# DETECTION OF CARDIAC ARREST IN NEWBORN BABIES USING NEURAL NETWORKS

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**Abstract**
Cardiac arrest in newborn babies is an alarming yet typical medical emergency. Early detection is critical for providing these babies with the best care and treatment. Recent study has focused on identifying the potential indicators and biomarkers of cardiac arrest in newborn babies and developing accurate and efficient diagnostic tools for early detection. An array of imaging techniques, such as echocardiography and computed tomography may help provide early detection of cardiac arrest. We aims to develop Detection model and Sevierity Prediction model using ANN for the early detection of cardiac arrest in newborn babies in the Cardiac Intensive Care Unit (CICU). The cardiac arrest events were identified using a combination of the neonate’s physiological parameters. The proposed model will be used in the CICU to enable early detection of cardiac arrest in newborn babies.

**Introduction**
Early detection of cardiac arrest in Newborns, especially those with congenital heart defects, are vulnerable to cardiac complications, including sudden cardiac arrest, which can have life-threatening consequences if not detected and treated promptly. Traditional monitoring methods may not always provide timely alerts, leading to delays in intervention and poorer outcomes.
The project employs a machine learning approach, utilizing statistical models to analyze physiological data collected from newborns in the CICU. Various vital signs such as heart rate, respiratory rate, blood pressure, and oxygen saturation levels are continuously monitored and recorded using medical devices. These data serve as inputs to the Neural Network models, which are trained- to identify patterns indicative of impending cardiac arrest.The performance of the developed models is rigorously evaluated using metrics such as sensitivity, specificity, and area under the receiver operating characteristic curve
Ultimately, the successful implementation of this project could lead to the development of an early warning system integrated into CICU monitoring systems, alerting healthcare providers to intervene promptly and potentially prevent adverse cardiac events in newborns.

**MOTIVATION**
The motivation behind undertaking a project on the detection of cardiac arrest in newborn babies is multifaceted and driven by the urgent need to improve neonatal care and outcomes. This endeavor is propelled by a combination of medical, ethical, and societal imperatives, all centered around the well-being of the most vulnerable members of our population.
First and foremost, newborn babies are incredibly fragile, and any medical complication during this critical period can have profound and lasting consequences. Cardiac arrest in newborns represents a particularly dire situation, as the heart's sudden cessation of function can lead to irreversible damage or even death if not promptly addressed. Therefore, the primary motivation for embarking on this project is to develop reliable methods for early
detection of cardiac arrest in newborns, enabling swift intervention and potentially life-saving
treatment.Beyond the immediate medical urgency, there is also an ethical imperative to improve neonatal care. Babies, especially those born prematurely or with underlying health conditions, deserve every opportunity for a healthy start in life. Detecting cardiac arrest early can mean the difference between life and death, but it can also impact the long-term health outcomes of survivors.
The conclusion, the motivation to undertake a project on the detection of cardiac arrest in newborn babies stems from a confluence of medical, ethical, societal, and technological factors. By addressing this critical healthcare challenge, researchers aim to save lives, enhance the quality of neonatal care, promote health equity, and harness the power of innovation to safeguard the most vulnerable members of our society

**OBJECTIVE**

The objective of the "Detection of Cardiac Arrest in Newborn Babies" project is to develop an effective and reliable system for early identification of cardiac arrest in newborn infants. This project aims to address the critical need for prompt intervention in neonates experiencing cardiac arrest, as timely detection can significantly improve their chances of survival and reduce the risk of long-term complications.

The primary goal is to design a non-invasive monitoring system capable of continuously assessing vital signs and cardiac activity in real-time. This system will utilize advanced sensor technology to detect subtle changes in heart rate, rhythm, and other physiological parameters associated with cardiac arrest in newborns. By analyzing these data streams, the system will be able to identify signs indicative of impending or occurring cardiac arrest with high accuracy and sensitivity.

Another key objective is to ensure the practicality and usability of the system in clinical settings. This involves developing user-friendly interfaces and incorporating feedback from healthcare professionals to optimize workflow integration and facilitate rapid response to detected cardiac events.

Ultimately, the successful implementation of this project aims to revolutionize neonatal care by providing healthcare providers with a powerful tool for early detection of cardiac arrest in newborns, thereby improving outcomes and saving lives.

**Literature Review**

The impact of a machine learning early warning score on hospital mortality: A multicenter clinical intervention trial

"C. J. Winslow, D. P. Edelson, M. M. Churpek, M. Taneja, N. S. Shah"

The study aimed to evaluate the impact of implementing a machine learning-based EWS on patient outcomes across multiple healthcare facilities. The EWS utilized various clinical parameters and patient data to generate real-time risk scores, allowing clinicians to identify patients at high risk of deterioration or adverse events. The findings suggest that leveraging machine learning-based EWS can have a positive impact on patient outcomes by enabling early identification and intervention for individuals at high risk of deterioration or adverse events.

Diagnosis and management of cancer treatment-related cardiac dysfunction and heart failure in children

"M. Hegazy, S. Ghaleb, and B. B. Das"

Discussed a cancer treatment-related cardiac dysfunction and heart failure in childrenisdiagnosed through a combination of medical history, physical examination, imaging studies, and laboratory tests. These includean echocardiogram to measure heart function, an electrocardiogramto measure the electrical activity of the heart,and cardiac biomarker tests to detect abnormal heart muscledamage. Clinicians may also request additional tests,such as cardiac catheterization or magnetic resonance imaging,to evaluate the structure and function of the heart.

Machine learning-based risk stratification tool for in-hospital mortality of intensive care unit patients with heart failure

"C. Luo, Y. Zhu, Z. Zhu, R. Li, G. Chen, and Z.Wang"

Machine learning-based risk stratification tool for in-hospital mortality of intensive care unit patients with heart failure is a tool that uses machine learning (ML) to identify patterns in patient data that can be used to determine their risk of mortality while they are in the ICU. The tool aggregates patient data such as age, medical history, ICU severity scores, laboratory values, and other data to generate a risk stratification score. The higher the score, the greater the chance of mortality. The tool can help healthcare providers predict and treat heart failure cases by identifying high-risk patients. It, in turn, allows for earlierinterventions and improved outcomes for these patients.

Motor imagery classification using sparse nonnegative matrix factorization and convolutional neural networks

"P. Chaudhary, Y. V. Varshney, G. Srivastava, and S. Bhatia"

Motor imagery classification using sparse nonnegative matrix factorization (SNMF) and convolutional neural networks (CNNs) is a technique used to classify motor imagery data acquired from electroencephalography (EEG). The SNMF decomposes the EEG signals into latent features that are then used as input to a CNN for classification.The SNMF is used to reduce the dimensionality of the data, making it more suitable for classification, while the CNNs are used to learn an interpretableclassification space. By combining the two, a more efficient and effective motor imagery classification can be achieved.

Neonatal hypertension: Concerns within and beyond the neonatal intensive care unit

"K. Altemose and J. M. Dionne"

Neonatal hypertension can have many causes includingdisorders of the cardiovascular system, endocrine system,or kidneys. It can also result from certain medications, severeinfection. It can lead to serious complications, such asseizures, poor feeding, anddevelopmental delays. Due to the seriousness of this condition, it is important for allneonatal intensive care unit physicians to remain vigilant inits diagnosis and treatment

Ventricular assist device support in neonates and infants with a failing functionally univentricular circulation

"M. S. Bleiweis, J. C. Fudge, G. J. Peek, H. V. Vyas, S. C. Beltran, A. D. Pitkin

Ventricular Assist Device is a type of mechanical device used to support the circulation of blood through the circulatory system of a neonate or infant with a failing functionally univentricular circulation. It works by helping the heart pump blood to the body and absorbing some of the work it has to do. This device usually consists of an electric motor that is attached to a pump which communicates with the heart and produces a flow of blood all throughout the body. This device can help reduce the workload on the heart which may lead toimproved overall circulation and heart function.

Potential biases in machine learning algorithms using electronic health record data

"M. A. Gianfrancesco, S. Tamang, J. Yazdany, and G. Schmajuk"

Potential biases in machine learning algorithmsusing electronic health record (EHR) data can come fromvarious sources. First, there may be biases in the data dueto sampling or coding errors. If the data used to train thealgorithm does not represent the population, the algorithmmay be biased toward specific outcomes. Second, there maybe biases in how the algorithm processes the data, such asfavouring certain data types or giving too much weight tocertain variables. Third, there may be biases in evaluating thealgorithm, such as using metrics that favour 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 favour specific outcomes.In conclusion, the paper highlights the complexities inherent in using EHR data for ML applications in healthcare and underscores the need for proactive measures to mitigate biases and ensure the integrity and fairness of ML algorithms. By addressing issues such as missing data, data quality, and disparities in healthcare access, researchers can harness the full potential of EHR data to drive meaningful improvements in patient care and medical research while minimizing the risk of perpetuating existing inequities in healthcare delivery.

Soft computing-based EEG classification by optimal feature selection and neural networks

"M. H. Bhatti, J. Khan, M. U. G. Khan, R. Iqbal, M. Aloqaily, Y. Jararweh"

Soft computing based EEG classification by optimal feature selection and neural networks, a technology that uses neural networks and evolutionary algorithms to classify brain activity in electroencephalogram (EEG). The approach is based on optimizing feature selection and neural network structure to find the most accurate model. It uses a combination of traditional machine

learning algorithms and optimization techniques for feature selection, such as Genetic Algorithms and Particle Swarm Optimization. Once the optimal feature set and structure have

been determined, a feed-forward neural network is trained to recognize the patterns in the EEG signal and classify them. The network is trained using back-propagation, a standard gradient descent algorithm that measures the output error and adjusts the weights accordingly. The result is an accurate, reliable EEG classifier that can be used to detect and classifyvarious types of brain activities.

Early prediction of sepsis in the ICU using machine learning: A systematic review

"M. Moor, B. Rieck, M. Horn, C. R. Jutzeler, and K. Borgwardt"

Discussed the Sepsis is a life-threatening condition caused by an overwhelming immuneresponse 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 analyse 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

**Proposed Method**

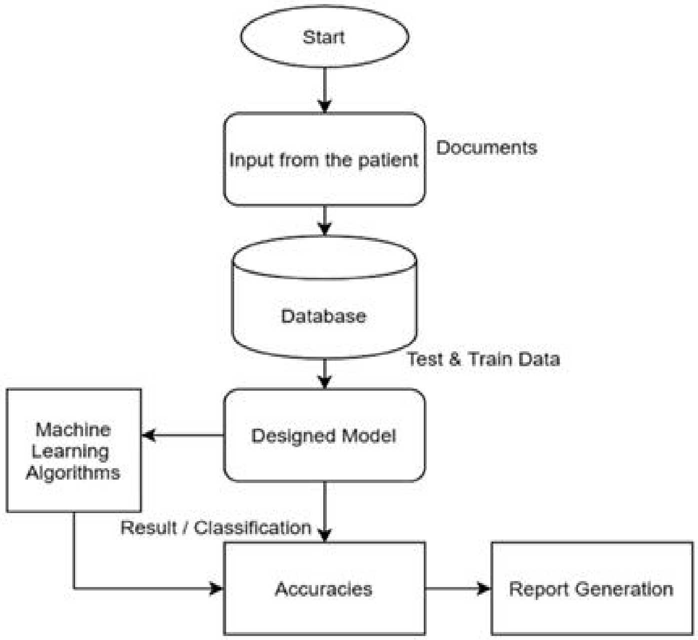



Fig.1. System Architecture

Constructing the proposed Artificial Neural Network modelrequires several steps. First, the data must be collected andpre-processed. It includes gathering relevant cardiac datasuch as electrocardiograms (ECG), other medical images, andany relevant patient information, such as age and gender. Thedata must then be cleaned and transformed into a format suitablefor machine learning algorithms, such as numerical orcategorical values. Once the data is ready, a machine-learningmodel must be selected. It is typically a neural networkmodel, as it can handle the complex relationships between thevarious data points. The model must then be trained using thedata and evaluated for accuracy. If necessary, the model canbe tweaked to improve its performance. Finally, the modelmust be deployed. It involves creating an application or webinterface for the model to be used by medical professionals.

**WORKING OF ANN**

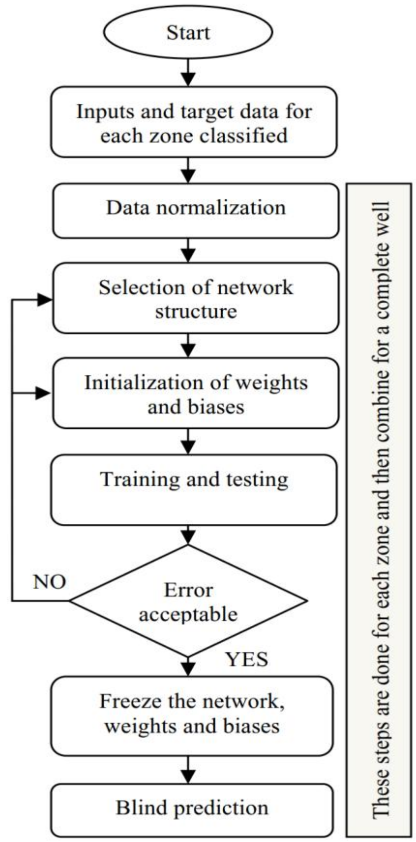



Fig 4.2.1 Flow Chart of ANN

- **Input Layer:** The input layer receives raw data or features from the input source. Each input is associated with a weight, indicating its importance.
- **Hidden Layers:** In the hidden layers, each neuron processes the weighted sum of inputs and biases using an activation function.
- **Weights and Biases Adjustment:** During the learning phase, the network adjusts weights and biases through a process called back propoagation. It compares the network's output to the desired output, calculates the error, and adjusts weights to minimize this error.
- **Output Layer:** The processed information propagates through the hidden layers to the output layer. The output layer provides the final prediction or classification result.
- **Training:** The network iteratively updates weights and biases using training data to minimize the prediction error. This process fine-tunes the network's ability to make accurate predictions.
- **Prediction:** Once trained, the network can process new, unseen data and generate predictions or classifications based on the patterns it has learned.
- **SYSTEM MODULES**
- Implementing data quality evaluation for a Deep Learning-based Detection of cardiac arrest in new born babies project involves a series of practical steps. verse fields and disciplines.
- **Data Collection**:
- Data collection is a fundamental process in research and analytics, involving systematic gathering of raw information from various sources. This process serves diverse purposes, from understanding trends and patterns to informing decision-making. Researches employ a range of methods, including surveys, interviews, observations, and data mining, tailored to their specific objectives and the nature of the data sought. Ethical considerations play a critical role, necessitating adherence to guidelines to protect participant privacy and rights. Quality assurance measures are implemented to ensure the reliability and validity of the collected data, encompassing meticulous planning, training

of personnel, and ongoing monitoring. Once collected, data undergoes organization and management, readying it for analysis where it is transformed into valuable insights to inform further actions or research directions. Thus, data collection forms the bedrock of evidence-based inquiry and decision making processes across disciplines.

**Data Preprocessing**:
Data preprocessing is a crucial step in the data analysis pipeline, involving the transformation and manipulation of raw data to make it suitable for analysis. This process encompasses several tasks aimed at enhancing the quality and usability of the data. Common preprocessing steps include handling missing values, removing duplicates, and dealing with outliers to ensure the integrity of the dataset. Additionally, data may be normalized or standardized to bring features to a similar scale, facilitating comparison and analysis. Categorical variables are often encoded into numerical representations, while text data may undergo tokenization and vectorization for machine learning applications. Feature selection or dimensionality reduction techniques may be applied to reduce the complexity of the dataset and improvemodel performance.

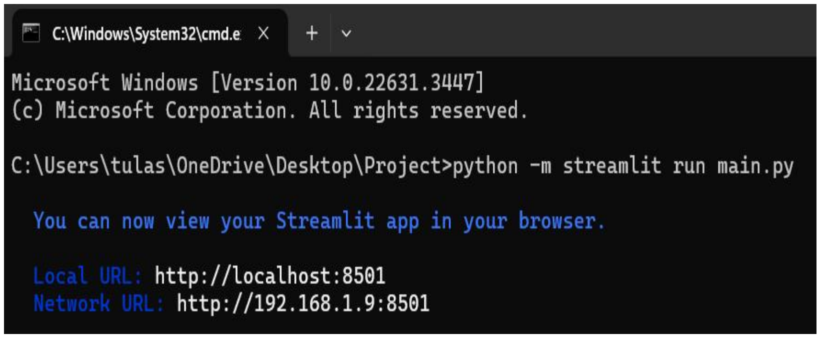
**Data Splitting**:
Data splitting is a fundamental step in deep learning and data analytics, involving the partitioning of dataset into multiple subsets for training, validation, and testing purposes. The primary goal of data splitting is to assess and validate the performance of deep learning models on unseen data, thereby evaluating their generalization ability. Typically, the dataset is divided into two or three subsets: a training set, a validation set, and a test set. The training set is used to train the model, while the validation set is employed to fine-tune model hyperparameters and assess performance during training. The test set, held out until the very end, serves as a completely unseen dataset to evaluate the final model's performance objectively. The splitting process must be performed carefully to ensure that each subset is representative of the overall dataset's characteristics. Random splitting is commonly used, ensuring that each subset contains a proportional representation of the different classes or patterns present in the data. Additionally, techniques like cross-validation can be employed to further validate model performance and mitigate the risk of overfitting. By splitting the dataset into distinct subsets, data splitting enables researchers and practitioners to iteratively develop and evaluate machine learning models, ensuring their robustness and effectiveness in real-world scenarios. It also helps in identifying potential issues such as overfitting or data leakage, ultimately leading to more reliable and trustworthy model deployment.

**Designing ANN model for detection**
Here the ANN model consists of one input layer, two hidden layers and one output layer. The two hidden layers are dense, dense_1. One hidden layer consists of 8 nodes and another hidden layer consists of 4 nodes.Output layer consists of only one node because we get only one output from that node. Total number trainable parameters are 153.

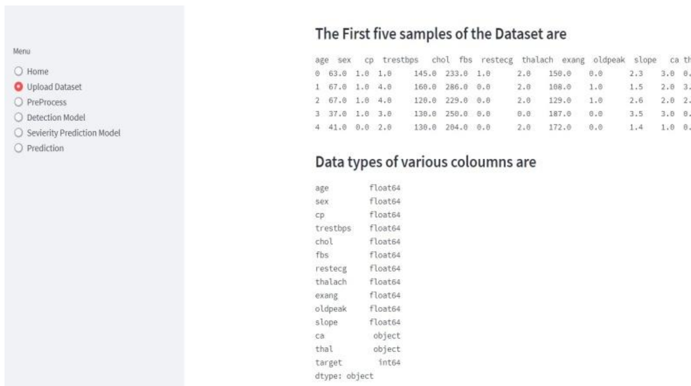
**Designing ANN model for Severity Prediction**
Here the ANN model consists of one input layer, two hidden layers and one output layer. The two hidden layers are dense_3, dense_4. One hidden layer consists of 8 nodes and another hidden layer consists of 4 nodes.Output layer consists of only 5. Total number trainable parameters are 173.

**Testing ANN models:**
Testing in the context of deep learning involves evaluating the performance of a trained model on a separate dataset that it hasn't seen during training. This process assesses the models ability to generalize to new, unseen data and provides an indication of its predictive accuracy and effectiveness in real-world scenarios. During testing, the model makes predictions on the testing dataset, and its performance is evaluated using various metrics such as accuracy, precision, recall, F1-score, and confusion matrix. These metrics provide insights into the model's ability to correctly classify instances and its overall performance across different classes or categories.

**Experimental Results**
The execution of the process will be explained clearly with the help of continuous screenshots. The whole process is uploading the details of patient, after uploading details, the system will automatically detect the cardiac arrest and also tells the severity of the cardiac arrest.
**Launching Application Streamlit**

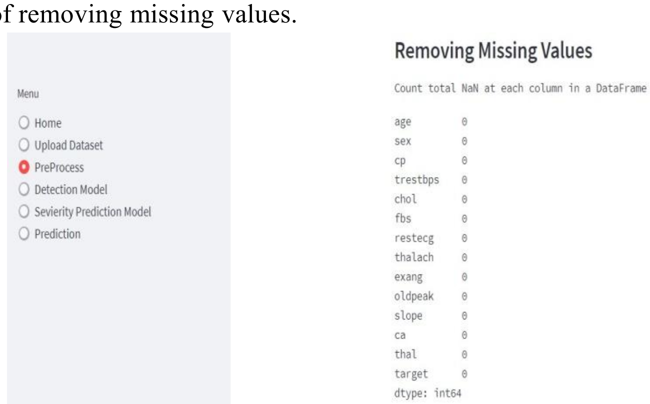



**UCI heart disease prediction dataset**



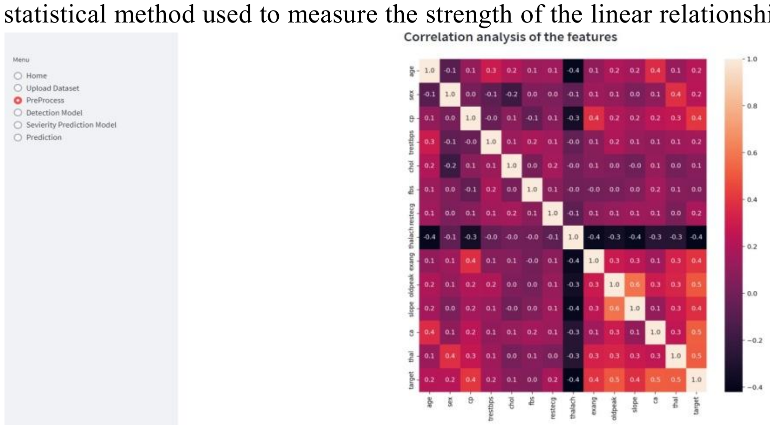

**Preprocessing**

Preprocessing is the process of removing missing values.



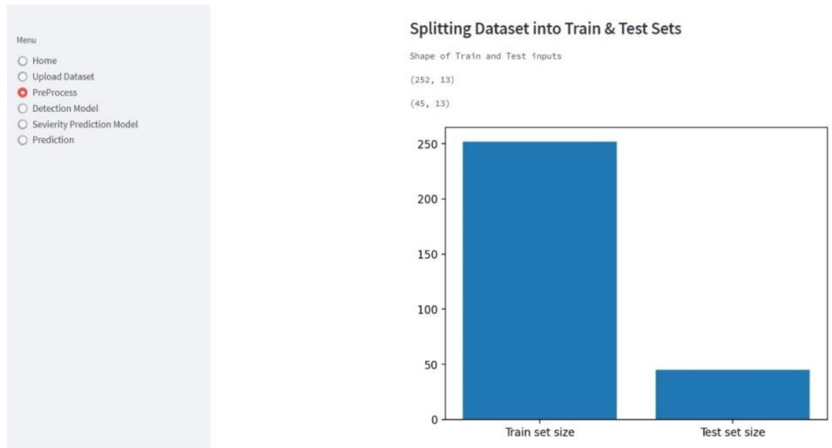

**Correlation Analysis graph**

Correlation Analysis is a statistical method used to measure the strength of the linear relationship between two variables.



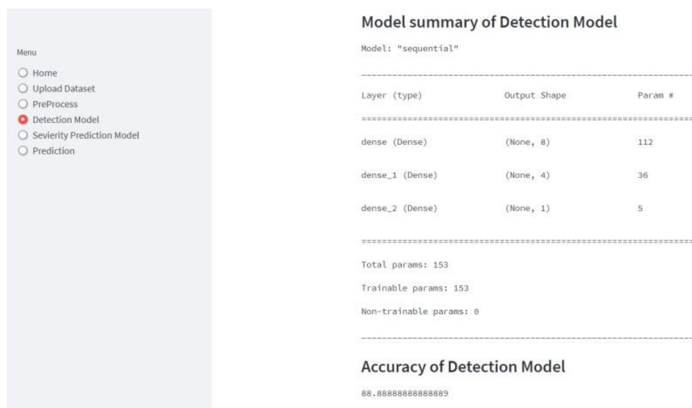

**Data Splitting**

The whole dataset is divided into two sets. They are training set and testing set.

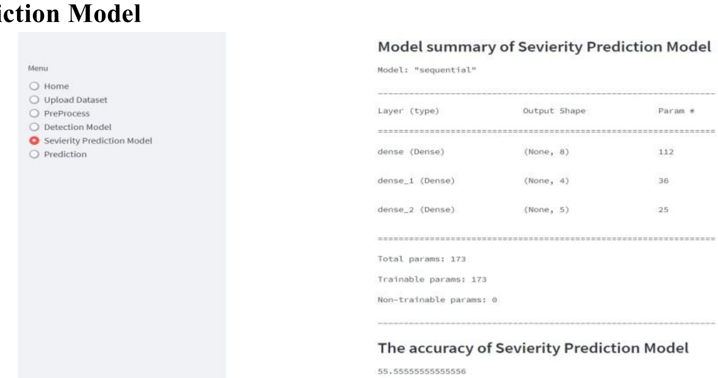



**Training Detection Model**

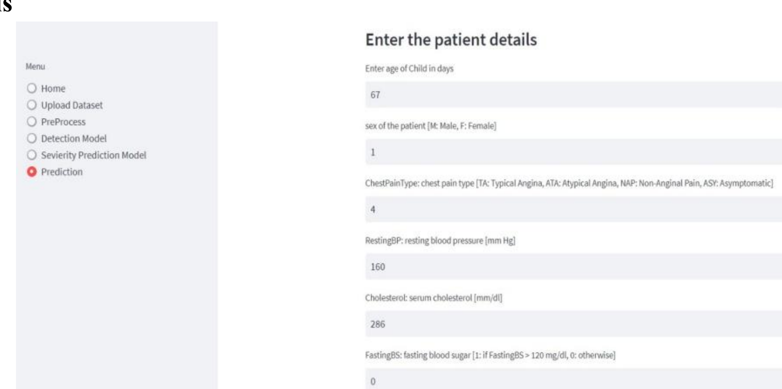
Here the model is trained with 80% of dataset.

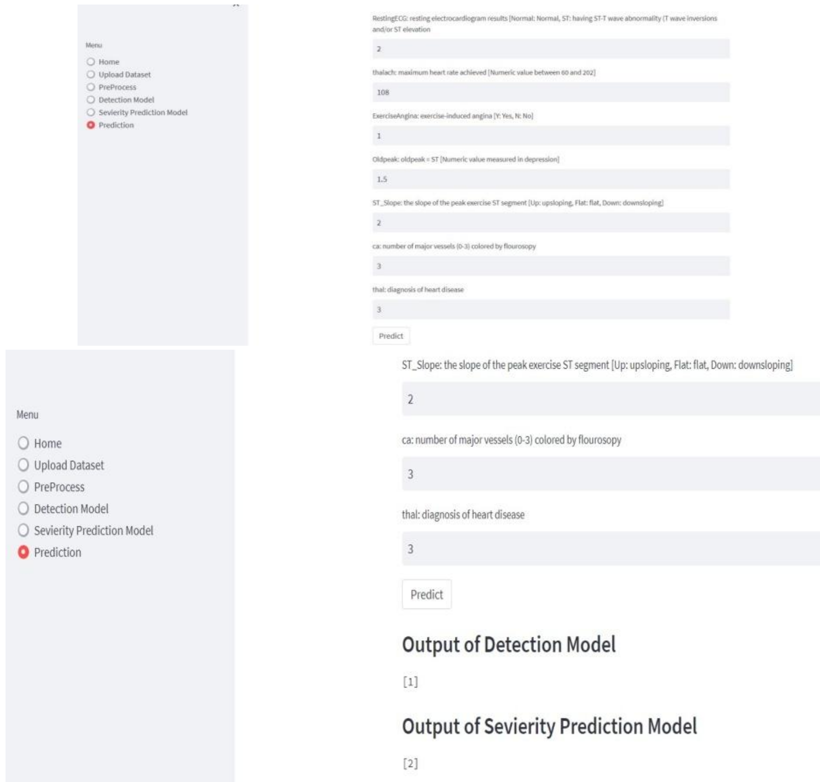



**Training Seviierity Prediction Model**




**Entering Patient details**






**CONCLUSION**

Detecting cardiac arrest in newborn babies is a critical challenge in neonatal care, demanding swift and accurate intervention to prevent severe outcomes. Artificial Neural Networks (ANNs) offer a promising avenue for improving early detection in this vulnerable population. By leveraging large datasets comprising physiological parameters, ANNs can learn intricate patterns indicative of cardiac distress, enabling timely intervention. ANN's excel at recognizing complex, nonlinear relationships within data, making them adept at discerning subtle indicators of cardiac arrest in newborns. Parameters such as heart rate variability, respiratory patterns, and oxygen saturation levels can be analyzed comprehensively by ANNs, allowing for the identification of pre-arrest patterns and facilitating proactive measures. Moreover, ANNs have the potential for continuous monitoring, providing real-time assessment and alerts to healthcare providers, thus enhancing vigilance and response times. Their adaptability to diverse clinical settings and the ability to integrate with existing monitoring systems make ANNs a viable solution for enhancing neonatal care. In conclusion, the application of ANNs holds significant promise in the early detection of cardiac arrest in newborn babies, offering the potential to save lives and improve long-term outcomes through timely intervention and effective management of critical events.

**FUTURE SCOPE**

Future scope 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 otherphysiological measures. The cardiac machine learning algorithms can then be used to analysethis data todevelop models that can accurately predict thelikelihood of cardiac arrest. The proposed model can thenbe used to alert medical staff in order to allow for earlierand more effective interventions. Future enhancements mayalso include using artificial intelligence to detect patternsin the data and make more accurate predictions. It couldincorporate data from other sources, such as previous recordsand medical histories. Finally, these models could be usedto develop personalized interventions for individual patients,allowing for more effective treatments. Enhancing the proposedmachine learning algorithm could also pave the wayfor predicting potential complications in foetuses or newborns.A healthcare team can determine risk levels for specificcardiac abnormalities before a baby is even born, which helps provide better interventions during the prenatal period.In addition, the proposed machine learning algorithm couldbe used to improve diagnostics and treatments. By studyinghistorical patient data, diagnostics can be improved, anddoctors can be presented with more accurate and up-todateinformation when diagnosing a patient. It can lead toearlier interventions, better patient outcomes, and more cost-effectivetreatments.

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