Early detection of cardiac arrest, enabling timely interventions that can improve the outcome.
- Reduction in the time and cost associated with traditional monitoring methods.

• Improved patient outcomes due to early diagnosis and treatment of cardiac arrest.

II. LITERATURE SURVEY

Carlisle et al. [21] has discussed the Heart failure is when the heart cannot pump enough blood to the rest of the body. Various conditions, including high blood pressure, coronary artery disease, and diabetes, can cause it. Atrial fibrillation is an arrhythmia (irregular heartbeat) in which the heart's upper chambers (atria) beat rapidly and irregularly. It can cause a decrease in the amount of blood pumped to the rest of the body, leading to symptoms such as shortness of breath and fatigue. Atrial fibrillation is a common cause of heart failure. Heart failure and atrial fibrillation treatment usually involve medications to control the heart rate and rhythm, lifestyle changes, and sometimes surgery to repair or replace the heart. Yaku et al. [22] has discussed the Risk factors for functional decline during hospitalization in very old patients with acute decompensated heart failure include age, gender, co-morbidities, and frailty. In addition, complex medical problems, the need for aggressive treatments, and the presence of cognitive impairment may increase the risk of functional decline. Clinical outcomes associated with a functional decline during hospitalization in very old patients with acute decompensated heart failure include increased length of stay, healthcare utilization, mortality, and decreased quality of life. The functional decline may also lead to higher rates of re-hospitalization, as well as an increased risk of institutionalization. Additionally, the functional decline may lead to an increased risk of falls and delirium due to decreased mobility and activity levels. Fonarow et al. [23] has discussed the Risk stratification for in-hospital mortality in acutely decompensated heart failure determines which patients are at higher risk of dying while in the hospital. It is done by using classification and regression tree analysis. Classification and regression tree analysis is a type of predictive analytics that uses trees to classify and predict outcomes. The trees are nodes representing various conditions, characteristics, or features associated with the outcome. Using a combination of these nodes, the model can determine the likelihood of a particular outcome occurring. The model can then be used to identify patients at a higher risk of in-hospital mortality and to guide the treatment of the patient.

Gaies et al. [24] has discussed the Vasoactive–inotropic score (VIS) is designed to predict morbidity and mortality in infants after cardiopulmonary bypass (CPB). The VIS is calculated from the levels of vasoactive and inotropic drugs administered to the infant during and after CPB. These drugs are used to regulate the patient's blood pressure and heart rate. The VIS is believed to accurately predict post-CPB morbidity and mortality because it reflects the degree of hemodynamic instability in the infant. Higher VIS scores indicate greater hemodynamic instability and, therefore, a greater risk of morbidity and mortality. Studies have found that higher VIS scores are associated with increased mortality, extended hospital stays, and an increased need for vasopressor and inotropic support. The VIS is a significant predictor of outcome after CPB and can help clinicians identify infants who may require closer monitoring and more aggressive management. Shah et al. [25] has discussed the Phenomapping is a novel classification system for heart failure with preserved ejection fraction (HFpEF). It is based on the analysis of phenotypic characteristics, such as demographics, clinical profile, laboratory values, electrocardiographic findings, echocardiography findings, and biomarkers. The goal of Phenomapping is to provide a more comprehensive and meaningful classification system for HFpEF that is based on the distinct phenotypes of the disease. This classification system will enable clinicians to more accurately diagnose and stratify patients with HFpEF, leading to better management and improved outcomes. The Phenomapping system also provides a platform for further research into the underlying path physiology of HFpEF, allowing for a better understanding of the disease and the potential for improved treatments. Lee et al. [26] has discussed the Heart failure with preserved or reduced ejection fraction (HFPEF or HFREF) is a form of heart failure in which the heart's ability to pump blood is impaired, but the amount of blood pumped from the heart with each beat (ejection fraction) is either normal or reduced. The underlying cause of this type of heart failure is poorly understood, but various disease pathologies and risk factors have been associated with it. Disease pathologies, such as coronary artery disease, hypertension, and diabetes, can lead to HFPEF or HFREF. These conditions can impede blood flow through the heart and its associated vessels, accumulating fluid in the lungs and other parts of the body. Additionally, these diseases can cause damage to the heart muscle and its inner lining, making it more difficult for the heart to pump blood efficiently. Risk factors for HFPEF or HFREF include advancing age, obesity, gender, smoking, and alcohol consumption. People who are older, overweight, and lead an unhealthy lifestyle are more likely to develop HFPEF or HFREF. Additionally, gender may play a role, as women are more likely to develop HFPEF than men.

Saeed et al. [27] has discussed the Multiparameter Intelligent Monitoring in Intensive Care (MIMIC) is a system that uses artificial intelligence and machine learning algorithms to continually monitor a patient's health and vital signs in an intensive care unit (ICU) setting. MIMIC is designed to alert healthcare providers to changes in a patient's condition that may require medical intervention. It is an effective tool for detecting subtle changes in a patient's condition that clinicians may find difficult to detect with only physical exams and laboratory tests. The system can monitor vital signs, including heart rate, respiration rate, blood pressure, and temperature. Additionally, MIMIC can detect changes in a patient's oxygen saturation and provide alerts when abnormalities are detected. By combining data from multiple sources and using advanced analytics, MIMIC can provide early warnings and enable healthcare providers to make more informed decisions about a patient's care. Lee et al. [28] has discussed the Predicting mortality among patients hospitalized for heart failure is an essential task for healthcare professionals. It is essential to identify those at higher risk of death so that they can receive more aggressive treatment and better management of their condition. The study aimed to develop a clinical model to predict mortality among patients hospitalized for heart failure accurately. To do that, researchers used data from an extensive database of patient records to identify risk factors associated with mortality. They used various statistical methods to evaluate the risk factors and develop a predictive model. Gianfrancesco et al. [29] has discussed the Potential biases in machine learning algorithms using electronic health record (EHR) data can come from various sources. First, there may be biases in the data due to sampling or coding errors. If the data used to train the algorithm does not represent the population, the algorithm may be biased toward specific outcomes. Second, there may be biases in how the algorithm processes the data, such as favoring certain data types or giving too much weight to certain variables. Third, there may be biases in evaluating the algorithm, such as using metrics that favor specific outcomes or data sets that do not reflect the full range of potential outcomes. Finally, there may be biases in how the algorithm is deployed, such as using the algorithm to make decisions that favor specific outcomes.

Moor et al. [30] has discussed the Sepsis is a lifethreatening condition caused by an overwhelming immune response to an infection, and it is one of the leading causes of death in intensive care units (ICUs). Early detection and intervention are essential for successful treatment, and machine learning algorithms can help to identify sepsis patients in the ICU at an earlier stage. To identify sepsis-associated patterns, machine learning algorithms can analyze various data sources, such as patient vital signs, laboratory test results, and medical history. These algorithms can be trained to identify sepsis patients earlier, allowing clinicians to intervene before the patient's condition deteriorates. Using machine learning algorithms in the ICU to predict and diagnose sepsis earlier can reduce mortality, morbidity, and length of stay. Furthermore, this technology can help to reduce costs associated with sepsis-related complications and improve the quality of care provided to patients. Deo et al. [31] has discussed the predictive model was then validated by comparing its predictions to actual mortality rates among a separate group of patients. The model accurately predicted mortality among patients with heart failure, indicating its effectiveness in identifying those at high risk of death. This study highlights the importance of using predictive models to identify those at high risk of death among patients hospitalized for heart failure. Such models can help healthcare professionals manage and treat patient's better, improving outcomes and patient safety.

III. SYSTEM ANALYSIS

EXISTING SYSTEM

Carlisle et al. has discussed the Heart failure is when the heart cannot pump enough blood to the rest of the body. Various conditions, including high blood pressure, coronary artery disease, and diabetes, can cause it. Atrial fibrillation is an arrhythmia (irregular heartbeat) in which the heart's upper chambers (atria) beat rapidly and irregularly. It can cause a decrease in the amount of blood pumped to the rest of the body, leading to symptoms such as shortness of breath and fatigue. Atrial fibrillation is a common cause of heart failure. Heart failure and atrial fibrillation treatment usually involve medications to control the heart rate and rhythm, lifestyle changes, and sometimes surgery to repair or replace the heart.

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DISADAVANTAGES

❖ The complexity of data: Most of the existing machine learning models must be able to accurately interpret large and complex datasets to detect cardiac arrest in newborn babies.

❖ Data availability: Most machine learning models require large amounts of data to create accurate predictions. If data is unavailable in sufficient quantities, then model accuracy may suffer.

❖ Incorrect labeling: The existing machine learning models are only as accurate as the data trained using the input dataset. If the data has been incorrectly labeled, the model cannot make accurate predictions.

PROPOSED SYSTEM

In the existing system, ml models can be used to identify the most critical risk factors associated with the condition and predict the likelihood of an infant experiencing an arrest. Therefore, these statistical models should be used to improve newborns' early detection and intervention of cardiac arrest.

Machine learning is increasingly used to predict and detect cardiac arrest in newborn babies. Cardiac arrest is a life-threatening condition in which the heart suddenly stops beating, and blood flow to the brain and other organs stops. It can lead to permanent brain damage or death. Due to the complexity of the condition, early detection of cardiac arrest in newborns has been difficult. However, machine learning is changing that.

Machine learning algorithms analyze large amounts of complex data, such as patient medical histories, vital signs, and other physiological data. The algorithms can detect patterns in the data indicative of cardiac arrest and alert medical personnel. For example, one study used machine learning to detect signs of cardiac arrest in newborns by analyzing their heart rates, breathing patterns, and other vital signs. The algorithm detected signs of cardiac arrest up to eight hours before conventional methods. It could significantly improve the chances of survival for newborns and reduce the damage caused by the condition. In addition, machine learning is used to predict newborns' risk of cardiac arrest. By analyzing large amounts of patient data, machine learning algorithms can identify risk factors associated with the condition. It can help medical personnel identify newborns at an increased risk of cardiac arrest to receive the care they need. The machine learning is revolutionizing the early detection of cardiac arrest in newborns.

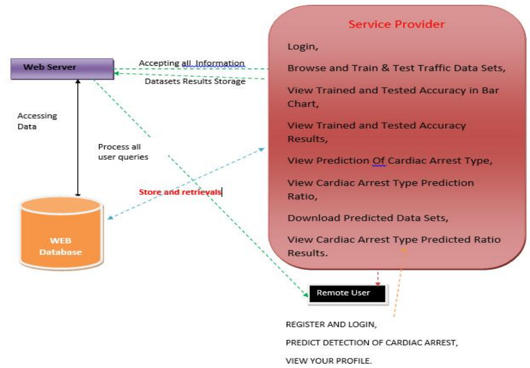
By analyzing large amounts of complex data, machine learning algorithms can detect signs of cardiac arrest and identify newborns at an increased risk of the condition. This technology could save lives and reduce the damage caused by cardiac arrest in newborns. The critical contribution of machine learning models used for the Early Detection of Cardiac Arrest in Newborn Babies is that these models can detect subtle changes in vital signs such as heart rate, respiratory rate, and oxygen saturation that are difficult to detect with the naked eye. This early detection can help to identify newborns at risk of cardiac arrest and allow for timely intervention and treatment. Additionally, machine learning models can be used to analyze patient data to provide personalized advice and care to patients, enabling better long term management of their condition.

ADAVANTAGES:

- Automated and accurately detected critical signs associated with cardiac arrest in newborn babies.
- Ability to recognize subtle changes in the baby's vital signs that can indicate potential cardiac arrest.
- Ability to identify high-risk babies likely to suffer from cardiac arrest.
- Early detection of cardiac arrest, enabling timely interventions that can improve the outcome.
- Reduction in the time and cost associated with traditional monitoring methods.
- Improved patient outcomes due to early diagnosis and treatment of cardiac arrest

IV. SYSTEM DESIGN

4.1 SYSTEM ARCHITECTURE:



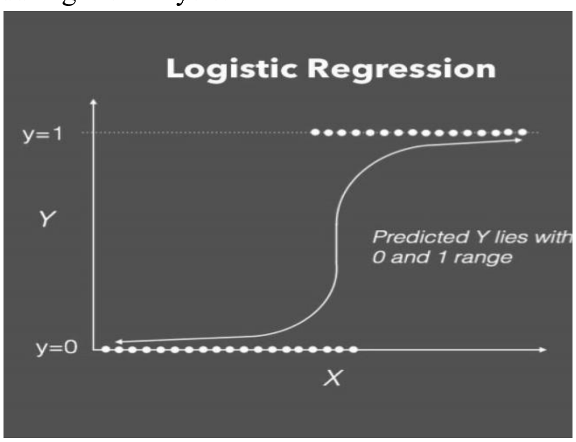
ALGORITHM'S:

Logistic Regression Classifiers:

Logistic regression analysis studies the association between a categorical dependent variable and a set of independent (explanatory) variables. The name logistic regression is used when the dependent variable has only two values, such as 0 and 1 or Yes and No. The name multinomial logistic regression is usually reserved for the case when the dependent variable has three or more unique values, such as Married, Single, Divorced, or Widowed. Although the type of data used for the dependent variable is different from that of multiple regression, the practical use of the procedure is similar.

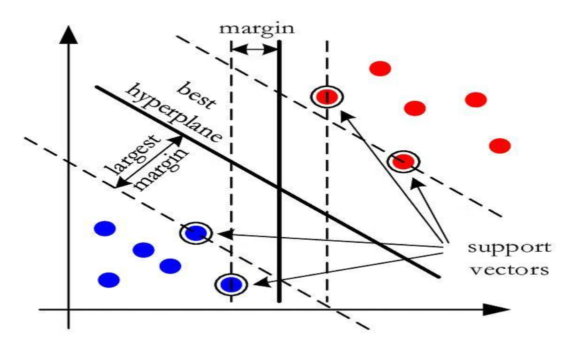
Logistic regression competes with discriminant analysis as a method for analyzing categorical-response variables. Many statisticians feel that logistic regression is more versatile and better suited for modeling most situations than is discriminant analysis. This is because logistic regression does not assume that the independent variables are normally distributed, as discriminant analysis does.

This program computes binary logistic regression and multinomial logistic regression on both numeric and categorical independent variables. It reports on the regression equation as well as the goodness of fit, odds ratios, confidence limits, likelihood, and deviance. It performs a comprehensive residual analysis including diagnostic residual reports and plots. It can perform an independent variable subset selection search, looking for the best regression model with the fewest independent variables. It provides confidence intervals on predicted values and provides ROC curves to help determine the best cutoff point for classification. It allows you to validate your results by automatically classifying rows that are not used during the analysis.



Support Vector Machine (SVM):

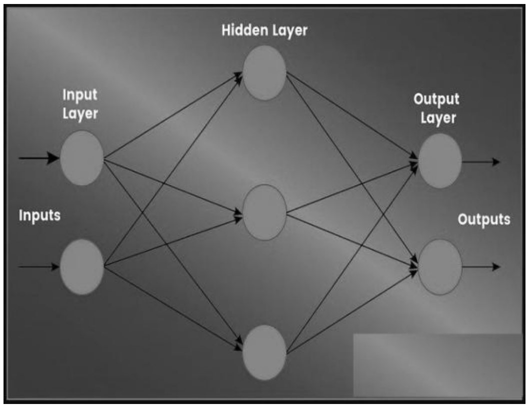
In classification tasks a discriminant machine learning technique aims at finding, based on an independent and identically distributed (iid) training dataset, a discriminant function that can correctly predict labels for newly acquired instances. Unlike generative machine learning approaches, which require computations of conditional probability distributions, a discriminant classification function takes a data point x and assigns it to one of the different classes that are a part of the classification task. Less powerful than generative approaches, which are mostly used when prediction involves outlier detection, discriminant approaches require fewer computational resources and less training data, especially for a multidimensional feature space and when only posterior probabilities are needed. From a geometric perspective, learning a classifier is equivalent to finding the equation for a multidimensional surface that best separates the different classes in the feature space.



SVM is a discriminant technique, and, because it solves the convex optimization problem analytically, it always returns the same optimal hyperplane parameter—in contrast to genetic algorithms (GAs) or perceptrons, both of which are widely used for classification in machine learning. For perceptrons, solutions are highly dependent on the initialization and termination criteria. For a specific kernel that transforms the data from the input space to the feature space, training returns uniquely defined SVM model parameters for a given training set, whereas the perceptron and GA classifier models are different each time training is initialized. The aim of GAs and perceptrons is only to minimize error during training, which will translate into several hyperplanes' meeting this requirement.

Artificial Neural Networks (ANN):

An ANN is perhaps the most popular machine learning model in today's AI landscape, given its wide applications in deep learning in the form of convolutional neural networks. However, a normal ANN comprised of a handful of linear nodes can perform comparable to the best standard ML models. The architecture of a standard ANN is shown in the figure below. As we can see, the hidden layer is the most crucial part of an ANN, and is made up of several linear nodes.

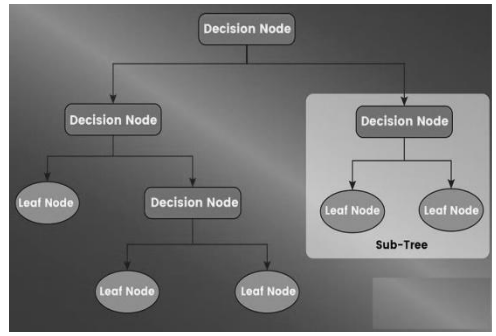


You can wrap several hidden layers in between the input and the output layer to increase the complexity and, thus, the learning ability of the model. Adding more nodes to a layer and more layers to the network would allow the model to learn more non-linear and complex relationships between the categorical variables and input features.

This ability makes the network very capable of capturing relationships between the various biological and personal markers that are already independently affecting the probability of the presence of heart disease.

Decision Tree Classification:

Decision Trees are the individual models that make a random forest after ensembling. Each decision tree classifier uses the dataset's attributes to create a tree. As shown in the image below, the branches end up in the leaves that are made up of target values. Using visual components and an information gain index, the tree identifies the leading features of the labels of each class. Thus, the branches are created that maximize the information gained in each split and lead up to the leaf node of that class. Decision trees are fast and robust for disease prediction if the dataset has powerful features for a simple use-case.



V. SYSTEM IMPLEMENTATION MODULES

Service Provider Module:

This module encompasses all the core functionalities of the system. It handles user management (login and registration) and provides various data-related operations such as training, testing, and predicting cardiac arrest types. It also offers data visualization through bar charts and allows users to view and download prediction results. This module is central to the system, connecting the web server with remote users and managing the overall workflow.

Responsibilities:

- User Management:
  - Login
  - Register
- Data Operations:
  - Browse and train & test traffic datasets.
  - View trained and tested accuracy in bar chart.
  - View trained and tested accuracy results.
  - View prediction of cardiac arrest type.
  - View cardiac arrest type prediction ratio.
  - Download predicted datasets.
  - View cardiac arrest type predicted ratio results.
  - View all remote users.

Interactions:

- Interfaces with the web server to store and retrieve data.

- Provides various functionalities related to data operations and user management for remote users.

Remote User Module:

This module is dedicated to the end-users of the system. It allows users to register and login to their accounts, manage their profiles, and access predictive analysis tools for cardiac arrest detection. This module relies on the service provider to perform its functions and provides users with necessary interfaces to interact with the system.

Responsibilities:

- User Account Management:
    - Register and login.
    - View profile.
- Predictive Analysis:
    - Predict detection of cardiac arrest.
    - View cardiac arrest type prediction results.

Interactions:

- Interacts with the service provider to register, login, and view profiles.
- Utilizes the service provider's predictive analysis functionalities to predict and view results related to cardiac arrest.

Web Server Module:

This module is responsible for handling data transactions and processing user requests. The web server acts as an intermediary between the service provider and the database, ensuring data is stored and retrieved as needed. It processes queries from users and facilitates smooth communication between different system components.

Responsibilities:

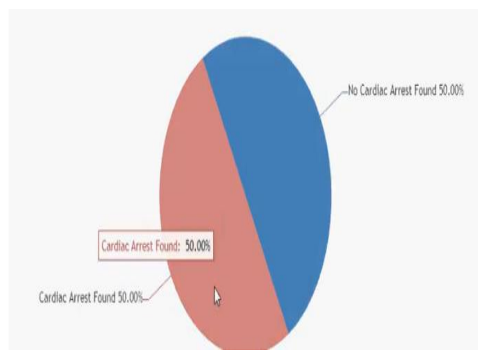
- Web Server:
    - Accepting all information from the service provider.
    - Processing all user queries.
    - Storing and retrieving data from the web database.
- Web Database:
    - Storage of datasets and results.
    - Facilitates data access for the web server.

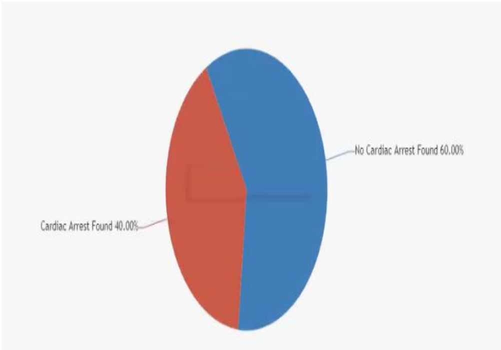
Interactions:

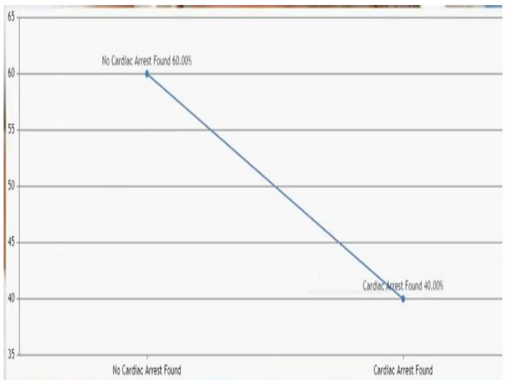
- The web server communicates with the service provider to accept information and process user queries.
- The web server accesses and retrieves data from the web database as needed.

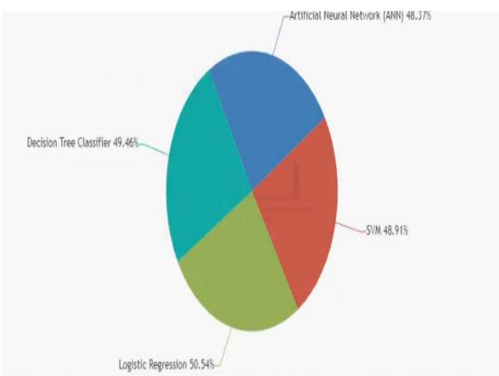
Each module has specific responsibilities and interacts with other modules to ensure the system operates smoothly. The web server manages data transactions, the service provider offers core functionalities and data operations, and the remote user module provides user-specific features and interfaces. This modular division allows for organized, efficient management and development of the system's components.

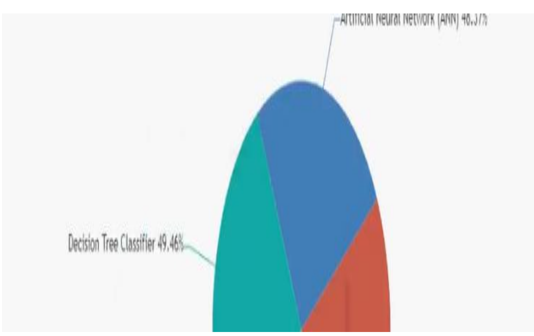
VI. SCREENSHOTS

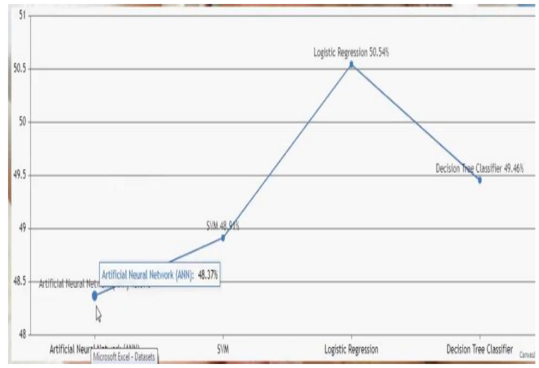


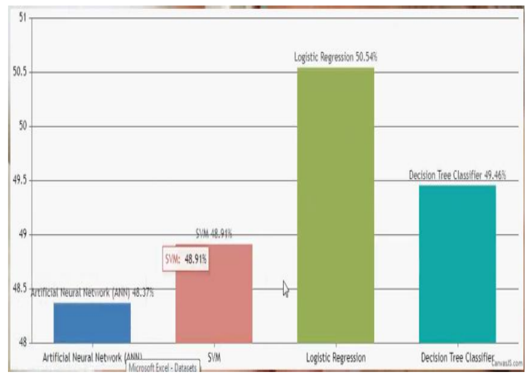












VII. CONCLUSION

These models could be used to develop personalized interventions for individual patients, allowing for more effective treatments. Enhancing the proposed machine learning algorithm could also pave the way for predicting potential complications in fetuses or newborns. A healthcare team can determine risk levels for specific cardiac abnormalities before a baby is even born, which helps provide better interventions during the prenatal period. In addition, the proposed machine learning algorithm could be used to improve diagnostics and treatments.

By studying historical patient data, diagnostics can be improved, and doctors can be presented with more accurate and up-to date information when diagnosing a patient. It can lead to earlier interventions, better patient outcomes, and more cost effective treatments.

FUTURE ENHANCEMENT

- Future enhancements of the proposed model will focus on using real-time data to identify critical indicators of cardiac arrest. It can involve collecting various data types such as heart rate, breathing rate, temperature, and other physiological measures.

- The cardiac machine learning algorithms can then be used to analyze this data to develop models that can accurately predict the likelihood of cardiac arrest. The proposed model can then be used to alert medical staff in order to allow for earlier and more effective interventions.
- Future enhancements may also include using artificial intelligence to detect patterns in the data and make more accurate predictions. It could incorporate data from other sources, such as previous records and medical histories.

REFERENCES

1. E. Choi, A. Schuetz, W. F. Stewart, and J. Sun, ''Using recurrent neural network models for early detection of heart failure onset,'' J. Amer. Med.Inform. Assoc., vol. 24, no. 2, pp. 361–370, Mar. 2017.
2. K. W. Johnson, J. T. Soto, B. S. Glicksberg, K. Shameer, R. Miotto, M. Ali,E. Ashley, and J. T. Dudley, ''Artificial intelligence in cardiology,'' J. Amer.College Cardiol., vol. 71, pp. 2668–2679, Jun. 2018.
3. C.-M. Yu, L. Wang, E. Chau, R. H.-W. Chan, S.-L. Kong, M.-O. Tang,J. Christensen, R. W. Stadler, and C.-P. Lau, ''Intrathoracic impedance monitoring in patients with heart failure: Correlation with fluid status and feasibility of early warning preceding hospitalization,'' Circulation,vol. 112, no. 6, pp. 841–848, Aug. 2005.
4. C. P. Bonafide, A. R. Localio, K. E. Roberts, V. M. Nadkarni,C. M. Weirich, and R. Keren, ''Impact of rapid response system implementation on critical deterioration events in children,'' JAMA Pediatrics,vol. 168, no. 1, pp. 25–33, 2014.
5. S. A. Bernard, T. W. Gray, M. D. Buist, B. M. Jones, W. Silvester,G. Gutteridge, and K. Smith, ''Treatment of comatose survivors of out-ofhospital cardiac arrest with induced hypothermia,'' New England J. Med.,vol. 346, no. 8, pp. 557–563, Feb. 2002.
6. Z. I. Attia, P. A. Noseworthy, F. Lopez-Jimenez, S. J. Asirvatham,A. J. Deshmukh, B. J. Gersh, R. E. Carter, X. Yao, A. A. Rabinstein,B. J. Erickson, S. Kapa, and P. A. Friedman, ''An artificial intelligenceenabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: A retrospective analysis of outcome prediction,'' Lancet, vol. 394, no. 10201, pp. 861–867, Sep. 2019.
7. A. Rajkomar et al., ''Scalable and accurate deep learning with electronic health records,'' NPJ Digit. Med., vol. 1, no. 1, p. 18, 2018.
8. O. Bernard et al., ''Deep learning techniques for automatic MRI cardiac multi-structures segmentation and diagnosis: Is the problem solved?''IEEE Trans. Med. Imag., vol. 37, no. 11, pp. 2514–2525, Nov. 2018.
9. T. J. Pollard, A. E. W. Johnson, J. D. Raffa, L. A. Celi, R. G. Mark, and O. Badawi, ''The Eicu collaborative research database, a freely available multi-center database for critical care research,'' Sci. Data, vol. 5, no. 1,pp. 1–13, Sep. 2018.
10. E. Christodoulou, J. Ma, G. S. Collins, E. W. Steyerberg, J. Y. Verbakel,and B. Van Calster, ''A systematic review shows no performance benefit of machine learning over logistic regression for clinical prediction

models,''J. Clin. Epidemiol., vol. 110, pp. 12–22, Jun. 2019.