CHAPTER1

INTRODUCTION

Miscarriage prediction systems have emerged as a crucial aspectofmaternalhealthcare,aimingtoidentifyandmitigatetheriskofmiscarriageduringpregnancy.Miscarriage, the spontaneous loss of a pregnancy before the 20th week, can be emotionally andphysicallychallengingforexpectantmothers.Developingtechnologiesthatpredictthelikelihood of miscarriage can provide valuableinsightsfor timely medical intervention andemotionalsupport.Inrecentyears,advancementsinsensortechnology,datascience,andpredictive modeling have paved the way for innovative approaches to miscarriage prediction.Wearablesensors,suchastemperature,pulse,andaccelerationsensors,enablecontinuousmonitoring of maternal health, offering a wealth of data. Integrating these sensors with mobiledevices and microcontrollers, like the ESP 32, allows for efficient data collection andprocessing.

Miscarriage, defined as the spontaneous loss of a pregnancy before the 20th week, is aprevalent and emotionally challenging event, representing the most common adverse outcomeduring pregnancy. Given its irreversible nature, the primary approach to addressing this issue isthrough prediction and prevention. The psychological impact of miscarriage on women and theirpartnersissignificant.Studiesindicatethataround50percentofpregnanciesmayendinmiscarriage, emphasizing the need for effective strategies. Well-established risk factors include ahistory of previous miscarriages, advanced maternal age, and infertility. In addition to medicalfactors, certain behaviors and social aspects, such as smoking, alcohol consumption, and caffeineintake,arerecognizedaspotentialcontributorstoincreasedmiscarriagerisk.However,it'simportant to note that the associations between behavioral factors and miscarriage risk, such assmoking and alcohol consumption, are not universally confirmed. Some studies suggest theseconnections within the context of mitigating factors like nausea, which paradoxically may reducethe risk of miscarriage. Therefore, understanding and addressing these multifaceted factors arecrucialfordevelopingeffectivestrategiestopredictandpreventmiscarriagesandsupportindividuals and couples facing this challenging experience.

Maintaining emotional wellbeing is crucial during pregnancy, as stress, especially whencombined with life events, increases the risk of miscarriage. Emotional responses to pregnancyloss include anxiety, shock, sadness, anger, blame, depression, and sleep disturbance. Regular,moderate exercise is encouraged for pregnant women, but extreme physical activity has beenlinked to a higher risk of miscarriage.Nutrition is another vital aspect, with a focus on safeeating practices. Pregnant women are particularly susceptible to food borne illnesses, especiallywhendiningout.Obesityisanindependentriskfactorformiscarriage,withratesrangingfrom1 7 to 27 percent, and it is associated with increased pregnancy complications. The question mayrevolve around leveraging reality mining, Big Data analytics, and machine learning algorithms toassist pregnant women in avoiding miscarriages. The goal is to capitalize on the accessibility ofmobiles and sensors for a Capturing daily data. Applying data mining techniques and big datapredictive analytics to this information aims to enhance the safety and health of pregnant women,offeringaproactiveapproach to minimizethe risk of miscarriage.

Figure1.1: Differenttypesofpregnancycomplications

CHAPTER2

LITERATURESURVEY

1. "Towardsasmarthealth:bigdataanalyticsandIoTforreal-timemiscarriageprediction",by H. Asri and Z. Jaririn Journalof big data, 2023.

The study utilizes sensor, mobile phone, and patient-generated data to predict miscarriages,employing IoT systems like Raspberry Pi and K-means clustering algorithms in DatabricksSpark. The system, validated through clustering techniques, provides doctors with proactiveintervention results via a mobile app and offers personalized advice to pregnant women based on15 real-time risk factors froma large dataset.The literature survey emphasizesthe significanceoftheirfindings,confirmingoptimalclusternumbersandwell-separatedclustersthroughclusteringvalidationmethods,withassociatedkeywordsincludingBigData, MiscarriagePrediction,Predictive Analytics, K-means, and Clustering.

2. "Bigdataanalyticsinhealthcare:casestudy-miscarriageprediction",by AsriH,Mousannif H, Moatassime H A and et.al, International Journal of Distributed Systems andTechnologies,October-December2019.

The study introduces a versatile disease prediction system that utilizes big data tools, machinelearning algorithms, and IoT for accurate outcomes. Specifically applied to real-time miscarriageprediction using the K-means centroid-based algorithm, the system demonstrates its adaptabilityand effectiveness by categorizing outcomes into three groups: Miscarriage, No Miscarriage, andProbableMiscarriage.

3. "Comprehensive miscarriage dataset for an early miscarriage prediction", by HibaAsri,HajarMousannif, HassanAl Moatassime, ElsevierJournals, 2018.

The study improves a miscarriage prediction model by expanding the dataset to include 15attributes, all directly related to real-time miscarriage risk factors. To enhance efficiency, theresearchers streamline data collection by exclusively using Raspberry Pi, eliminating ArduinoUNO. The refined clustering approach categorizes outcomes into three clusters, achieving anotable99%accuracyratevalidatedbytheSilhouettemethod,highlightingthemodels

Reliability and precision in predicting miscarriage outcomes and contributing to advancements inearlymiscarriageprediction.

4. "A risk-prediction nomogram for patients with second-trimester threatened miscarriageassociated with adverse outcomes", by Zheng Li, Ying-Dong He, Qian Chen, ResearchSquareJournals, November2020.

This paper collected information from the patients hospitalized with second-trimester threatenedmiscarriage and used the logistic regression analyzes to determine the most significant predictivefactors associated with miscarriage. The area under the receiver operating characteristic curvesand the Hosmer-Lemeshow test were utilized to verify the discrimination and calibration of thepredictionmodel,respectively.Thisstudydemonstratesthatgestationalweeks,C-reactiveprotein,vaginalbloodloss,prematureruptureofmembranes,anduterineadenomyosisoradeno myomawerethemostsignificantindependentriskfactorsofthesecond-trimesterthreatenedmiscarriageassociated withadverseoutcomes.

5. "Predictionofsubsequentmiscarriageriskinwomenwhopresentwithaviablepregnancy at the first early pregnancy scan", by Nicole STAMATOPOULOS, Chuan LU,IshwariCASIKAR,ShannonREID,MaxMONGELLI,NigelHARDYandGeorgeCONDOUS,AustralianandNew Zealand Journal of Obstetrics andGynaecology, 2015.

Inthispapertheydevelopedanewpredictionmodelwhichindicatesthelikelihoodofmiscarriage. In women who present with a viable IUP at the primary scan, advancing maternalage in the presence of clots PV increases the probability of subsequent miscarriage. Whereas, inwomen with a higher EHR in the presence of an increased GS volume/CRL ratio, the likelihoodof subsequent miscarriage is reduced. This new model outperforms the previously publishedmodel developed in ourunit.

6. "High and low BMI increase the risk of miscarriage after IVF/ICSI and FET", byZdravkaVeleva, AilaTiitinen, SirpaVilska, ChristelHyden-Granskog, CandidoToma,HannuMartikainen1andJuhaS.Tapanainen,AdvanceAccesspublicationonFebruary15, 2018.

Analysis was carried out on 3330 first pregnancy cycles, performed during the years 1999–2004,of which 2198 were fresh, 666 were spontaneous and 466 were hormonally substituted FETcycles. A categorical, a linear and a quadratic models of the effect of BMI on miscarriage werestudied by logistic regression. Factors related to patient characteristics, protocol and embryoparameterswerealsoexamined.MRwashigherinhormonallysubstitutedFET(23.0%),compared with the fresh cycles (13.8%) and spontaneous FET (11.4%, $P < 0.0001$). Multivariatelogistic regression revealed that the relationship between BMI and the risk of miscarriage is notlinear but quadratic (U-shaped) (P 5 0.01), indicating a higher risk of miscarriage in underweightand obese women. Hormonal substitution for FET wasalsoassociatedwitha 1.7-fold higherMR, compared with the fresh cycles (P 5 0.002, 95% confidence interval 1.2–2.3). Obese andunderweight women have an increased risk of miscarriage, and hormonally substituted FET isassociatedwith aneven higherMR.

7. "Physical Activity, Physical Exertion, and Miscarriage Risk in Women Textile Workersin Shanghai, China", by Eva Y. Wong, Roberta Ray, Dao L. Gao and et.al, AmericanJournalof Industrial Medicine, December2019.

A retrospective study in the Shanghai, China textile industry study collected women's self-reported reproductive history. Occupational physical activity assessment linked complete workhistory data to an industry-specific job-exposure matrix. Odds ratios (OR) and 95% confidenceintervals (CI) were estimated by multivariate logistic regression for the first pregnancy outcomeandutilized generalizedestimating equationsto considerall pregnanciesper woman.

8. "BestPracticeandResearchClinicalObstetricsandGynaecologyDiagnosingmiscarriage",byCeciliaBottomley,TomBourne,BestPractice&ResearchClinicalObstetricsandGynaecology, 2019.

This article provides the definitions, terminology, prevalence and aetiology of miscarriage with afocus on the clinical and ultrasound diagnosis. It also includes discussion of the demographic andultrasoundfeatures which may behelpful in the prediction ofmiscarriage.

9. "Role of maternal age and pregnancy history in risk of miscarriage: prospective

registerbasedstudy",MariaCMagnus,AllenJWilcox,Nils-HalvdanMorken,ClariceR Weinberg, Siri E Haberg, Centre for Fertility and Health, Norwegian Institute of Public aHealth,February 2019.

This article is about the population based data from Norway provide precise estimates of the riskof miscarriage related to maternal age, with the lowest risk at age 27. The risk of miscarriageincreasesasmuchasfourfoldafterthreeconsecutivepreviousmiscarriages,implyingconsi derablevariability in risk betweencouples.

10. "Obesity, fat distribution and infertility", by Renato Pasquali, Elsevier Journals, 2017.

Theinferenceisinbothsexes,obesitymayimpairfertility.Thisadverseeffectappearstobemainlyrelated todisordersofsexhormonesecretionand/ormetabolism,leadinginturntoaconditionofrelativehyperan drogenisminobesewomenandofhypotestosteronemiainobesemen.Thesehormonalalterationsmayal soplayanimportantroleinthepathophysiologyofdifferentobesityphenotypesandassociatedmetabolic andcardiovascularcomorbidities.Thesetopics,however,havenotbeenaddressedinthisshortreview.In terestedreaderscanthereforereferto recent review articles on this emerging topic.

11. "Ultrasonographic prediction of early miscarriage", by George I. Papaioannou, ArgyroSyngelaki, NereaMaiz, Jackie A. Ross, Kypros H. Nicolaides, Oxford Academic Journal,July 2021.

Embryonic crown-rump length (CRL), heart rate (HR), gestational sac diameter (GSD) and yolksacdiameter(YSD)werecomparedintwogroupsofwomenwithsingletonpregnanciesattending an early pregnancy unit. In the first group the initial scan demonstrated a live embryobut in a subsequent visit the scan showed a dead embryo, complete or incomplete miscarriage. Inthesecond group witha live embryotherewas subsequentlive birth ofanormal neonate.

12. "Ultrasoundpredictionofriskofspontaneousmiscarriageinliveembryosfromassisted conceptions", by S. Choong, L. Rombauts, A. Ugoni, S. Meagher, An internationalJournalod obestetrics andgynaecology, December2020.

Thispilotstudyaimedtodeterminethemostdiscriminatoryultrasound-basedmodelforpredictingspontaneousmiscarriageafterembryoniclifewasfirstdetectedinassistedcon ceptions.A methodfor estimating individualrisk ofmiscarriage was developed.

CHAPTER 3

OBJECTIVES

- To develop and implement Machine Learning Algorithms using Random Forest for miscarriage risk prediction.
- To analyze extensive pregnancy-related data such as Heart Rate, Temperature, β HCG, Thyroid, Number of Previous Miscarriage and various risk factors associated with it.
- To validate the effectiveness and efficiency of the developed system through used Predictive model and to reach greater accuracy of the outcome.

CHAPTER 4

METHODOLOGY

4.1 Block Diagram

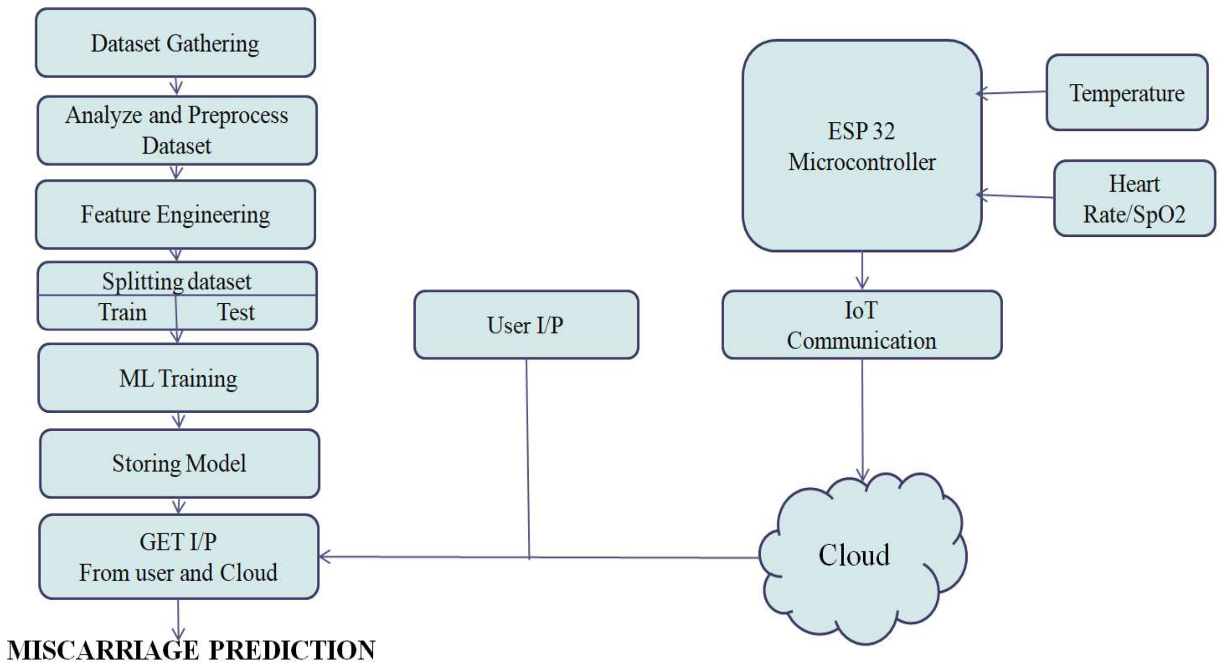

Figure 4.1: Block Diagram of Miscarriage Prediction System

1. Data Collection:

- Gather diverse datasets from various sources such as medical records, wearable IoT sensors, and environmental data.
- Utilize IoT sensors to collect physiological data such as heart rate, blood pressure, temperature, and activity levels.
- Ensure data collection is continuous and real-time to provide up-to-date insights into maternal health.
- Consider privacy and security measures to protect sensitive health information.

2. Data Preprocessing:

- Cleanse the collected data to remove inconsistencies, errors, and irrelevant information.
- Normalize the data to ensure consistency and comparability across different features.

- Handle missing values using techniques like imputation or deletion based on the nature of the data.
- Identify and handle outliers that may distort the analysis and modeling process.

3. Feature Engineering:

- Select relevant features that are likely to have a significant impact on predicting maternal health outcomes.
- Create new informative features by transforming or combining existing ones to capture additional insights.
- Use domain knowledge and statistical techniques to guide the feature selection and creation process.
- Employ dimensionality reduction techniques if dealing with a large number of features to improve model efficiency.

4. Model Development:

- Implement machine learning algorithms such as logistic regression, random forests, or deep learning models to predict maternal health outcomes.
- Tune hyperparameters to optimize model performance and generalization.
- Consider ensemble methods to combine the predictions of multiple models for improved accuracy.
- Ensure scalability and efficiency of the models, especially for real-time prediction on IoT devices.

5. Model Evaluation:

- Assess model performance using various evaluation metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC).
- Validate the model using techniques like cross-validation to ensure its generalization ability.
- Perform sensitivity analysis to understand the impact of different features on model predictions.
- Address any overfitting or underfitting issues by adjusting the model complexity or dataset size.

6. IoT Integration:

- Develop protocols for interfacing with IoT sensors to collect and transmit data securely.
- Ensure compatibility and seamless integration with different types of IoT devices and communication protocols.
- Handle data streaming efficiently to minimize latency and ensure real-time processing of physiological data.
- Implement data encryption and authentication mechanisms to protect the integrity and privacy of the transmitted data.

7. User Interface Design:

- Design an intuitive interface for healthcare professionals and expectant mothers to visualize predictions and monitor maternal health parameters.
- Incorporate interactive features such as alerts and notifications for abnormal health conditions or trends.
- Ensure accessibility and usability of the interface across different devices and platforms.
- Gather user feedback through iterative design processes to improve the interface's effectiveness and user experience.

8. System Integration and Testing:

- Integrate software components with IoT hardware systems to create a cohesive system architecture.
- Conduct thorough testing to validate the functionality, reliability, and performance of the integrated system.
- Perform unit testing, integration testing, and system testing to identify and fix any issues or bugs.
- Collaborate with domain experts and stakeholders to ensure the system meets the requirements and expectations.

9. Deployment and Validation:

- Deploy the system for real-world testing in clinical settings or home environments.
- Collaborate with healthcare professionals to validate the accuracy and effectiveness of the predictive models and monitoring system.

- Collect feedback from users to identify areas for improvement and iterate on the system design.
- Ensure regulatory compliance and ethical considerations are addressed throughout the deployment process.

4.2 HARDWARE COMPONENTS

ESP 32 MICROCONTROLLERS:

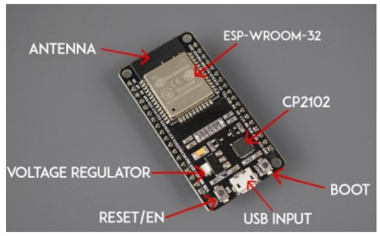

Figure 4.2.1: ESP32 Microcontroller

ESP32 is a dual-core microcontroller system-on-chip developed by Espressif Systems. It is a cost-effective and flexible solution that can be used for a wide range of applications such as IoT, robotics, smart home systems, and more. The ESP32 comes with built-in Wi-Fi and Bluetooth capabilities, making it easy to connect to wireless networks and devices. It also includes a range of sensors, such as an accelerometer, in-built GPS, and a range of digital and analog inputs and outputs. The ESP32 is powered by a 32-bit Arm Cortex-M4 processor and comes with 296 KB of flash memory and 51.

ONE WIRED TEMPERATURE SENSOR:

Figure 4.2.2: ONE WIRED TEMPERATURE SENSOR

A one-wired temperature sensor is a type of temperature sensor that uses a single connection wire to transmit temperature data. The specifications of such sensors typically include the measurement range, accuracy, resolution, temperature coefficient, hysteresis, and response time. It is important to choose the right specifications for the intended application to ensure accurate and reliable temperature readings. Some common temperature ranges for one-wired temperature sensors include -40°C to 125°C, 0°C to 100°C, and 20°C to 100°C.

MAX 30100SENSORS:

Figure 4.2.3: MAX 30100SENSORS

The MAX30102 is a heart rate sensor that measures heart rate variability (HRV) and blood oxygen saturation (SpO2) levels. It uses a non-invasive, wearable design that can be attached to the fingertip or earlobe. The sensor operates in the red and infrared wavelengths to measure blood flow and oxygenation. It is suitable for use in various applications, including fitness tracking, health monitoring, and medical research. The MAX30100 is compatible with a range of microcontrollers and can be easily integrated into wearable devices or other electronic systems.

GAS/ALCOHOLSENSOR:

Figure 4.2.4: GAS/ALCOHOL SENSOR

An alcohol sensor, also known as a MQ-3 sensor, is a semiconductor device that detects ethanol in the air. It is commonly used to detect alcohol concentration in driver's breath. The sensor is sensitive to alcohol, hydrogen, and carbon monoxide and gives out different signals in different concentrations. The MQ-3 sensor has a high sensitivity and fast response time. It provides an analog resistive output based on alcohol concentration.

4.3 SOFTWARE USED

ARDUINO IDE:

Figure 4.2.5: ARDUINO IDE

The Arduino Software (IDE) makes it easy to write code and upload it to the board offline. This software can be used with any Arduino board.

4.4 Algorithm of Software Code

1. Import Libraries: Import necessary libraries like pandas, numpy, matplotlib, seaborn, and scikit-learn modules for data manipulation, visualization, and machine learning algorithms.

2. Load Data: Read the dataset from a CSV file into a pandas DataFrame.

3. Data Exploration: Check the first few and last few rows of the dataset, its size, shape, columns, unique values in the target variable, data types, and visualize the correlation matrix using a heatmap.

4. Feature and Target Separation: Separate the features and the target variable from the dataset.

5. Train-Test Split: Split the dataset into training and testing sets using the `train_test_split` function from scikit-learn.

6. Model Training and Evaluation:
   - Decision Tree: Train a Decision Tree classifier, evaluate its accuracy, print classification report, perform cross-validation, and save the trained model using pickle.
   - Naive Bayes: Train a Gaussian Naive Bayes classifier, evaluate its accuracy, print classification report, perform cross-validation, and save the trained model using pickle.
   - Support Vector Machine (SVM): Train an SVM classifier with polynomial kernel, normalize the data, evaluate its accuracy, print classification report, perform cross-validation, and save the trained model using pickle.
   - Random Forest: Train a Random Forest classifier, evaluate its accuracy, print classification report, perform cross-validation, and save the trained model using pickle.

7. Accuracy Comparison: Visualize and compare the accuracies of different models using a bar plot.

8. Making Predictions:
   - Make predictions using the trained Random Forest model on sample data inputs and interpret the results

CHAPTER 5

RESULTS AND DISCUSSION

The methodology outlined encompasses a comprehensive approach to developing a predictive system for monitoring maternal health using IoT sensors. It begins with data collection, where diverse datasets and physiological data are gathered using IoT sensors such as Temperature sensor, MAX30100 sensor, Gas sensor etc, ensuring a rich source of information. Following this, the data undergoes preprocessing, which involves cleansing, normalizing, and handling missing values and outliers to ensure data quality and reliability. Feature engineering then comes into play, where relevant features are selected, and new informative ones are created to enhance the model's performance, ensuring that the predictive model has access to the most pertinent information.

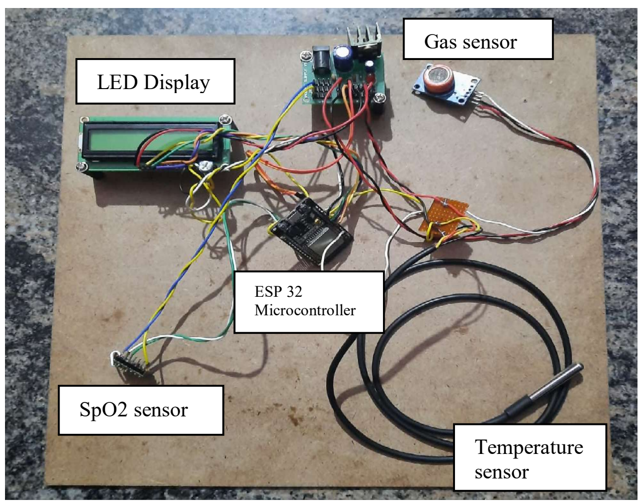

Figure 5.1: Hardware Connection

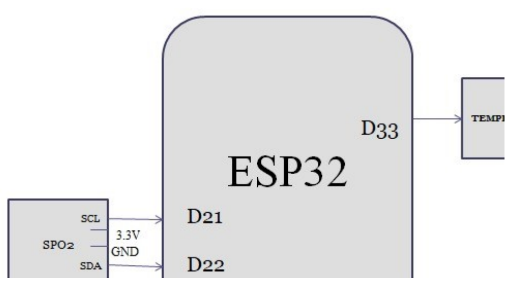

Figure 5.2: Hardware Circuit Diagram

Moving on to model development, various machine learning algorithms are implemented, and their performance is optimized to achieve the best results. Model evaluation is a crucial step, wherein the performance of the developed models is assessed using various metrics, and generalization is ensured through techniques like cross-validation, guaranteeing that the models can perform well on unseen data.

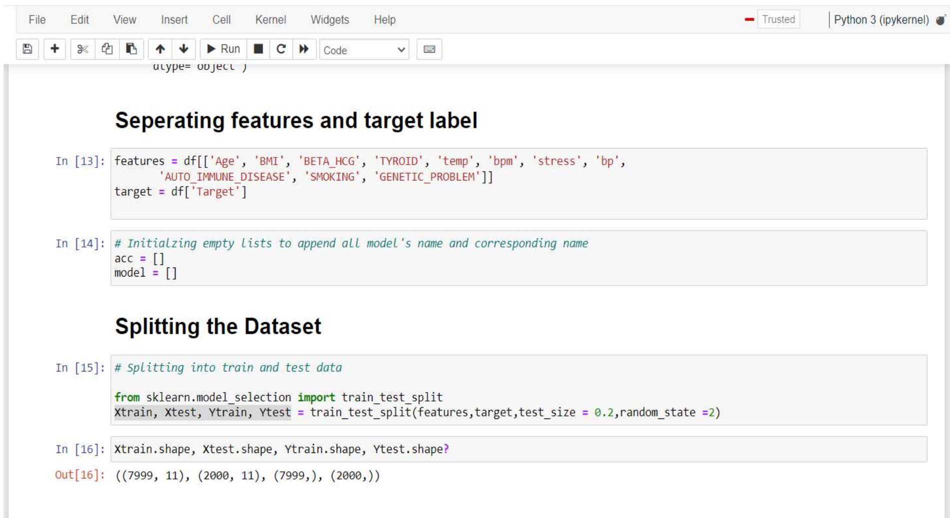

Figure 5.3: Software Code

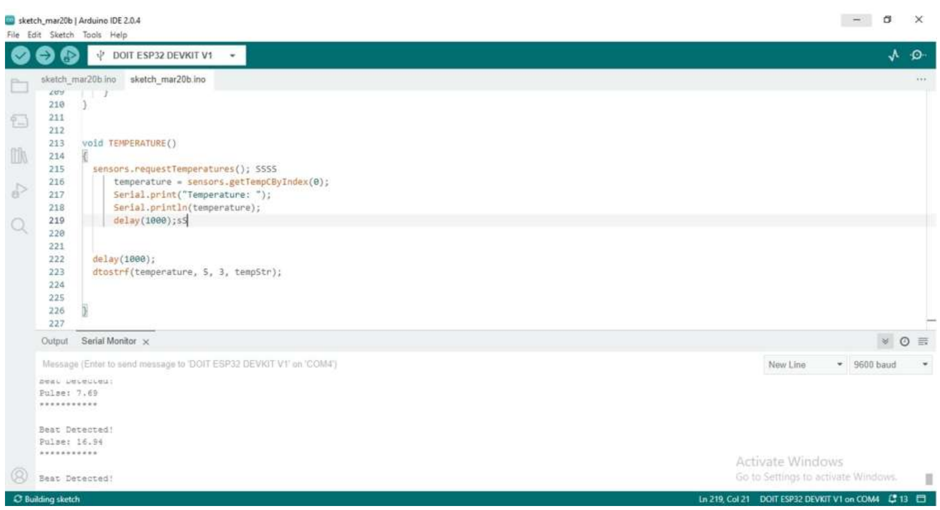

Figure 5.4: Arduino IDE Code

The integration of IoT is vital, and protocols are developed to interface with IoT sensors, ensuring seamless data streams integration with predictive models. User interface design plays a significant role in making the system accessible and user-friendly, as it involves designing an intuitive interface for visualizing predictions and monitoring maternal health parameters, thereby empowering users to interpret and act upon the insights provided by the system effectively.

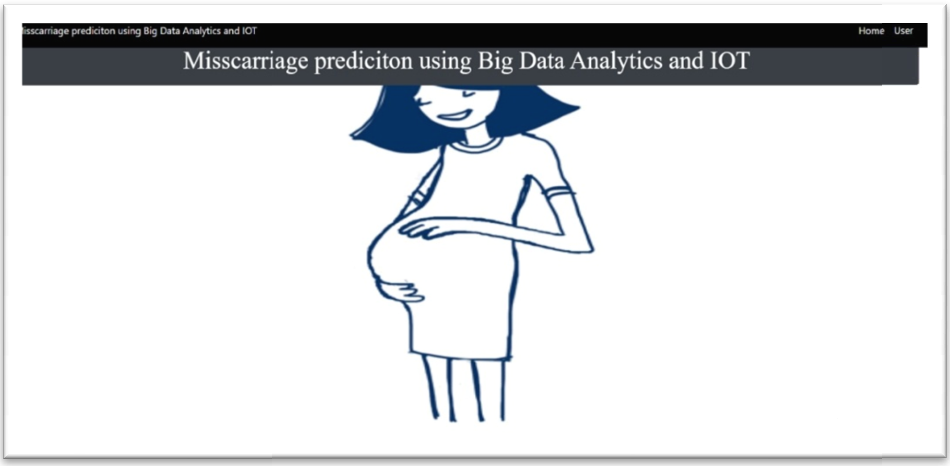

Figure 5.5: Web Page of the Miscarriage Prediction System

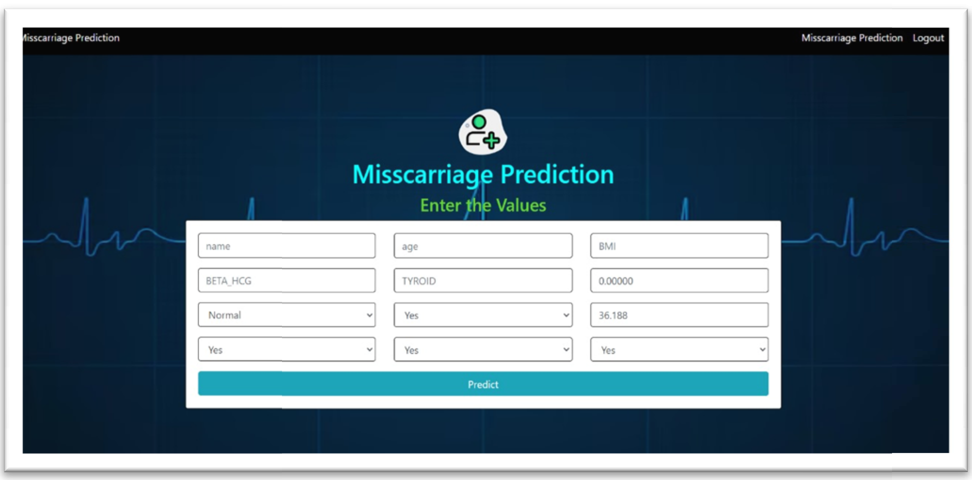

Figure 5.6: Patient Details Entry

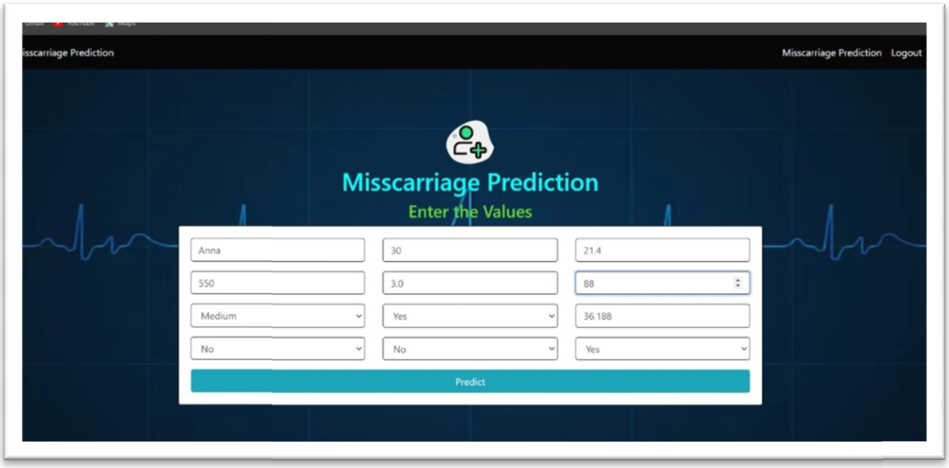

Figure 5.7: After the Patient’s Details Entry

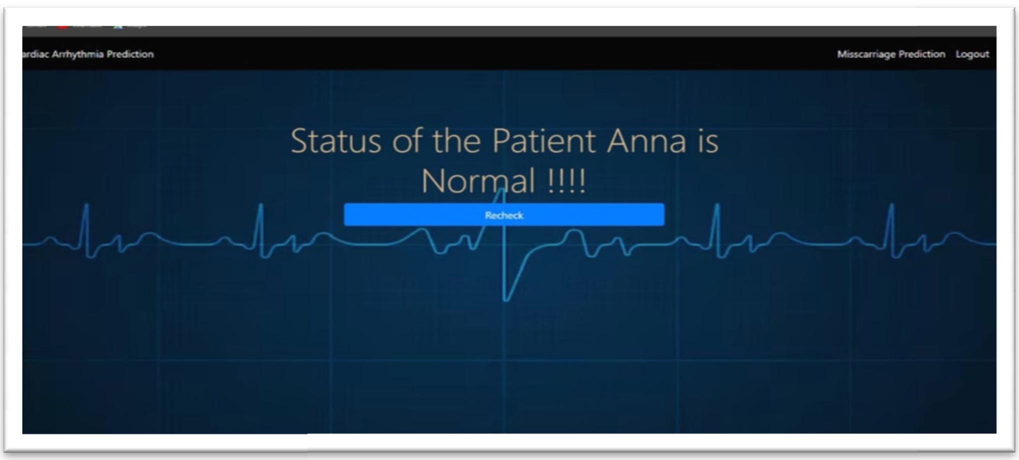

Figure 5.8: Result Obtained after Analysing the patient Data

System integration and testing are essential steps to ensure that all software components integrate seamlessly with IoT hardware and that the system functions as intended. Thorough testing is conducted to identify and address any potential issues or bugs before deployment. Finally, deployment and validation involve deploying the system for real-world testing, collaborating with healthcare professionals to gather feedback for improvement, and validating the system's effectiveness in monitoring maternal health. Overall, this result ensures a robust and effective predictive system for monitoring maternal health using IoT sensors, with careful consideration given to data quality, model performance, user interface design, and real-world applicability.

CHAPTER 6

CONCLUSION

Integrating IoT sensors with the predictive model presents a revolutionary approach to maternal health monitoring by offering real-time monitoring and analysis capabilities. By continuously collecting data from IoT sensors embedded in various devices, such as wearables or medical equipment, the system can provide insights into maternal health parameters, including heart rate, blood pressure, and fetal movements, among others. This continuous monitoring allows for early detection of potential complications, such as gestational diabetes or pre-eclampsia, by identifying subtle changes in physiological patterns that may indicate underlying health issues. Early detection is critical in maternal healthcare as it enables healthcare providers to intervene promptly, potentially preventing adverse outcomes for both the mother and the baby. By leveraging IoT sensors, the predictive model can provide timely alerts and recommendations based on the analyzed data, empowering healthcare professionals to take proactive measures to ensure the well-being of pregnant women.

Collaborating with healthcare professionals and gathering feedback during deployment is essential for ensuring the continuous enhancement and adaptation of the predictive model to meet the evolving needs of maternal healthcare. Healthcare professionals bring invaluable expertise and insights into the nuances of maternal health, including clinical guidelines, best practices, and patient preferences. By actively involving them in the deployment process, the predictive model can benefit from their input, such as refining the model's algorithms, incorporating domain-specific knowledge, and customizing the system to suit different healthcare settings and patient populations.

Additionally, gathering feedback from healthcare professionals allows for the identification of any usability issues or areas for improvement, ensuring that the predictive model remains relevant and effective in clinical practice. This collaborative approach fosters a partnership between technology developers and healthcare practitioners, driving continuous innovation and improvement in maternal healthcare delivery.

To assess the efficacy and efficiency of the implemented predictive model and enhance outcome accuracy, rigorous validation procedures are employed, ensuring robust evaluation of the system's performance. Validation is a critical step in the development of predictive models as it verifies whether the model can reliably predict maternal health outcomes based on the available data. Rigorous validation procedures involve testing the predictive model on diverse datasets, including both training and testing data, to assess its generalizability and ability to perform well on unseen data. Various performance metrics, such as sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC), are used to evaluate the model's accuracy and discriminatory power.

Additionally, validation procedures may include comparing the predictive model's performance against existing clinical standards or expert consensus to assess its clinical utility and relevance. By rigorously validating the predictive model, stakeholders can have confidence in its ability to assist healthcare professionals in making informed decisions about maternal health management, ultimately improving outcomes for pregnant women and their babies.

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APPENDIX

List of Abbreviations

- IUP – Intra Uterine Pregnancy
- EHR – Electronic Health Record
- CRL – Crown-Rump Length
- GS – Gestational Sac
- FET – Frozen Embryo Transfer
- GSD – Gestational Diabetes
- IOT- Internet of Things

Workflow of the Code

1. Libraries are imported for data manipulation, visualization, and machine learning.

2. The dataset is loaded and basic exploratory analysis is performed.

3. Features and target labels are separated.

4. The dataset is split into training and testing sets.

5. Decision Tree, Naive Bayes, SVM, and Random Forest classifiers are trained and evaluated.

6. Cross-validation scores are calculated for each classifier.

7. Trained models are saved using Pickle for future use.

8. The accuracy of each model is compared and visualized using a bar plot.

9. A prediction example is demonstrated using the trained Random Forest model.

Specifications of Hardware Components:

ESP 32 Microcontroller

- Dual-core Tensilica LX6 microprocessors

- Clock frequency up to 240 MHz

- 520 KB SRAM

- Integrated 802.11 b/g/n Wi-Fi

- Bluetooth v4.2 BR/EDR and BLE connectivity

- Integrated TCP/IP protocol stack

- Ultra-low power consumption

- Integrated Hall sensor

- 12-bit SAR ADC with up to 18 channels

- SPI, I2C, I2S, UART, ADC interfaces

- Hardware security features (Secure boot, Flash encryption, Digital signature, etc.)

- Operating voltage range: 2.2V to 3.6V

One Wired Temperature Sensor

- Sensor Type: Wired temperature sensor

- Measurement Range: -40°C to 125°C

- Accuracy: ±0.5°C

- Resolution: 0.1°C

- Connection Interface: Wired (e.g., USB, RS-485, or Ethernet)

- Power Supply: Typically powered through the connection interface (e.g., USB or Ethernet)

MAX 30100 Sensor

- The MAX30100 sensor is a compact, integrated pulse oximeter and heart-rate sensor module.

- It features low power consumption, making it suitable for battery-operated devices.

- The sensor operates on a supply voltage ranging from 1.8V to 5.5V.

- It utilizes two LED drivers for emitting red and infrared light for pulse oximetry measurements.

- The MAX30100 sensor includes an integrated photo detector and signal conditioning circuitry for accurate pulse oximetry and heart-rate measurements.

- It communicates with the microcontroller through an I2C interface.

- The sensor offers high-resolution measurements with a 16-bit ADC.

- It has programmable sample rates and LED current levels to optimize power consumption and measurement accuracy.

- The MAX30100 sensor provides a digital output of both pulse oximetry and heart-rate data.

- It is housed in a small, surface-mount package, making it suitable for integration into wearable devices and medical equipment.

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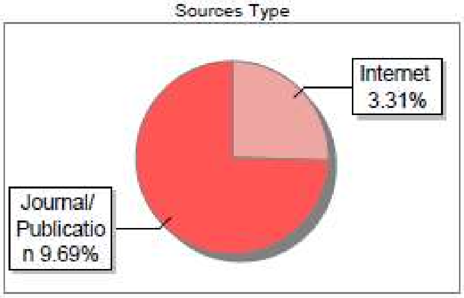

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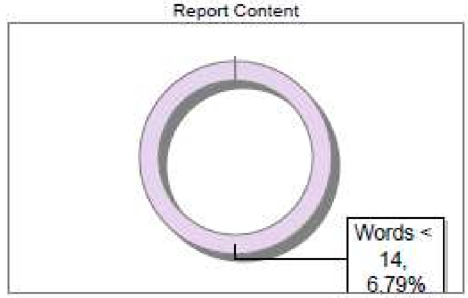

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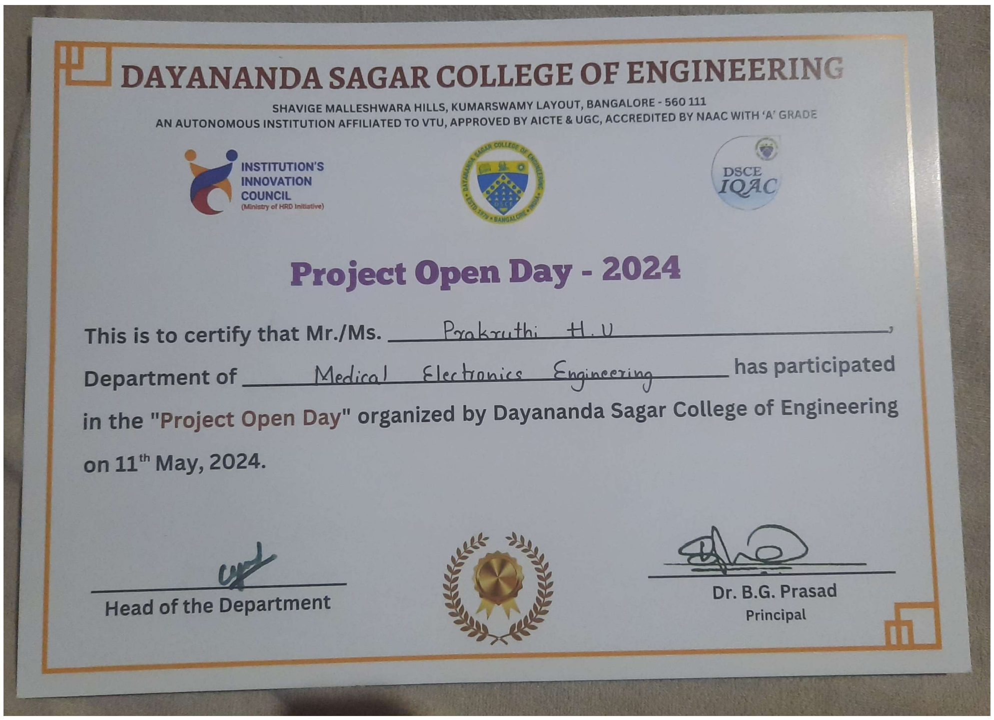
CERTIFICATES AND PUBLICATIONS

A Certificate of Participation for Presenting a Poster and Project on the project Titled "Miscarriage Prediction Using Big Data Analytics and IoT", during Project Open Day conducted at Dayananda Sagar College og Engineering, Bangalore on 11th May, 2024



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