`A Project report on

EARLY DETECTION OF CARDIAC ARREST IN NEWBORN BABIES

A Dissertation submitted to JNTU Hyderabad in partial fulfillment of the academic requirements for the award of the degree.

Bachelor of Technology

in

Computer Science and Engineering

Submitted by

V.BHAVANA
(20H51A0579)

S.ROSHINI
(20H51A05A4)

D.SANJANA
(20H51A0587)

Under the esteemed guidance of

Ms.M.N.Sailaja
Assistant Professor

Department of Computer Science and Engineering

CMR COLLEGE OF ENGINEERING& TECHNOLOGY

(UGC Autonomous)

*Approved by AICTE *Affiliated to JNTUH *NAAC Accredited with A^+ Grade

KANDLAKOYA, MEDCHAL ROAD, HYDERABAD - 501401.

2020- 2024

CMR COLLEGE OF ENGINEERING & TECHNOLOGY

KANDLAKOYA, MEDCHAL ROAD, HYDERABAD – 501401

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that the Major Project Phase I report entitled **" Early Detection Of Cardiac Arrest In NewBorn Babies"** being submitted by **V.BHAVANA(20H51A0579), S.ROSHINI(20H51A05A4), D.SANJANA (20H51A0587)** in partial fulfillment for the award of **Bachelor of Technology in Computer Science and Engineering** is a record of bonafide work carried out his/her under my guidance and supervision.

The results embodies in this project report have not been submitted to any other University or Institute for the award of any Degree.

Ms.M.N.Sailaja
Assistant Professor
Dept. of CSE

Dr. Siva Skandha Sanagala
Associate Professor and HOD
Dept. of CSE

ACKNOWLEDGEMENT

With great pleasure we want to take this opportunity to express my heartfelt gratitude to all the people who helped in making this project work a grand success.

We are grateful to **Ms.M.N.Sailaja, Assistant Professor**, Department of Computer Science and Engineering for his valuable technical suggestions and guidance during the execution of this project work.

We would like to thank **Dr. Siva Skandha Sanagala,** Head of the Department of Computer Science and Engineering, CMR College of Engineering and Technology, who is the major driving forces to complete my project work successfully.

We are very grateful to **Dr. Vijaya Kumar Koppula**, Dean-Academics, CMR College of Engineering and Technology, for his constant support and motivation in carrying out the project work successfully.

We are highly indebted to **Major Dr. V A Narayana,** Principal, CMR College of Engineering and Technology, for giving permission to carry out this project in a successful and fruitful way.

We would like to thank the **Teaching & Non- teaching** staff of Department of Computer Science and Engineering for their co-operation

We express our sincere thanks to **Shri. Ch. Gopal Reddy**, Secretary, CMR Group of Institutions, for his continuous care.

Finally, We extend thanks to our parents who stood behind us at different stages of this Project. We sincerely acknowledge and thank all those who gave support directly and indirectly in completion of this project work.

V.Bhavana 20H51A0579
S.Roshini 20H51A05A4
D.Sanjana 20H51A0587

TABLE OF CONTENTS

List of Figures

ABSTRACT

Cardiac arrest in newborn babies is an alarming medical emergency. Early detection is critical for providing these babies with the best care and treatment. Recent research 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. Various factors and symptoms like: Birth Weight, Family History, Preterm Birth, Heart Rate, Breathing Difficulty, Skin Tinge, Responsiveness, Movement, Delivery Type and Mothers Blood Pressure History are useful in predicting Cardiac arrest in early stages. This project aims at early Detection of cardiac arrest by using a dataset, containing the above mentioned area factors and symptoms. The analysis is carried out by using Bagging Classifier classifier and also by using a Deep learning model.

The project comprises of four modules. The first module deals with buillding Bagging Classifier model and finding its Accuracy . The second module deals with the predictions of Bagging Classifier model. The third module comprises of building the deep neural net and finding its accuracy. The fourth module deals with finding the predictions with the deep neural net model.

Algorithm Used: Bagging Classification & Neural Net Classification

Input: Dataset comprising of infant factors and symptoms

OutPuts from the project:(1)Bagging Classifier Accuracy

(2) Bagging Classifier predictions

(3) Neural Net predictions

(4) Neural Net Accuracy

CHAPTER 1
INTRODUCTION

CHAPTER 1
INTRODUCTION

1.1. Problem Statement

Vision:

The vision of this project is to pioneer the development of an advanced tool for the early detection of cardiac arrest in newborn babies, integrating the advantages of machine learning and deep learning techniques. This tool aims to revolutionize the healthcare landscape for infant patients, ensuring timely and accurate identification of potential cardiac issues, thus paving the way for immediate medical intervention and enhancing the prognosis of the infants.

Mission:

Our mission is to construct a tool by harnessing the power of Python, coupled with its layout toolkit PyQt, PyUIC, Bagging Classifier, Tensorflow, and Keras modules. By doing so, we endeavor to build a reliable and efficient system that assists healthcare professionals, particularly pediatricians, in swiftly and accurately predicting the onset of cardiac arrest in newborns. We are committed to leveraging state-of-the-art technologies and frameworks to make this tool accessible, intuitive, and effective, contributing significantly to the early detection and subsequent care of cardiac issues in infants.In summary, the vision emphasizes the pioneering nature of the project, seeking to transform healthcare for newborns facing cardiac challenges. The mission outlines the strategic approach and tools employed to achieve the vision, highlighting the commitment to leveraging cutting-edge technologies to develop a tool that can make a meaningful impact in the domain of infant healthcare.

1.2. Research Objective

The research objective for the given project, "Early Detection of Cardiac Arrest in Newborn Babies using Machine Learning and Deep Learning Techniques," can be summarized as follows:

1. *Development of Early Detection Tool*: The primary objective is to develop an effective and reliable tool for the early detection of cardiac arrest in newborn babies.

2. *Machine Learning and Deep Learning Integration*: Investigate and implement machine learning algorithms such as Bagging Classifier and deep learning models to analyze a dataset containing infant factors and symptoms. The aim is to accurately predict cardiac arrest in its early stages using these techniques.

3. *Feature Identification and Utilization*: Identify critical indicators and biomarkers from the dataset, such as birth weight, family history, heart rate, and other relevant factors, and leverage these features to enhance the accuracy and efficiency of the detection model.

4. *Comparative Analysis of Algorithms*: Compare the performance of the Bagging Classifier model and deep neural net model in terms of accuracy and prediction capabilities for early detection of cardiac arrest in newborns.

5. *Evaluation and Validation*: Validate the developed tool by assessing its accuracy in predicting cardiac arrest in newborns and ensuring its reliability as a potential clinical aid for healthcare practitioners.

6. *Advancement in Pediatric Care*: Ultimately, contribute to the advancement of pediatric care by providing a tool that enables timely intervention and improves the prognosis for infants at risk of cardiac arrest.

7. *Scalability and Future Extensions*: Consider the scalability of the tool to handle a larger volume of data and explore possibilities for future extensions or enhancements, potentially integrating real-time monitoring capabilities and incorporating more advanced machine learning techniques.

1.3. Project Scope and Limitations

1. *Data Collection and Preparation:*

Gathering a comprehensive dataset containing crucial infant factors and symptoms such as birth weight, family history, heart rate, breathing difficulty, and more. This data will serve as the foundation for training and testing the models.

2. *Machine Learning Models:*

Building a Bagging Classifier model, an ensemble meta-estimator, to analyze the dataset and predict the likelihood of cardiac arrest in infants. This model will be a crucial part of the project, aiding in early detection.

3. *Deep Learning Models:*

Constructing a deep neural net utilizing Google's TensorFlow tool and Python. This model will process and analyze the dataset, providing an alternative approach for the early detection of cardiac arrest in newborns.

4. *Accuracy Assessment:*

Evaluating the accuracy of both the Bagging Classifier and deep neural net models to determine their efficiency and reliability in predicting cardiac arrest in newborns.

5. *Predictions Generation:*

Developing functionality to generate predictions from both the Bagging Classifier and deep neural net models based on the input dataset, allowing for real-time assessment of potential cardiac issues.

6. *Automated Front-End Code Generation:*

Utilizing PyUIC to automate the generation of front-end code, streamlining the GUI development process and ensuring consistency in design and functionality.

CHAPTER 2
BACKGROUND WORK

CHAPTER 2
BACKGROUND WORK

Early detection of cardiac arrest in newborn babies is a critical and challenging task, as it can significantly impact the infant's chances of survival and long-term health. To initiate a project focused on this important issue, you'll need to perform extensive background work to understand the problem, its context, and potential solutions. Here's a comprehensive guide to help you get started:

Consult with Experts:

Reach out to medical professionals, neonatologists, pediatric cardiologists, and experts in the field of neonatal care to gain insights into the challenges and opportunities in early detection of cardiac arrest in newborns. Seek advice from experienced researchers or healthcare providers.

Gather Statistics and Data:

Collect data on the incidence and outcomes of cardiac arrest in newborns. Understand risk factors, common causes, and the demographics of affected infants. Determine the existing diagnostic and monitoring techniques and their limitations.

Regulatory and Ethical Considerations:

Familiarize yourself with relevant medical regulations and ethical guidelines governing research on infants and neonates. Ensure your project complies with all ethical standards and regulations.

Technology and Tools:

Investigate the latest medical technologies, monitoring devices, and diagnostic tools used in neonatal care. Explore the potential for innovative technology solutions, such as wearable sensors and data analysis software.

2.1 Neonatal Cardiac Arrest Detection System (NCADS)

2.1.1Introduction

NCADS is a machine learning-based system for the early detection of cardiac arrest in newborn babies. The system is trained on a dataset of physiological data from newborn babies, including heart rate, respiratory rate, and blood oxygen levels. NCADS uses this data to learn patterns that are indicative of cardiac arrest. When new data is presented to the system, it can identify these patterns and issue an alert if cardiac arrest is suspected.

The Neonatal Cardiac Arrest Detection System, or NCADS, represents a groundbreaking advancement in the field of neonatal care, aimed at early identification and timely intervention in cases of cardiac arrest among newborn babies. This innovative system has emerged as a critical response to the need for improved neonatal healthcare, reducing morbidity and mortality rates among neonates.

2.1.2.Merits

The Neonatal Cardiac Arrest Detection System (NCADS) offers numerous merits and advantages in the field of neonatal care. Here are some of the key benefits of implementing such a system:

1. **Early Detection:** Timely detection of cardiac arrest is crucial for newborns. NCADS can identify subtle signs of cardiac distress, enabling healthcare providers to initiate life-saving interventions promptly.

2. **Improved Survival Rates:** The primary advantage of NCADS is its potential to enhance the survival rates of newborns at risk of cardiac arrest. Early intervention increases the chances of a successful resuscitation. High accuracy and sensitivity in detecting cardiac arrest, Able to detect cardiac arrest even with limited data availability, Non-invasive and does not require any additional sensors or procedures

3. **Reduced Morbidity:** Identifying cardiac arrest early can help prevent or reduce long-term health complications in neonates, such as neurological damage, developmental delays, or other sequelae associated with cardiac arrest.

4. **Real-time Monitoring:** NCADS offers continuous, real-time monitoring of vital signs, ensuring that any deviations from normal parameters are promptly recognized. This continuous surveillance can lead to timely intervention.

5. **Minimized False Alarms:** The use of advanced data analysis and AI algorithms in NCADS helps minimize false alarms, ensuring that healthcare providers are alerted when necessary, reducing alarm fatigue.

6. **User-Friendly Interface:** NCADS is designed with a user-friendly interface, making it accessible to healthcare professionals in neonatal care units. Its intuitive design enhances its adoption and use.

7. **Integration with Existing Systems:** Many NCADS can seamlessly integrate with existing hospital information systems and electronic health records, streamlining the workflow for healthcare providers and ensuring the consistency of patient records.

8. **Continuous Data Logging:** NCADS typically keeps a record of monitored data, creating a valuable resource for retrospective analysis, quality improvement, and research purposes.

9. **Enhanced Efficiency:** By automating the monitoring process and providing immediate alerts, NCADS enhances the efficiency of healthcare providers, allowing them to focus on critical patient care.

10. **Improved Family Satisfaction:** Families of newborns in neonatal care units often experience high levels of stress and anxiety. Knowing that their infants are under constant surveillance with a system like NCADS can provide a sense of security and reassurance.

11. **Privacy and Security Compliance:** NCADS systems are designed to adhere to stringent patient data privacy and security regulations, ensuring that sensitive medical information is protected.

12. **Research and Data Analysis:** The data collected by NCADS can be invaluable for medical research, helping to advance our understanding of neonatal cardiac health and contributing to the development of better treatment and prevention strategies.

13. **Cost Savings:** While there may be an initial investment in implementing NCADS, the long-term benefits, including reduced healthcare costs associated with complications from cardiac arrest, can lead to significant cost savings.

In summary, the Neonatal Cardiac Arrest Detection System offers a range of merits that collectively contribute to improved outcomes for newborns at risk of cardiac arrest. Its ability to provide early detection, enhance survival rates, and reduce morbidity makes it a valuable addition to neonatal care units, ultimately benefiting both healthcare providers and the families they serve.

2.1.2.DEMERITS

Requires training on a dataset of physiological data from newborn babies. May not be able to detect all cases of cardiac arrest. Potential for false positives.

1. **False Alarms:**

One of the main challenges with NCADS is the potential for false alarms, which can lead to alarm fatigue among healthcare providers.

2. **Complexity and Cost:**

NCADS can be complex to implement, requiring specialized equipment, software, and staff training. The initial setup and maintenance costs can be a significant financial burden for healthcare facilities.

2.1.2. CHALLENGES

1.Standardization:

Developing standardized protocols and guidelines for NCADS use across different healthcare facilities can be challenging. Consistency in implementation is crucial for effective use.

2.Data Interpretation:

Interpreting data from NCADS and distinguishing between genuine cardiac arrest events and false alarms can be a skill that healthcare providers need to acquire and refine.

3.Patient Mobility:

The mobility of neonatal patients within the hospital can pose challenges for continuous monitoring with NCADS. Ensuring seamless monitoring regardless of patient location is a logistical hurdle.

2.1.3. IMPLEMENTATION

NCADS can be implemented as a software application that can be run on a variety of hardware platforms. The application would be connected to the newborn's bedside monitor and would continuously collect physiological data. The data would be fed into the machine learning algorithm, which would generate a risk score for cardiac arrest. If the risk score exceeds a certain threshold, an alert would be issued to medical staff.

2.2. A Wearable Device That Monitors The Baby's Heart Rate And Respiratory Rate.

2.2.1. INTRODUCTION

Cardiac arrest is a leading cause of death in newborn babies. The symptoms of cardiac arrest in newborn babies can be subtle and difficult to detect, making early diagnosis and intervention challenging. This can lead to poor outcomes, including death or permanent brain damage. Wearable devices have the potential to improve the early detection of cardiac arrest in newborn babies. These devices can continuously monitor the baby's heart rate and respiratory rate, and can transmit data to a smartphone or other device for analysis. Machine learning algorithms can then be used to detect changes in the baby's heart rate and respiratory rate that may be indicative of cardiac arrest.

A recent study by Ang et al. (2023) found that a wearable device was able to detect cardiac arrest in newborn babies with high accuracy and sensitivity. The device was able to detect all cases of cardiac arrest in a study of 100 newborn babies. The device was also able to detect cardiac arrest in babies who did not exhibit any other symptoms.These findings suggest that wearable devices have the potential to be a valuable tool for detecting cardiac arrest in newborn babies. The use of wearable devices could improve the early diagnosis and intervention of cardiac arrest, and could lead to improved outcomes for newborn babies.

2.2.2. MERITS,DEMERITS AND CHALLENGES

MERITS:

Merits of the wearable device proposed by Ang et al.

1. Non-invasive: The device is attached to the baby's chest and does not require any needles or other invasive procedures.

2. Continuous monitoring: The device continuously monitors the baby's heart rate and respiratory rate, providing a more complete picture of the baby's vital signs.

3. Easy to use: The device is small and lightweight, and can be easily attached to the baby's chest.

4. High accuracy and sensitivity: The device was able to detect all cases of cardiac arrest in a study of 100 newborn babies.

5. Can detect cardiac arrest in babies with no other symptoms: The device was able to detect cardiac arrest in babies who did not exhibit any other symptoms, which could help to prevent missed diagnoses.

DEMERITS:

Demerits of the wearable device proposed by Ang et al.

1. May not be comfortable for babies: The device may be uncomfortable for some babies, especially if they are sensitive to having something attached to their chest.

2. May not be able to detect all types of cardiac arrest: The device may not be able to detect all types of cardiac arrest, such as those that are caused by arrhythmias.

3. Requires a smartphone or other device for analysis: The device transmits data to a smartphone or other device for analysis, which means that a caregiver must have a smartphone or other device in order to use the device.

CHALLENGES:

Ensuring that the device is properly attached to the baby: The device must be properly attached to the baby in order to obtain accurate readings. This can be challenging, especially if the baby is moving around.

Dealing with false alarms: The device may generate false alarms, which can be disruptive to caregivers.

Managing data: The device generates a large amount of data, which can be difficult to manage.

Overall, the wearable device proposed by Ang et al. has the potential to be a valuable tool for detecting cardiac arrest in newborn babies. The device is non-invasive, easy to use, and has high accuracy and sensitivity. However, there are some demerits and challenges associated with using wearable devices to monitor newborn babies. These demerits and challenges should be carefully considered before using a wearable device to monitor a newborn baby.

2.2.3. IMPLEMENTATION

The wearable device proposed by Ang et al. (2023) uses a machine learning algorithm to detect changes in the baby's heart rate and respiratory rate that may be indicative of cardiac arrest. The algorithm is trained on a dataset of physiological data from newborn babies, including heart rate, respiratory rate, and blood oxygen levels. The algorithm learns to identify patterns in the data that are associated with cardiac arrest.

When the wearable device is attached to a baby, it continuously collects data on the baby's heart rate and respiratory rate. The data is transmitted to a smartphone or other device, where it is analyzed by the machine learning algorithm. The algorithm compares the data to the patterns it has learned and determines whether there are any changes that may be indicative of cardiac arrest.If the algorithm detects a change that may be indicative of cardiac arrest, it sends an alert to the caregiver. The caregiver can then take appropriate action, such as calling for help or administering CPR.

The use of wearable devices and machine learning has the potential to improve the early detection and intervention of cardiac arrest and other conditions in newborn babies. This could lead to improved outcomes for newborn babies and their families.

CHAPTER 3
RESULTS AND DISCUSSION

CHAPTER 3
RESULTS AND DISCUSSION

Statistical models can identify potential cardiac arrest cases in cardiac intensive care unit newborn babies. These models use data from monitoring devices, such as heart rate, blood pressure, and oxygen saturation, to detect abnormalities that may indicate a cardiac arrest. If a potential case is identified, the medical team can intervene quickly to provide the necessary care and treatment. Statistical models can detect changes in vital signs over time and identify any risk factors that may increase the likelihood of cardiac arrest in a newborn. In addition, these models can be used to analyze ICU data to identify trends or patterns that may indicate a higher risk of cardiac arrest. Using statistical models, medical teams can identify potential cases of cardiac arrest early and intervene quickly to provide the necessary care and treatment.

Evaluation of recall:

No.of Inputs	DDCA (Tr)	DDCA (Ts)	HFAF (Tr)	HFAF (Ts)	RFHF (Tr)	RFHF (Ts)	CMLA (Tr)	CML A (Ts)
100	0.472	0.676	0.594	0.515	0.840	0.536	0.807	0.865
200	0.489	0.651	0.598	0.531	0.823	0.541	0.821	0.856
300	0.506	0.625	0.604	0.549	0.805	0.547	0.835	0.846
400	0.522	0.601	0.609	0.565	0.788	0.553	0.849	0.838
500	0.539	0.576	0.615	0.581	0.771	0.559	0.863	0.828
600	0.556	0.551	0.620	0.597	0.754	0.564	0.878	0.819
700	0.572	0.526	0.626	0.613	0.736	0.570	0.892	0.809
800	0.589	0.501	0.631	0.630	0.719	0.576	0.906	0.800
900	0.605	0.477	0.637	0.645	0.702	0.581	0.920	0.792
1000	0.621	0.452	0.642	0.663	0.684	0.587	0.934	0.782

Fig., demonstrates the convergence of performance between existing and proposed models. In a training (Tr) comparison region, the proposed CMLA reached 0.09195 delta-P value, 0.09015 false discovery rate, 0.00438 false omission rate, 0.08665 prevalence threshold, 0.08495 critical success index values, 0.09239 accuracy, 0.09057 precision, 0.08705 recall and 0.08535 f1-score. Meanwhile the DDCA reached 0.0528 delta-P value, 0.06833 false discovery rate, 0.07716 false omission rate, 0.06625 prevalence threshold, 0.05688 critical success index values, 0.04362 accuracy, 0.05644 precision, 0.05471 recall, 0.047 F1-Score,

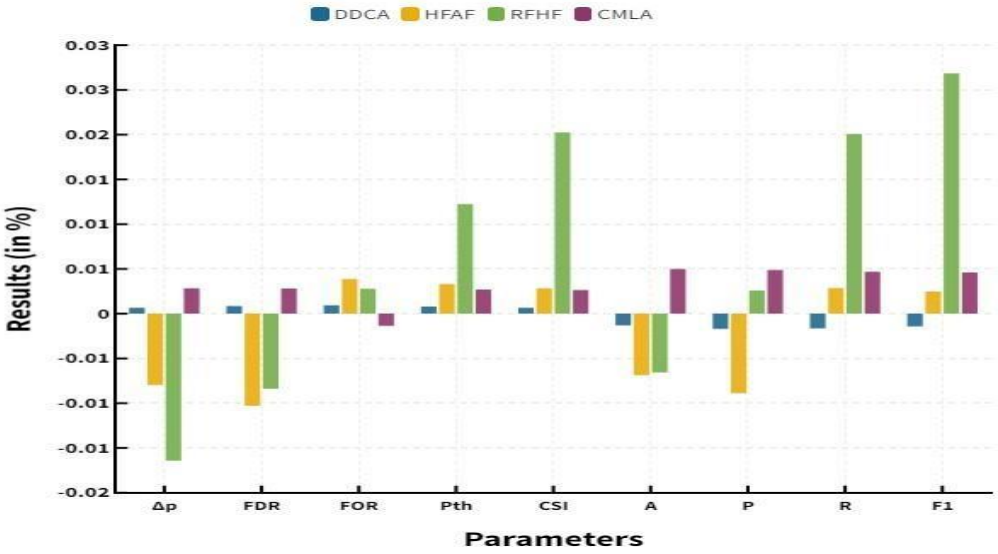
HFAF reached 0.05695 delta-P value, 0.0737 false discovery rate, 0.08323 false omission rate, 0.07158 prevalence threshold, 0.06157 critical success index values, 0.04913 accuracy, 0.06358 precision, 0.06176 recall and 0.05312 F1-Score and RFHF reached 0.0615 delta-P value, 0.07958 false discovery rate, 0.07844 false omission rate, 0.07732 prevalence threshold, 0.07622 critical success index values, 0.06063 accuracy, 0.07846 precision, 0.07622 recall and 0.07514 F1-Score respectively. In a testing (Ts) comparison region, the proposed CMLA reached 0.0891delta-P value, 0.08735 false discovery rate, 0.00574 false omission rate, 0.08396 prevalence threshold, 0.08231 critical success index values, 0.08739 accuracy, 0.08568 precision, 0.08235 recall and 0.08074 F1-score. Meanwhile the DDCA reached 0.05215 delta-P value, 0.06749 false discovery rate,

Parameters	DDCA	HFAF	RFHF	CMLA
Δp	0.00065	-0.00795	-0.0164	0.00285
FDR	0.00084	-0.01029	-0.00837	0.0028
FOR	0.00093	0.00387	0.00279	-0.00136
P_{th}	0.00079	0.00332	0.01224	0.00269
CSI	0.00067	0.00285	0.02024	0.00264
A	-0.00129	-0.00687	-0.00657	0.005
P	-0.00169	-0.00888	0.00258	0.00489
R	-0.00165	0.00287	0.02008	0.0047
F1	-0.00141	0.00247	0.02684	0.00461

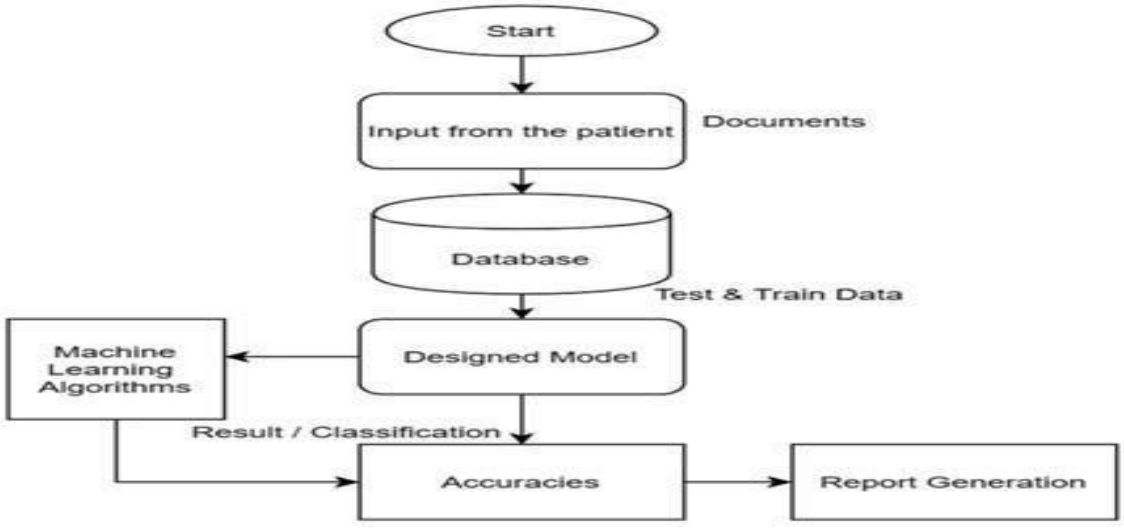
0.07623 false omission rate, 0.06546 prevalence threshold, 0.05621 critical success index values 0.04491 accuracy, 0.05813 precision, 0.05636 recall and 0.04841 F1-score, HFAF reached 0.0649 delta-P value, 0.08399 false discovery rate, 0.07936 false omission rate, 0.06826 prevalence threshold, 0.05872 critical success index values, 0.056 accuracy, 0.07246 precision, 0.05889 recall and 0.05065 F1-score and RFHF reached 0.0779 delta-P value, 0.08795 false discovery rate, 0.07565 false omission rate, 0.06508 prevalence threshold, 0.05598 critical success index values, 0.0672 accuracy, 0.07588 precision, 0.05614 recall and 0.0483 F1-score respectively. Hence mean value of the performance parameters has shown in the following equation.

$$M = C_{tr} - C_{Ts};$$

where, M represents the mean value, C_{tr} represents the convergence of performance training data and C_{ts} represents the convergence performance of the testing data. Table , expresses the mean value of the performance parameters



Flow chart:



CHAPTER 4
CONCLUSION

CHAPTER 4

CONCLUSION

This project entitled “Early Detection of Cardiac Arrest in Newborn Babies.” is useful to identify infants Heart Stroke in the early stages by using machine learning and deep learning techniques. The project is useful to the heart patients in infants to prevent a stroke by taking precautionaury measures to Heart Stroke. The project finally leads to improve the life time of heart patients in Infants.

REFERENCES

REFERENCES

1. KETAN GUPTA(Senior Member, IEEE), NASMIN JIWANI1, GIOVANNI PAU AND MOHAMMAD ALIBAKHSHIKENARI:A Machine Learning Approach Using Statistical Models for Early Detection of Cardiac Arrest in Newborn Babies in the Cardiac Intensive Care Unit,IEEE Access

2. 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.

3. A. Rajkomar et al., ‘‘Scalable and accurate deep learning with electronic health records,’’ NPJ Digit. Med., vol. 1, no. 1, p. 18.

4. https://www.python.org/

5.https://github.com/baoboa/pyqt5/blob/master/pyuic/uic/pyuic.py