PREGNANCY MORTALITY PREDICTION USING MACHINE LEARNING

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ABSTRACT

Using our web-based tool, users may quickly get in touch with doctors to schedule consultations. The user enter their login details if exist or create new I'd if they are new user. They also get to enter if they are doctor or patient. The user has to enter their health related query based on that assistant gives the appropriate answer and suggest doctors. Experimental result shows that: Compared with traditional methods ,the proposed method is more accurate and faster also patient can get service anywhere and anytime. This application of AI can be adopted to increase patient engagement and improve their self-management skills to prevent chronic situations from getting worse. Moreover, the virtual assistant would be available 24/7, which means it can answer your questions and provide answers in real-time. It will increase the interaction between humans and machines with the help of different technologies, vast dialogue ,conversational knowledge based, general knowledge based.

1.INTRODUCTION

The stage of gestation or pregnancy of a girl is a section that would convey headaches for each the mom and the fetus. The fetal fitness can be suffering from the maternal adaptive changes for the duration of this period, further to via the medical facts of the mother and maternal/familial attributes. As a result, the announcement of fetal fitness and antenatal care at some point of this segment is crucially essential for maternal and fetal fitness.

Clinicians (mainly gynaecologists) choice to tell the mother and father approximately properly-being in their unborn toddlers and that they do, based on already studied cases and beyond memories. Therefore, defining the viable familial (predominantly maternal) medical information that is susceptible to steer fetal health may want to assist antenatal maternal care.

But, affected person-orientated health care won't be completely finished because of a few problems, i.e. Insufficient variety of hospitals close to the affected individual’s whereabouts (villages outlying in the rural regions) or overcrowded hospitals in towns. In turkey, m-fitness packages that provide get entry to health services and health statistics thru cell services are hooked up on a country wide degree, in which cellular-cellular subscriptions cover 96.02% and net customers cowl fifty 3.74% of the population of turkey. These establishments and cell offerings display the supportive and vital function m-health performs in insufficient conditions.

We want to create a prediction tool with 32 helpful e-fitness programs that will be available for rent to all expectant mothers and fitness professionals.Using the suggested e-health software, expectant mothers can obtain their fitness celebrity and clinical records factors as inputs, recommend physical activities for them to engage in during pregnancy, and eventually educate the patients and practitioners about the potential risks of fetal abnormalities. The stage of pregnancy a girl is in can be a contributing factor to potential complications for both the mother and the fetus.

Maternal mortality—defined as the death of a woman during pregnancy, childbirth, or shortly after delivery due to complications related to pregnancy—continues to pose a major global health challenge, especially in developing regions. Despite progress in maternal healthcare, many women still lose their lives to conditions that are often preventable with timely and appropriate care.A major barrier to reducing maternal deaths is the difficulty in accurately identifying high-risk pregnancies before complications arise. Traditional methods of risk assessment, which rely heavily on clinical experience and basic statistical tools, may fall short in capturing the wide range of variables—medical, social, demographic—that influence maternal outcomes.Machine learning (ML), a branch of artificial intelligence, presents a promising solution to this problem. By analyzing large volumes of healthcare data, ML models can detect patterns and relationships that may not be obvious through conventional means. These models can incorporate a wide range of inputs—including patient history, clinical signs, test results, and pregnancy-specific indicators—to estimate the risk of maternal mortality or severe complications with high accuracy.

Integrating machine learning into maternal care can help healthcare professionals recognize at-risk individuals earlier, enhance clinical decision-making, and ensure timely intervention. This is particularly beneficial in settings with limited medical resources, where early detection can make a critical difference. Furthermore, predictive models can support national and global efforts to reduce maternal mortality in line with Sustainable Development Goals (SDGs).This study focuses on the use of machine learning algorithms to forecast pregnancy-related mortality, aiming to contribute to the development of intelligent health systems that improve safety and outcomes for expectant mothers.

2. Literature Survey

Sulaiman Salim(2024) offered In this study, various machine learning algorithms were utilized to predict maternal risk levels, using real-world data from Oman for the first time. Among the models tested, the Random Forest (RF) classifier demonstrated the highest performance in addressing this classification task. Generating accurate predictions of maternal risk can assist healthcare professionals in developing timely intervention strategies, ultimately contributing to the reduction of maternal mortality.Maternal mortality remains one of the most critical public health issues globally. Although Oman has reported the highest maternal mortality ratio (MMR) among the Gulf Cooperation Council (GCC) countries, there has been no prior research focused on developing predictive models for assessing maternal risk levels. Accurate prediction of these risks could support healthcare professionals in implementing timely interventions to prevent maternal deaths. This study applied ten widely recommended machine learning (ML) algorithms to predict maternal risk levels. ML techniques are increasingly advocated for the early identification of high-risk groups and the timely detection of adverse outcomes, such as complications and fatalities. Despite their potential, studies exploring ML applications in this area are limited—particularly within the Omani healthcare context. To the best of our knowledge, this is the first study to apply ML approaches to predict maternal risk and determine key contributing factors using nationwide maternal mortality data from oman.

Lavanya Vasudevan(2025)offered More than 80% of maternal deaths in the United States are considered preventable. Leveraging machine learning (ML) models developed from electronic medical records (EMRs) presents a promising strategy for predicting the risk of adverse maternal outcomes and supporting timely interventions to reduce maternal mortality. However, existing reviews of ML applications in this area often have a narrow focus—either concentrating on specific maternal complications, addressing topics unrelated to risk prediction, or lacking a comprehensive overview of the entire process from model development to integration into clinical practice. Important recommendations for future research and practice involve placing greater emphasis on investigating maternal morbidity and mortality during the postpartum period, enhancing study transparency and reproducibility by applying standardized reporting guidelines, and increasing initiatives to integrate machine learning models into clinical settings.

Issac Neha Margret(2017) offered Maternal mortality remains a significant global public health issue, representing a high number of preventable deaths related to pregnancy and childbirth each year. This study explores the potential of machine learning (ML) to help reduce maternal mortality. By utilizing historical maternal health data, ML techniques are employed to build predictive models, support early detection of complications, and optimize the distribution of healthcare resources. These technologies can uncover risk factors, track vital signs, and enhance access to medical services, enabling more precise interventions and improved care delivery. The study also discusses challenges such as data availability and the complexity of interpreting ML models, while underscoring the importance of ethical and equitable implementation. Ultimately, this research highlights the promise of ML in lowering maternal mortality and the urgent need for its integration into healthcare systems globally.

Alaa O. Khadidos(2024) recomanded Maternal health complications can arise from various conditions experienced during pregnancy, including hypertension, abnormal blood glucose levels, depression, and anxiety. These issues can significantly increase the risk of adverse pregnancy outcomes. Timely identification and monitoring of such risk factors are crucial in minimizing complications. This study focuses on leveraging real-world data to identify and predict Maternal Health Risk (MHR) factors. To achieve this, a novel framework called Quad-Ensemble Machine Learning for Maternal Health Risk Classification (QEML-MHRC) was designed and implemented.

The methodology employed multiple machine learning models, which were then combined using four ensemble techniques to enhance predictive accuracy. Data was gathered from several maternity clinics and hospitals, and subjected to nineteen different training and testing scenarios. Exploratory data analysis revealed that key predictors of maternal risk include elevated blood pressure, hypotension, and high blood sugar levels. This research introduces an innovative method for addressing critical risk factors affecting maternal health, with a focus on differentiating between high, medium, and low-risk categories using class-specific performance analysis. All predictive models showed strong performance in estimating pregnancy risk levels. Notably, the high-risk ("HR") category demonstrated the highest predictive accuracy, with a correct classification rate of 90%. Among all models tested, Gradient Boosted Trees (GBT) combined with ensemble stacking achieved the highest performance, with an overall evaluation score of 0.86 across all risk classes. A key strength of this framework lies in its ability to assess model performance based on individual class distributions, enhancing its reliability.This predictive approach offers valuable support to healthcare providers in assessing maternal health risks, thereby aiding in the prevention of complications and saving lives through early detection and intervention. The outcomes of this study also have the potential to improve public understanding and awareness of maternal health challenges.

Avnish Malde(2025) Maternal mortality continues to be a major global health concern, particularly in low- and middle-income countries (LMICs), where, according to the World Health Organization, 94% of maternal deaths occur. In 2020, the maternal mortality rate in LMICs was recorded at 430 per 100,000 live births, significantly higher than the 13 per 100,000 observed in high-income nations. Despite this disparity, limited research has explored the effectiveness of using minimal or sparse data—such as vital signs—for predicting maternal health risks. This study aims to fill that gap by assessing how well vital sign information can be used in machine learning (ML) models to predict maternal risk levels. Using a dataset of 1,014 pregnant women from rural Bangladesh, the study applied various ML algorithms to predict maternal health outcomes based on inputs like age, blood pressure, temperature, heart rate, and blood glucose levels. Model performance was evaluated using three sampling methods: regular, random, and stratified sampling. A novel aspect of this work is the development of a stacking ensemble ML model that incorporates stratified sampling—an approach not previously applied in the context of maternal health risk prediction.The ensemble model using stratified sampling achieved the highest accuracy rate of 87.2%, outperforming other models such as CatBoost (84.7%), XGBoost (84.2%), Random Forest (81.3%), and Decision Trees (80.3%) when stratified sampling was not used. The findings suggest that it is feasible to use limited health data to accurately predict maternal health risks through machine learning. By concentrating on data from under-resourced settings, this study demonstrates that ML offers a practical and scalable solution to enhance prenatal care and reduce maternal mortality in LMICs.

Katerina D. Tzimourta(2025) offered Maternal health risks continue to pose significant challenges globally, contributing substantially to both maternal and infant morbidity and mortality, particularly among vulnerable populations. Recent advancements in artificial intelligence and machine learning have shown great potential for enabling early detection and effective management of these risks. This study aims to classify maternal health risk levels—high, medium, and low—using machine learning techniques based on physiological data.

Materials and Methods: The dataset employed includes 1,014 records, each with seven features: Age, Systolic Blood Pressure (SystolicBP), Diastolic Blood Pressure (DiastolicBP), Blood Sugar (BS), Body Temperature (BodyTemp), Heart Rate, and Risk Level. After preprocessing, six different classifiers were trained and evaluated using 10-fold cross-validation. The performance of these models was assessed and compared using metrics such as Accuracy, Precision, and True Positive Rate. Random Forest demonstrated the best overall performance, achieving the highest scores in Accuracy (88.03%), True Positive Rate (88%), and Precision (88.10%), highlighting its effectiveness in classifying maternal health risks. Among all risk categories, the mid-risk group proved to be the most difficult for the models to classify accurately, reflected in lower Recall and Precision values. This suggests that class imbalance remains a significant challenge affecting model performance.

In conclusion, machine learning algorithms show great promise for enhancing the prediction of maternal health risks. These results emphasize the important role that machine learning can play in advancing maternal healthcare by enabling more personalized and data-driven decision-making.

Nora El-Rashidy(2022) offered Gestational diabetes mellitus (GDM) is a common pregnancy-related complication that poses serious risks to both the mother and the fetus. Typically diagnosed between the 22nd and 26th weeks of gestation, early detection is crucial as it can significantly reduce associated health risks. Continuous monitoring of a pregnant woman's vital signs plays a key role in identifying potential health deteriorations throughout pregnancy.This study introduces a novel and comprehensive monitoring framework specifically designed for pregnant women. The proposed Data Replacement and Prediction Framework is structured into three distinct layers: (i) the Internet of Things (IoT) Layer, (ii) the Fog Layer, and (iii) the Cloud Layer. In the IoT layer, invasive and non-invasive sensors are used to collect real-time physiological data from pregnant women. This data is then sent to fog computing nodes for intermediate processing before being stored in the cloud layer for long-term analysis and access.

Annemarie Hennessy(2024) recomanded The potential of machine learning (ML) in advancing maternal health—particularly in predicting conditions like preeclampsia—can only be fully realized with access to high-quality clinical data, inclusion of diverse and representative populations, comparative studies across different healthcare systems and care models, and the adoption of a data-driven culture that emphasizes the real-time use of clinical information and outcomes.This review aims to present an overview of the terminology and early findings related to the use of ML in pregnancy care, with a specific focus on preeclampsia. It encourages healthcare professionals from all disciplines to become familiar with the fundamentals of Machine Learning (ML) and Artificial Intelligence (AI), as understanding these technologies is essential to leveraging their potential in improving maternal and neonatal health outcomes.The review introduces key definitions and concepts of ML relevant to clinicians working in the area of preeclampsia and discusses how acquiring foundational AI knowledge can open new possibilities for clinical practice. Additionally, it emphasizes the importance of clearly defining the risks and outcomes being targeted in ML models to ensure clinical relevance and practical utility.

Ayleen Bertini(2022) offered Advancing research in this field remains essential, particularly in developing machine learning solutions with broad, multicenter clinical relevance to help minimize perinatal complications. This systematic review makes a valuable contribution to the growing body of literature on artificial intelligence in the context of women's health.A total of 31 studies were included after applying the defined inclusion and exclusion criteria. The most commonly used features for predicting perinatal complications were electronic medical records (48%), followed by medical imaging data (29%), and biological markers (19%). A smaller portion (4%) relied on other data sources, such as sensor readings and fetal heart rate measurements. Among the perinatal complications explored, pre-eclampsia and premature birth were the most frequently studied.Across the 31 studies, sixteen different complications were targeted for prediction. The Area Under the Curve (AUC) was the most frequently reported performance metric. Notably, the highest-performing machine learning models included a Support Vector Machine (SVM) used for predicting preterm birth from medical images, which achieved an accuracy of 95.7%, and an XGBoost model for forecasting neonatal mortality, which reached an accuracy of 99.7%

3 Methodology

High-level design refers to the primary components that form the proposed solution and offers an overview of the system's intended functionality. Very little implementation-related details should be included. This provides further details so the user can comprehend the reasoning.

3.1 Design consideration*s*

The system's behavior in boundary contexts and the appropriate course of action in case of an abnormal situation are briefed in the design consideration. Design considerations include methods such as data collection and preprocessing, as well as classification and prediction techniques. These considerations aim to guide designers in applying universally accessible design principles and standards to structures and facilities. Additionally, they can be utilized to pinpoint obstacles in current systems.

The proposed system has the following steps for Cervical Nodule Detection are

1. Image Pre-Processing

To train the network and make accurate predictions on new data, images must match the required input size of the network. If the image dimensions need adjustment, you can resize or crop them accordingly to fit the network's input specifications. By using randomized augmentation on data, we may efficiently expand the quantity of training data. Additionally, augmentation makes it possible to train networks to be resistant to picture data distortions.

2. Segmentation

Image segmentation is the task of clustering parts of an image together that belong to the same object class. This process is also called pixel-level classification. In other words, it involves partitioning images (or video frames) into multiple segments or objects.

3.Extraction of Features

Raw data is converted into numerical values through feature extractionformats that are easier to analyze and interpret, while preserving the key information from the original dataset. This process usually leads to better performance compared to using machine learning algorithms on unprocessed data.

4. Classification

Using training data, the classification algorithm—a Supervised Learning technique—identifies the category of fresh observations. A program learns from the provided dataset or observations in classification.

3.2 Architecture of the System

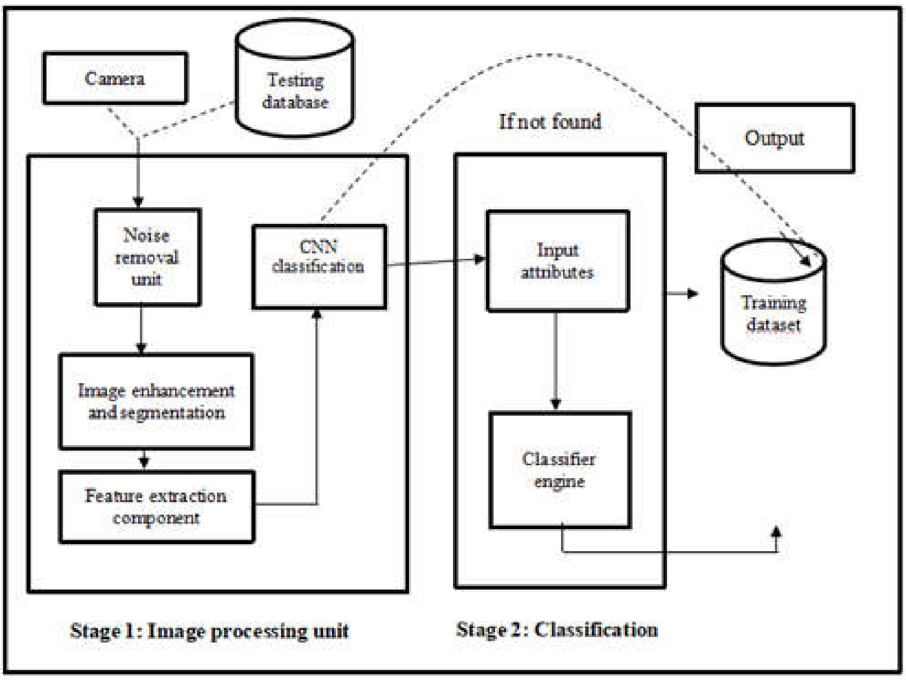


Figure 3.1 shows the architecture design for the categorization and image processing units

The framework can be thoroughly divided into the important stages listed below:

1.Acquisition of image

Images are taken with a lens or by secretly deleting something from the contraction. No matter the source, the data image's transparency and prudence are vital. This requires a fantastic image.

2. Image pre-processing

Since it hides hair and bone and could confound the evaluation, the photo is normalized in this procedure by removing the noise. Likewise, images used for informational purposes might not have the correct dimensions needed for a specific model or visualization, so resizing them to the proper size becomes necessary.

3. Aspect of data storage to maintain informational pictures for training and testing Data sets must be prepared if controlled learning is to take place, as it does in this instance. The sample database consists of images collected during the image acquisition processThe total count of imagesrequired for a specific task is steadily growing. Often abbreviated as CNNs, convolutional neural networksor convnets, are algorithms that can process and even learn from massive image datasets.

4. Classifying the type of cervical disease using a diagnostic model

The classifier serves as the final layer of the system, delivering the probability associated with each outcome. The project primarily consists of two key modules: the classification unit and the image processing unit. The image processing component enhances image quality by reducing noise and disturbances. After extracting the relevant image features to assess potential cervical infection, the cervical region and the image are segmented to isolate the cervical area for further analysis.

- **Noise reduction unit:**

Noise occurs continuously during the acquisition, coding, transmission, and processing of digital images. The traditional approach of filtering image data is used by nearly all image processing systems. Filters are used for this. They minimize noise in the image while preserving important details.

- **Segmentation and image improvement component:**

It centers the affected region within the scanned image and separates it from the surrounding areas by enhancing the region and dividing it into distinct segments.

- **Part of feature extraction:**

The extraction of key highlights represents a major advancement in tasks centered around collective or group-based concerns. The foundation for both planning and screening is appearance. Important visual data that will be utilized to diagnose the illness is contained in this feature.

- **Cervical disease identification unit:**

The findings strongly imply that a person possesses fetal info, regardless of how dangerous or considerate the fetal health may be.

- **Input Attributes:**

As an homage to Part II, the classifier part, all significant features, such as asymmetry, edge, concealment, distance, progression, etc., that were eliminated from the picture are now displayed.

3.3 Using a use case diagram created to illustratespecification:

A collection of scenarios that explain how a source and a destination interact is called a use case. A use case modelillustrates the connections between participants and use scenarios. Use cases and actors are the two primary parts a diagram representing use cases. In the Unified Modeling Language (UML), a diagram representing use cases is a specific type of behavioral diagram that is developed and described through a use-case analysis.The user can gather the data and enter it into the system, as seen in Figure 4.2. Here, the system is viewed as an actor that has the ability to store data for model testing and training. The CNN receives the training and test data for additional classification. Data classification is carried out via the various CNN layers. Following classification, a cervical nodule was found.

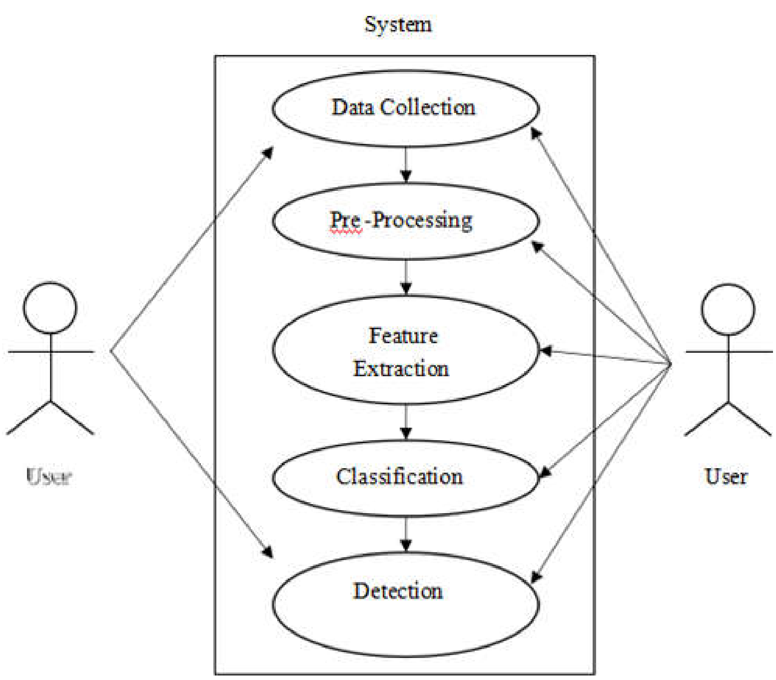


Fig 3.2 Use Case Diagram for Fetal Health Detection System

3.4 CNN Algorithm Explanation

Yann LeCun's development of the Convolutional Neural Network (CNN) in 1994 played a pivotal role in revitalizing interest in artificial intelligence and deep learning. Since then, the field has seen remarkable advancements. The first neural network model, LeNet-5, achieved a modest validation accuracy of just 42%. Today, CNNs are widely adopted by major technology companies to enhance performance and efficiency. In the context of mulberry leaf disease detection, CNNs play a crucial role. However, before exploring the functionality and operation of CNNs, it is important to first understand how the human brain is capable of recognizing objects despite variations in their appearanceWhile it's tempting to think of the brain as a basic "IF-THEN" system—and it does share some similarities—it possesses a powerful capability that sets it apart from typical algorithms: self-learning. Although no algorithm can fully replicate the human brain, some can come remarkably close in performance. The brain consists of intricate layers of neurons, each contributing specific information about an object. These neurons work together to extract the object's features and store them in our memory.A basic CNN is employed to analyze an image for identifying diseases affecting leaves. The following requirements must be met by the data training in our CNN model:

1.The dataset has no missing values.

2.The dataset must be clearly separated into training and testing sets. Neither the training nor the testing sets should include any extraneous data outside of our model domain. For example, if the dataset consists of images, all of the images must be the same size. An anomalous distribution of image sizes within the dataset can reduce the neural network's effectiveness.

3.To greatly reduce the model's execution time, images should be converted to black and white before being input into the convolutional layer. This is because processing images in RGB format requires a 3-D NumPy matrix.

4.Before putting the database into the neural network, any corrupted or blurry photos should also be removed. Having covered the data pre-processing steps, let's now dive into the functioning of a convolutional neural network.

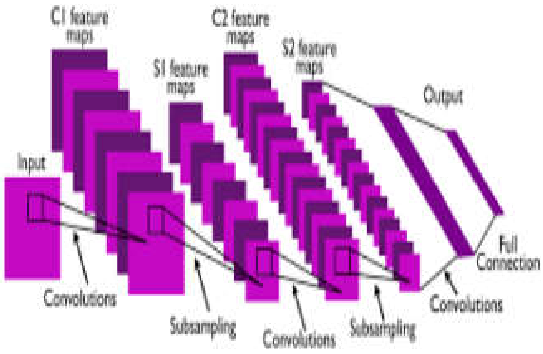


Fig 3.4 Convolutional Neural Network (CNN) Layer

Algorithm for User:

Step 1:Start

Step 2: Displays the Home page and different navigation bar and necessary details related to Fetal data.

Step 3: Click on the option Detect Fetal data

Step 4: Upload the X-ray image.

Step 5: Click on submit button

Step 6: View the results and make out the infection percentage.

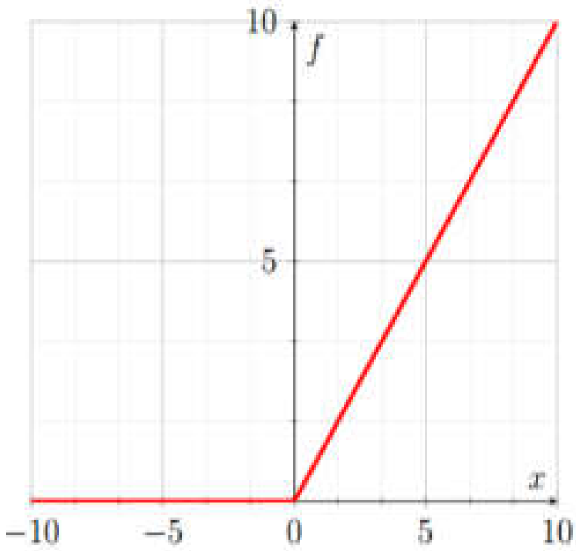
Step 7: View all the details.

Step 8: Stop

4 .Result and discussion

4.1 Layer of activation

Values are normalized, or fitting within a specific range, Within this part of convolutional neural networks. ReLU is the convolutional function that is employed; it only accepts positive values and rejects negative ones. It results from minimal computing costs.



then found, and the median value is written to that specific pixel spot. Figure 4.4 shows the use of the median filter for noise filtering.

4.2 Deriving Features

Image enhancement aims to adjust an image in order to highlight particular features more clearly. This often involves using contrast enhancement techniques to improve the overall visual quality. Conversely

- **Energy:**

∑i∑j(i−j)2C(i,j)\sum_i \sum_j (i - j)^2 C(i, j)

∑i∑jC2(i,j)\sum_i \sum_j C^2(i, j)

- **Homogeneity :**

∑i∑jC(i,j)1+|i−j|\sum_i \sum_j \frac{C(i, j)}{1 + |i - j|}

Feature extraction (GLCM) seeks to suppress the original picture data set by measuring particular values or attributes that help distinguish different images from one another.

4.3Testing Units

Unit testing is a software development process where the smallest testable parts of an application, referred to as units, are tested independently to ensure they function correctly. While it can be performed manually, unit testing is often automated. The goal is to isolate each component of the software and verify that it meets the required specifications and operates as expected. The test cases and their results are typically displayed in tables.4.3.1

4.3.1Unit Testing Benefits

- Confidence in updating and maintaining code is increased by unit testing.
- Codes can be used more often.
- Progress is quicker.
- Repairing a problem discovered during unit testing is less expensive than fixing one discovered at a higher level.
- Debugging is simple.
- Codes are more trustworthy.

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Test Case Sl #: UTC	1
Name of Test: -	Uploading image
Items under test include:	Tested for uploading various pictures
Sample Input:	Provide an example picture
Anticipated result:	The image should upload correctly.
Actual results:	Successful upload
Remarks: -	Pass.

Table 4.1 unit test case 1

SL # Test Case: -	UTC-2
Test name:	Finding healthy and unhealthy fetuses
Things under test:	Check for various X-ray pictures
Input Sample:	tested for various fetal pictures.
Anticipated results:	The health of the fetus should be shown.
Actual results:	Should fetal health be displayed?
Observations:	Expected outcome

Table 4.2 unit test case2

4.3.2 Integration Testing:

Software testing at the integration testing level involves combining and evaluating separate parts collectively. This level of testing aims to identify flaws in the way integrated units interact with one another. Integration testing is aided by test drivers and test stubs. Testing the combined components of an application to see if they work properly is known as integration testing. It takes place before to validation testing and following unit testing. Integration testing can be performed using both top-down and bottom-up approaches.

- **Bottom-upIntegration**

  Testing individual components or units of an application.the first step in this testing process. Module or build testing, which evaluates increasingly complex combinations of units, comes next.

- **Top-downIntegration**

  The testing process starts with the highest-level modules and works its way down to lower-level modules. In a comprehensive software development environment, top-down testing is usually conducted following bottom-up testing. At the end of the procedure, the entire program is tested several times, ideally in situations that are intended to mimic real-world situations. The table below presents the integration test cases and their corresponding results.

Sl # Test Case : -	ITC-1
Name of Test: -	How the Choose File option operates
Item being tested: -	Easy access to stored photographs for the user
Sample Input: -	Click and choose the picture.
Expected output: -	The chosen image should open.
Actual output: -	The chosen image ought to load.
Remarks: -	Pass.

Table 4.3.2.1 Integration testing 1

Sl # Test Case : -	**ITC-2**
Name of Test: -	Functioning of Segmentation and Fetal Health Display
Item being tested: -	Choosing various photos and confirming the health of the fetus
Sample Input: -	Click and choose the picture.
Expected output: -	Should display cervicals and forecast the health of the fetus
Actual output: -	Fetal health detected by image segmentation should be shown.
Remarks: -	Pass.

Table 4.3.2.2 Integration testing2

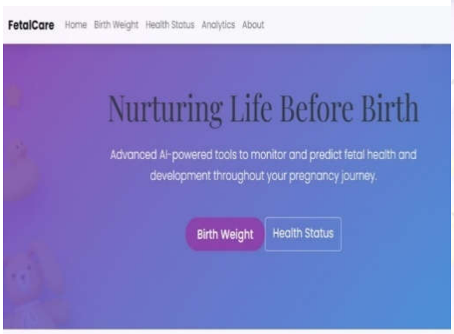
4.3.3 System testing:

Software or hardware system testing is the process of testing an entire, integrated system to see whether it satisfies its predetermined requirements. Since system testing is a subset of black-box testing, it shouldn't necessitate an understanding of the inner workings of the logic or code. The following factors make system testing crucial:

- The first stage of the Software Development Life Cycle is system testing, which involves testing the application as a whole.
- The application is put through a rigorous testing process to ensure that it satisfies all technical and functional requirements.
- The software is evaluated in a setting that closely resembles the production setting where it will be used.
- System testing allows us to test, validate, and confirm the application architecture in addition to the business requirements.

Sl # Test Case : -	STC-1
Name of Test: -	System testing in various versions of OS
Item being tested: -	OS compatibility.
Sample Input: -	Execute the program in windows XP/ Windows-7/8
Expected output: -	Performance is better in windows-7
Actual output: -	Same as expected output, performance is better in windows-7
Remarks: -	Pass

Table 4.3.3.1 system testing



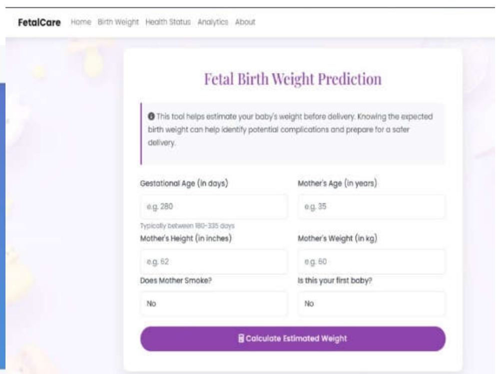
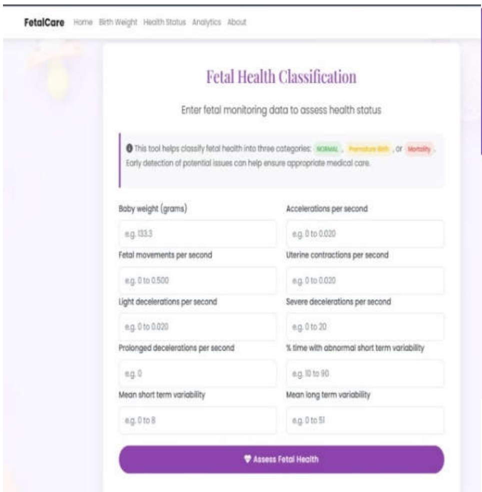


Fig 4.1 Home Page **Fig 4.2 Birth weight page**



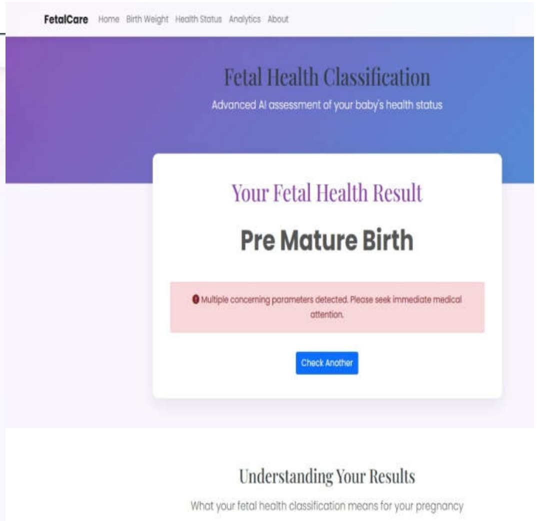
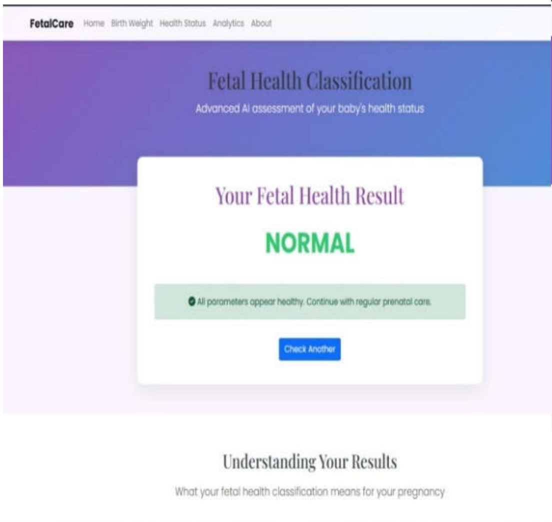


Fig4.3Fetal Mortality prediction page **Fig4.4Result page**



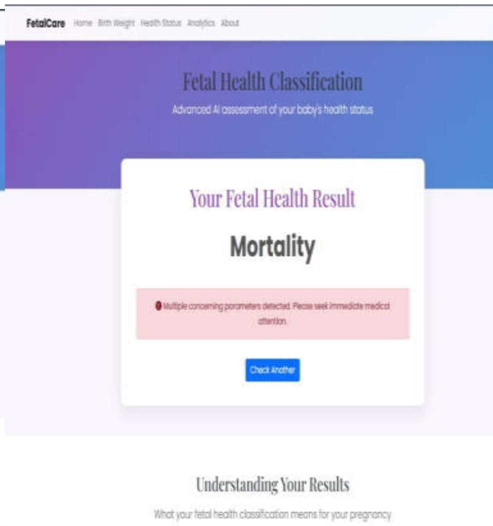


Fig4.5Normal page **Fig 4.6Mortality prediction**

5. Conclusion

The project on Pregnancy Mortality Prediction highlights how data science and intelligent computational methods can be effectively applied to healthcare decision-making. By examining essential maternal health parameters and utilizing machine learning models, the system is capable of predicting the likelihood of pregnancy-related complications and maternal mortality. Such predictive insights can assist healthcare providers in early detection and timely treatment, thereby helping to minimize avoidable maternal deaths.This study underlines the growing role of technology-driven approaches in tackling real-world healthcare issues, particularly in maternal care where rapid action is critical. Although the outcomes are encouraging, the overall accuracy of the model is dependent on the availability and quality of diverse medical datasets. Future improvements may focus on integrating IoT-enabled real-time monitoring, incorporating broader demographic data, and optimizing algorithms to achieve higher levels of accuracy and reliability.In essence, the project demonstrates a step forward in developing smart, data-driven maternal health solutions, with the long-term goal of improving maternal safety and ensuring healthier pregnancies.

Feature enhancement: refers to the process of improving the input variables (features) used by machine learning models to increase their predictive accuracy and robustness. In pregnancy mortality prediction, carefully engineered features can significantly improve the model's ability to identify high-risk cases early.

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