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Internet-of-Medical-Things Assisted Maternal Risk Prediction Using Explainable AI

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Abstract: Women undergo various types of maternal health difficulties during their pregnancy, childbirth, and postpartum period. Women are extremely vulnerable to health issues during pregnancy, which can frequently result in miscarriage and even death. Every stage of pregnancy requires careful monitoring in order to ensure that the health of both the mother and the unborn children, as mothers who give birth to healthy babies have a substantial impact on the child's development, adolescence, and adulthood. It is imperative to monitor the mother's health even through the postpartum period, as both mother and child are prone to mortality risks during the period. The present work emphasizes on maternal risk prediction wherein IoMT-assisted data are used. The dataset features are categorized based on their impact on levels of maternal risk. The dataset is fed into an ML model, and then explainable AI (XAI) is used to derive the explainability of the predicted outcomes. The XAI framework enables the identification of the most significant attributes which impact maternal risks and further allows medical practitioners to take specific, informed, and accurate treatment strategies. The explainability of the correlation of the factors enables early detection and analysis of the maternal co-morbidities, ensuring preventive treatment and reduction in mortality. The proposed work uses a multi-classifier model where multiple classification algorithms are implemented to classify the various types of risk categories. The results highlighted the efficiency of Random Forest Algorithm in generating optimised accuracy. The Multi-nominal Naïve Bayes provided balanced sensitivity and specificity values. The Random Forest algorithm based classifications were further explained using the SHAPELY explainer, and similarly the results generated by the Multi-nominal Naïve Bayes algorithm were explained by Local Interpretable Model Agnostic Explainer(LIME). This enabled achieving transparency in establishing relationships of the features in the realm of global and local surrogates.

1 Introduction

It is important to understand that when a pregnant mother's life is at risk, the child gets susceptible to risks as well. This section thus emphasizes on revealing various aspects pertaining to maternal risks, analyses the shortcomings associated with existing applications involved in maternal risk assessment and highlights its impact on the human life at large. Maternal health refers to the health condition of women during their period of pregnancy, childbirth, and post-natal stage wherein each of the phases are incredibly crucial to ensure that the woman and child both attain their complete health potential. The healthcare progress and awareness in this sector has gained immense momentum in the past few years, yet the data of the last two decades reveal alarming numbers of 295000 women deaths during and post-childbirth as on 2017, which stands unacceptably high and extremely unfortunate [1]. The primary reasons for maternal injury and deaths are consequences of pregnancy complications which affect both the health of the mother and the child [2]. Hence the need for a woman to receive adequate care before, during pregnancy, and post-childbirth in order to reduce associated risks and related complications is an absolute necessity. Majority of the maternal injuries and related fatal incidents are caused due to excessive blood loss, infections, increased blood pressure, obstructed labor, and risky abortion procedures. All of the aforementioned reasons are preventable with timely intervention of healthcare professionals and availability of supportive environment, which can contribute towards reduction of such unfortunate fatal consequences. The objective is not only to barely survive pregnancy and childbirth but also to ensure that the efforts are channelized towards reduction in maternal injury, and the related disability. It is also equally important to ensure sustained well-being of the mother and child, addressing all the challenges of reproductive healthcare thereby delivering optimum quality of maternal care [3].

The common reasons for complications in maternal health conditions are multi-dimensional which include high blood pressure, anemia, diabetes, maternal age, obesity, urinary tract infections, substance use and related orders, domestic violence, mental anxiety, and depression. The Centre for Disease Control and Prevention (CDC) conducts national mortality surveillance to analyze the risk factors and causes of pregnancy-related deaths in the United States. In this regard, Pregnancy Mortality Surveillance System (PMSS) has been framed, which considers the fatal conditions of women while pregnant or similar scenarios within one year of pregnancy as pregnancy-related death. Medical epidemiologists, as part of PMSS, analyze such birth and death records and pregnancy-related mortality ratios from 50 states of the USA including New York City and Washington [4] and further perform critical analysis to identify the underlying reasons for such unfortunate incidents.

The birth of a child from fertilized egg to a perfect infant is a miracle indeed. The fetus gets created and eventually develops inside the pregnant mother's body, and in this regard a mother becomes the direct and indirect guardian of the fetus. Although the mother holds the fetus, it is impossible for a mother to understand the health of the fetus and related risks without the intervention of external tools and related equipments. Thus fetal monitoring is one of the most essential tools for obstetricians to understand the vital signs of pregnant women and also the fetal health in order to provide the required healthcare services. The application of the Internet of Things (IoT) in maternal health monitoring leads to the development of smart maternal healthcare services with wearable devices that enables complete monitoring of pregnant women providing early warnings during the prenatal period. IoMT has further revolutionized patient treatment and services in healthcare, and digitization has established remote connectivity between patients and doctors. Remote monitoring is extremely crucial for prenatal care to provide quality medical services to expectant mothers without taking the additional efforts to reach hospitals frequently. Numerous studies have emphasized on the implementation of IoMT-integrated machine learning models for maternal risk predictions. As an example, the study in [5] developed an IoT-enabled framework to provide ubiquitous maternal health monitoring for pregnant women and also during their postpartum period. The study included the use of various health parameters pertaining to pregnant women and further conducted real-time subject study on pregnant women located in Southwestern Finland. The study used a smartwatch which ensured energy-efficient and long-term monitoring of the pregnant women using reliable photoplethysmography sensor data. The study in [6] developed a risk prediction model for Gestational diabetes mellitus (GDM) considering four techniques, namely score scaled model, logistic regression, decision tree, and random forest algorithm. The prediction framework enabled identifying pregnant women with a higher risk of GDM using common clinical indicators and interventions. The study in [7] highlighted the role of IoMT and AI in controlling mortality rate during pregnancy and enabled healthcare professionals to be more attentive and proactive in providing maternal healthcare services. The role of smart devices was emphasized in this regard which helped in constant health monitoring, and the findings could be visualized on the smartphone. The use of IoMT was also discussed as part of this study which included a network of interconnected medical devices that helped in data collection, processing, testing, and monitoring. A Collaborative Shared Health Care Plan is also discussed in the paper [8] for integrating various IoMT sensors as part of the clinical decision support systems. Although the use of AI and ML has various advantages and opportunities in healthcare enabling accelerated decision-making, the majority of these systems are "black box" wherein output is generated based on input without appropriate explainability of the generated results. The proposed model addresses the challenges of such "black box" framework and is described in Fig. 1. These systems are opaque, lagging the inability to explain the output, and thus, users fail to interpret how the system arrive at a particular decision. This consequentially leads to the lack of trust and confidence in the system. In terms of the healthcare sector, explainability and transparency of the generated outcomes are extremely crucial to justify health conditions and identification of its related contributing factors. Diagnosis is important equally with understanding of the potential causes and their individual contributory aspects towards occurrence of a health condition. Healthcare is a sector wherein the use cases demand explanation because mistakes in interpretation impact treatment strategies leading to dangerous and fetal consequences. Medical practitioners are trained to diagnose diseases with the support of various diagnostic tests, which act as the basis of treatment procedures. Explainable AI-based frameworks provide explainability, transparency, and fairness to the generated results overcoming the opaque nature of the traditional ML-based approaches. Various studies have been conducted in this regard wherein Explainable AI (XAI) based frameworks are implemented to provide explainability and transparency to the generated outcomes of the machine learning models.

1.1 Contributions of the Paper

Studies have been conducted emphasizing maternal health, the associated risks, and mothers' emotional and physical well-being. Machine learning techniques have also been quite predominant in predicting maternal risks and associated issues. Most of such studies have rendered results that are opaque and "black-box" based, lagging behind adequate explanation and transparency. The present study hence is a first-of-its-kind approach wherein explainable AI has been implemented for maternal risk prediction addressing the aforementioned challenges associated with the traditional machine learning approach. The major contributions of the paper are:

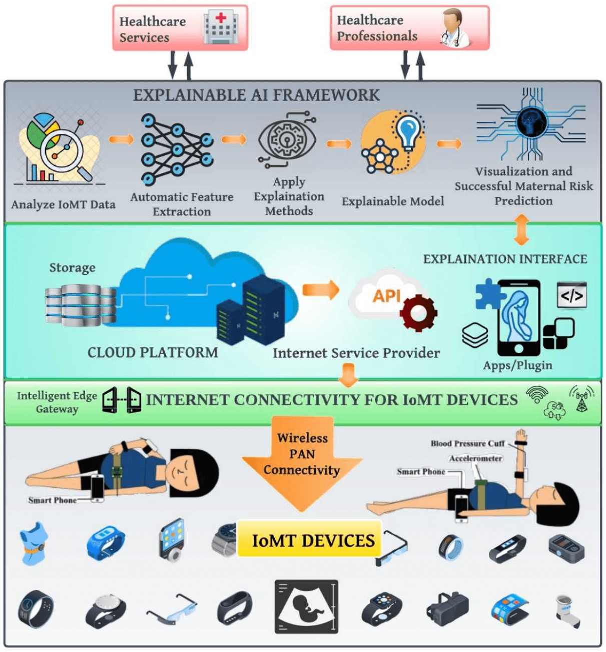

Fig. 1: IoMT in smart health diagnosis

- Extensive literature review on the use of traditional ML approaches in maternal health and related predictions
- Identification and categorization of the features based on their impact on different levels of maternal risks namely low, medium, and high
- Deriving explainability of the prediction outcomes yielding traceability of the contributing features
- Identification of the significant attributes impacting maternal risks enabling practitioners to take informed and accurate treatment-related decisions
- Providing explainability on the correlation of the factors using XAI models that enable early detection and analysis of co-morbid maternal health conditions resulting in preventive treatment.
- Providing technical feasibility in maternal risk assessment by enhancing the risk categorization transforming the black-box classification model with the white-box explanation.
- Providing explainability regarding the features that contribute to the high risk so that they are addressed immediately.

1.2 Paper Organization

Section 1 introduces various aspects of maternal risks, existing challenges and provides an overview of the of the proposed work highlighting the key contributions of the same. Section 2presents the review of literature, and discusses case study that have motivated the authors to pursue the proposed work. Section 3 provides the detailed methodology emphasizing on IoMT sensors and its applicability in this context, description of the dataset and the mathematical model of various methods used in association to the system architecture. Section 5 provides detailed explanation of the results generated from the implementation of AI and XAI models. Section 6 exposes the associated challenges, discusses potential responses and further deliberates directions of future research work. Section 7 provides the conclusive remarks and highlights the benefits and limitations of the proposed system providing valuable insights to the future researchers.

2 Literature Survey

This section provides an exhaustive review and systematic analysis of the relevant studies conducted in this domain which are directed towards resolution of issues pertaining to maternal risk factors. This summarized version of the relevant studies help authors narrow down to the problem objectives on the basis of the systematic analysis and further enables identification of research gap. A case study is also included as part of this section that enables identification of the potential challenges and opportunities while conducting practical implementation of the prominent tools and technologies.

As already iterated, maternal health is considered as an extremely important aspect encompassing stages of pregnancy, childbirth, and postpartum, wherein different health factors contribute to various pregnancy-related complications. Machine learning and related techniques have been used significantly in maternal health-related prediction. As an example, the study in [9] used a ML model for the prediction of HELLP (hemolysis, elevated liver enzymes, low platelets) syndrome which is considered as a rare complication of preeclampsia leading to high risk of feto-maternal mortality and morbidity rates. The study analyzed the patient's clinical and para-clinical attributes using four machine learning models, namely decision tree (DT), Naïve Bayes (NB), K-nearest neighbor (KNN), and random forest (RF). The performance of the models were further evaluated, which revealed random forest to be the most accurate model for HELLP syndrome prediction. It is evident from studies that the admission of pregnant in maternal ICU's often act as a serious affair wherein the unavailability of ICUs lead to significant counts of maternal deaths. On the contrary, flagging high-risk patients unnecessarily also leads to improper coordination and misutilization of ICU services. The study in [10] developed machine learning models considering data available at point-of-care units to predict the need for maternal ICU admission. In [11], the authors implemented an externally validated Explainable Boosting Machine (EBM) algorithm for predicting severe maternal morbidity while admitting patients in the hospital. The study used clinical data of 155,935 births at 24-43 weeks in US hospitals between 2016-2021. The model was evaluated against the logistic regression (LR) model, wherein the results justified the superiority of the EBM model. As individuals seek care from varied health care units, health data are increasingly becoming fragmented. Consequently, inconsistent health have derogatory impact on+ patient care. The ability of machine learning (ML) to analyze patient data and deduce inferences, thereby informing and enhancing patient care and related outcomes, makes it a disruptive force. The variations in each person's health records, the absence of health data standards, systemic problems that make the data untrustworthy and prevent the creation of a single perspective of each patient, and various other factors contribute towards challenges associated with ML implementations. The study in [12] aims to highlight that patient records retrieved from the Electronic Health Records (EHRs) at a large tertiary health care system are crucial for successfully using ML to identify maternal cardiovascular risks before evidence of diagnosis or intervention within the patient's record. An organized process was used in this regard to collect maternal patient records from the EHRs of a sizable tertiary healthcare system and turn them into patient-specific, comprehensive data sets. The authors concluded that an ML-based tool can be used to gather data from several EHRs and combine, anonymize, and normalize it before it can be used to identify cardiovascular risk in pregnant patients.

Another study focused on singleton, term-pregnant women who are in active labour and the first few weeks after delivery, which have a low risk of complications. The authors [13] proposed development of a clinical care algorithm considering scientific evidence for prevalent intrapartum urine anomalies. Proteinuria, ketonuria, glycosuria, and oliguria were chosen as the four most prevalent intrapartum urine abnormalities in this case. Four straightforward, approachable, and evidence-based clinical algorithms were created to improve intrapartum management of frequently occurring maternal urine anomalies. In low-resource nations, these algorithms may be utilized to assist medical practitioners in clinical decision-making when conducting routine and possibly complex labor.

The use of sensors, artificial intelligence (AI), information, and communication technologies enable health Institutions to render their services to underprivileged, unreserved groups of people working in remote locations. It is important to mention that maternity and infant health is extremely important for a sustainable and healthy society. Hence, applying such technologies is even more important to develop applications that cater to such needs. Numerous research activities have been channelized towards the study of sensing and the use of AI in maternal and newborn healthcare. Sensor-based technologies have been used to enable medical professionals to measure various healthcare attributes and then use ML techniques to predict potential health issues of patients. The use of wearable sensors and AI algorithms are discussed in [14] wherein such frameworks are used to forecast risk factors before, during, and after pregnancy for both mothers and children. The sensors and AI algorithms are critically studied to highlight relevant approaches, characteristics, results, and innovative aspects in chronological order. Traditional litigation in the field of maternal-fetal medicine makes up a significant share of compensation awards. The cost per case in a lawsuit is generally high in comparison to the total number of compensation claims. A South Korean estimate states that between 2015 and 2019, 61 million medical disputes were resolved, costing an average of 91 million won (KRW) per case [15]. AI, as already mentioned, is predominantly used in treatment decisions in healthcare, similar to various other domains. The authors [15] analyzed state-of-the-art developments involving AI in detecting maternal-fetal disorders emphasizing preterm birth and aberrant fetal growth. The results of this study reveal that a variety of ML approaches have been successfully used for the early identification of maternal-fetal disorders.

There is an immense necessity for healthcare professionals to possess an adequate combination of medical knowledge, experience, and skill sets to support maternal and child health. The present approaches adopted for rendering such services are patient-centric but require risky validation and diagnostic procedures, which are expensive yet fail to yield accurate results. The study in [16] developed an AI-based predictive model considering maternal healthcare data that enabled doctors to gain preventive insights thereby deciding on precision medicines ensuring explainability and interpretability. To create Explainable Machine Learning models in Quantum Space, the authors also introduced the idea of Quantum Lattice Learning. To enable clinicians like obstetricians, perinatologists, gynecologists, and midwives to transparently analyze and use the most significant features for strategic maternal and child predictive, preventive, and precision medicine, the authors implemented Explainable Artificial Intelligence (XAI) and feature interpretability analysis.

To prevent diseases for the mother and child, care is a necessity during pregnancy, childbirth, and puerperium. However, health problems might arise during this time, resulting in unfortunate events, such as the fetus's or newborn's death. The predictive models for fetal and newborn mortality act as a crucial technical tool that can lower mortality indices. The paper [17] presented a structured review of various computational models that enabled prediction about maternal mortality, occurrences of stillbirth, and chances of perinatal, neonatal, and infant deaths. The review also highlights the methodologies of related studies and describes the computational models that have been proposed. The AUC ROC assessment metrics were used as a metric to score the models, and the random forest model was identified to be most appropriate for predictive analysis in the study One of the evolving field in healthcare is immunoparasitology which detects the distinctive immunologic signatures of immunologic diseases, and develops ground-breaking preventive or treatment methods acting as the basic foundation for individualized neonatal intensive care for the most vulnerable newborns. The trans-disciplinary efforts by doctors, physician-scientists, basic science researchers, and computational biologists have made significant progress in this research area. The authors [18] emphasized omics techniques to study the maternal-fetal interface and discussed their contributions to immunopathology and immunobiology aspects of pregnancy. The authors analyzed the value of various trans-disciplinary and multi-omic attributes and then implemented machine-learning approaches for elucidating the mechanisms underlying unfavorable maternal and pediatric outcomes. The study also revealed the need and potential for novel treatments that would help in enhancing maternal and neonatal health.

The application of XAI for sentiment analysis to handle mental disorders is presented in the paper [19]. The paper used active learning with deep attention for handling mental disorder dataset of the various patients. A significant issue for precision medicine lies in the existence of conditionally-dependent clinical variables that influence cardiovascular health outcomes. The Electronic Health Records (EHRs) from the University of Utah and Primary Children's Hospital include almost 1.6 million patients and 77 million visit-related data. This huge dataset is analyzed to perform diagnoses relevant to comorbidity, selection of appropriate procedures, and to identify medications. One of the most scalable comorbidity discovery methods entitled is, Poisson Binomial based Comorbidity discovery (PBC) what has been used for the said purpose. In [20] the authors focused on cardiological aspects, namely heart transplant, sino-atrial node dysfunction, and various other factors that impacted co-morbid conditions, in terms of maternal healthcare. The attributes were analyzed using XAI and ensured that the availability of web-based tools for healthcare practitioners and users would guide further in-depth examinations and research.

One crucial process for regulating gene expression in the development of the heart is DNA cytosine nucleotide methylation, also known as epigenomics and epigenetics. The ability to identify embryonic congenital cardiac abnormalities by combining artificial intelligence and whole-genome epigenomic analysis of circulating cell-free DNA in maternal blood, is one of the efficient techniques. The authors [21] developed minimally invasive methods for detecting embryonic congenital heart abnormalities, including genome-wide DNA cytosine methylation and artificial intelligence studies of circulating cell-free DNA. The authors conclude by stating that the results also supported the notion that epigenetic modifications play a significant role in the emergence of congenital cardiac defects.

ML and AI has been increasingly employed in health care, prediction, diagnosis, and act as a technique of establishing priority. The maintenance of trustworthiness of medical data ensuring privacy is performed using the federated Learning approach as presented the paper [22]. The study is conducted on pneumonia disease data, wherein privacy protection of the medical records are presented [23]. The applicability of a trustworthy federated learning application in healthcare especially in a meta-verse application, with associated opportunities, challenges, and future directions, was discussed in the paper [24]. The Multi-Agent Reinforcement Federated Learning (MARFL) with Remote Procedure Call(RPC) is introduced in cyborg-assisted IoMT services for the treatment of patients through a remote interface as discussed in [25]. Privacy protection for IoMT-assisted dermatological image data is also supported by Federated Learning based implementations[26]. These studies showcase the potential of federated learning approaches in preserving privacy in healthcare environments.

Several instruments in the disciplines of obstetrics and childcare use machine learning techniques. In this regard an exhaustive search was conducted on the existing literature wherein 31 items were eliminated following the inclusion and exclusion criteria [27] and 31 articles remained. Electronic medical records (48%), medical imaging (29%), and biological markers (19%) were the most common data used to forecast perinatal problems. Only 4% of the predictions were based on features such as sensors and fetal heart rate. Pre-eclampsia and preterm are considered as significant factors pertaining to maternal risks as identified in the literature wherein machine learning has huge role to play.

The combination of artificial intelligence and the Internet of Medical Things demonstrates enormous advantages in healthcare. Accurate detection of the fetal QRS complex is essential to effectively monitor fetal heart rate. It seems like a potential alternative method to measure fetal heart rate by using electrophysiological impulses from abdominal electrodes. Due to such difficulties in detecting the fetal heart rate from an abdominal ECG (AECG), it is necessary to remove maternal components accurately and other disturbances from the signal. Krupa et al. [28] suggest a unique method for detecting fetal QRS complex in the abdomen ECG without removing the maternal components based on an IoT-based deep learning architecture. The technique increases the availability of rich data and enhances the accuracy of fetal QRS complex recognition by feeding abdominal signals' time-frequency image (TFI) into a deep neural network. The technique enhances fetal QRS detection by adapting previously learned models using transfer learning for classification.

The sudden outbreak of Coronavirus illness (COVID-19) has generated high prioritized alert in the healthcare system. Internet of Medical Things (IoMT) and related technologies have contributed immensely in this regard. COVID-19 has inspired scientists to create "smart" healthcare systems that focuses on early diagnosis, spreading-prevention, education, and treatment thereby making it easier to adapt to the new normal. In addition to analyzing the current state of the research demonstrating the effectiveness of IoMT benefits to patients and the healthcare system, the review in[29] aims to identify the role of IoMT applications in improving healthcare systems. It also briefly overviews technologies that complement IoMT and discusses the difficulties in creating a smart healthcare system. The use of Wearable sensor supports for managing Parkinson's disease is also discussed in the paper [30].

Hospitals have used the Internet of medical things (IoMT) in recent years for medical applications, and edge computing has been a key component of remote healthcare systems. The credit is well deserved by the recent advancements in IoMT, wearable sensors, and communication technologies which have provided smart healthcare services wherein human existence have become smarter in the age of pervasive computing. Prenatal Healthcare System of Remote Mother and Fetal observation through IoMT using a handheld ultrasound device and a small wearable worn by the mother are the primary components of the framework in [31]. The information pertaining to the the mother's health and well-being is gathered and then the gadgets provide surveillance for both the fetus and the mother. The metrics are sent to a server, using the relevant AI/ML module to analyze and forecast the mother's and the fetus' gestational state. Medical professionals caring for specific mothers and fetuses are provided access to the central system which alert the attending clinicians to take the necessary measures upon detection of irregularities.

2.1 *Motivation*

The motivation for this work is developed from the "Maternal Health Risk Dataset" from the University of California data repository. The data was used in the studies [32] and [33]. The author, Mr. Mariza Ahmed, Daffodil International University, Dhaka, Bangladesh were involved in collection of the data from different hospitals, community clinics, and maternal health care in the rural areas of Bangladesh through the IoT-based risk monitoring system.

2.2 *Detection of high-risk pregnancies in low-resource settings: a case study in Guatemala*

This survey [34] was conducted with 10,108 women for 2 years and 3 months. 55 twin gestation (0.54%) were diagnosed. From the 32 weeks of the survey, Non-cephalic presentation was found in 14.87% of the pregnant women. 20 patients were further examined and referred for non-evolutive gestation. Further, 11.08% were detected with the prevalence of anemia. Urinary tract infections were detected in 16.43% of the cases, out of which proteinuria was detected in 2.6% of patients. 17 patients had high blood pressure and were therefore referred with a suspected pre-eclampsia. The results show that the use of suitable equipment, training, and supervision, the nursing staff in charge of care in rural areas can identify and eliminate most of the obstetric risks in time, contributing towards reduction in maternal mortality.

3 Materials and Methods

This section deals with the state of art IoMT sensors [35], [36], which could be used as wearable devices, for detecting the risks associated with maternity. These devices can measure the vital signs and other body parameters like Blood sugar and Activity Detection. This section describes about the dataset, which is used in the proposed work, along with the detailed description of all the ML and XAI models used. This section covers up the description of the required hardware, ML and XAI models which are essential for the implementation of the system.

3.1 OVULA RING

This device is developed by VivoSensMedical GmbH [158]. This product is used to determine the proper ovulation cycle and decides whether the women are most fertile and the least fertile. The treatment can be suggested to improve women's fertility based on the observations of this sensor. Since the proposed work addresses the issues related to maternal risk assessment, this sensor could be closer to the proposed area of interest.

3.2 VITAL PATCH

This device $^{@R159}$ can monitor eight essential vital signs around the clock. The parameters which the sensor can monitor are as follows:

- Heart Rate
- ECG with a single lead
- Respiration
- Variable Heart Rate
- Fall detection
- Body Posture
- Skin Temperature
- Activity Detection

During pregnancy, Heart Rate, Activity monitoring, Fall detection, and ECG monitoring are essential. Hence the above body sensor can be used for maternal risk predictions

3.3 FreeStyle Libre

This is a product of Abbot[160]. This is a wearable sensor that can be used for the detection of pregnancy related diabetes. The results of this sensor are comparable with the strip-based evaluation, which is tested in fingers.

3.4 Dataset

The dataset for this work was acquired from the UCI repository. This real-time data was collected from different hospitals, community clinics, and maternal health care centers of Bangladesh, through IoT based health monitoring system. This data set contains 1014 instances with 7 attributes and can be used for the classification purposes with high, medium, and low-risk predictors. The dataset had been implemented in some research papers [32] and [33]. The proposed work is the first ever paper that applied XAI implementation in the above-said dataset, which is the uniqueness of the proposed system.

3.5 Logistic Regression

The proposed work applies logistic regression, since it can be used for maternal risk assessment based on the probability of the occurrence of an event. For example, rainy or no rain etc. Since the target of this proposed work is closer to a probabilistic function, logistic regression is applied in the proposed work. The outcome is a probability function it can be mapped anywhere between 0 and 1. This is normally expressed as the logarithmic of odd values represented by the Eqn. 1.

$$LR(pi) = 1/(1 + exp(-pi) \tag{1}$$

3.6 Multi-nominal Logistic Regression

This is a method that generalizes the logistic regression to multi-class problems. With the extension to binary output, this model can predict the multi-class categorically distributed dependent variable for the given set of independent variables. The independent variables can be real-valued, binary-valued, or categorically-valued. This model is represented with so many names such as Polytomus LR(Linear Regressor), multi-class LR, soft-max LR, maximum entropy classifier, or conditional maximum entropy classifier.

3.7 SVM

The support vector machine is a machine learning model that is useful for the classification and outlier analysis prediction. This uses a hyperplane across an n-dimensional space that can be used to predict the futuristic values in either part of the hyperplane, such as the positive or negative hyperplane This converges within an allowable boundary from both positive and negative slopes on the hyperplane. This algorithm chooses extreme data points to form the hyperplane, and these extreme data points are called support vectors.

3.8 Multi-nominal Naïve Bayes

This algorithm is fundamentally built from the Bayes Theorem formulated by Thomas Bayes. This works with the prediction of the probability of occurrence of an event based on the prior knowledge about conditions related to the event. This can be expressed as per the Eqn. 2.

$$P(A|B) = P(A) * P(B|A)/(P(B)) \tag{2}$$

where $P(A)$ is the probability of the prior event A and $P(B)$ is the probability of the present event B. This algorithm is expanded to predict multi-class problems as Multi-Nominal Naïve Bayes. Hence it is used in the proposed work. The best part of this algorithm is that it is even used in Natural Language Processors(NLP), to predict the tag of a word in a newspaper or article. This calculates the tag with the highest probability of occurrence and predicts that as the target value. Naïve Bayes is a collection of many algorithms that have a single purpose that is, no feature is dependent on the other, presence of one feature or absence will not affect the rest of the features.

3.9 Random Forest

Random Forest is a supervised machine learning model for the classification and regression analysis. This model is preferred for its simplicity. This provides better results even without the hyper-parameter tuning. This model generates multiple decision trees from different samples and builds a single model based on majority of the votes for the classification problem. This nature made this algorithm suitable and useful for predicting the target values in the proposed work. The prediction is based on multiple decisions through decision trees, which is later summarized into one unique model, through majority voting. The estimation of the target function for the random forest model classification is called as Gini index. This can be mathematically expressed as per the Eqn. 3.

$$GiniIndex - 1 - \sum_{i=1}^{n} 1 - p_i^2 \tag{3}$$

Where P_i can be the sum of the positive and negative cases in a target.

3.10 LIME

LIME is expressed as Local Interpretable Model-agnostic Explainer. This XAI model is used for predicting the feature importance, feature weights, and which features are positive and negative towards the prediction of the target variable. This model selects a random instance and estimates the surrogates to that feature and predicts the behavior of the model. The model estimates the feature distance and relationship between the selected instances with the neighboring data points through linear relationships using lasso or linear regression. This estimation explains how independent features correspond to a target classification or regression based on their impact and importance.

3.11 SHAPELY Values

The SHAPELY involves Game Theory which provides the solution for the fair distribution of the gain and cost to the players involved in the game. This inturn applied in XAI to predict the importance and usefulness of each feature, based on the contribution to the prediction of the target variable. This explainer uses several feature metrics, such as feature important plots, decision plots, dependency plots, and dataset convergence plots to determine the importance of the features. This also explains how individual feature values correspond to a classification category, through the decision plot. This model is suitable for explaining the classification and regression problems in both global and local scopes of predictions. Thus this model is applied to the proposed work for a global explanation.

4 System Model and Architecture

This section describes the mathematical model of the proposed work, as an evolution from the process of feature extraction to the development of XAI models with the interpretation. The section discusses about various mathematical operations carried out in each and every stage of the model evolution through equations, and finally presents an algorithm to understand the flow of the implementation. This section also describes the proposed framework through a detailed system architectural description with a neat diagram.

4.1 System model

The mathematical model of the system, along with the algorithm is discussed in this section. The dataset has attributes such as Age, Systolic BP, Diastolic BP, Blood Sugar(BS), Body Temperature, Heart Beat, and the target variable Risk Level. First, the dataset is checked for the missing values, and the imputation is done for the same, which is expressed by the following equation Eqn. 4. The missing data imputation is represented as Z. The variance calculation for an attribute in the dataset is given as γ_x. Where x is the attribute elements of the dataset and y is the output function of the dataset. The imputation δ is denoted for analysis of the combined data imputation given in Eqn. 4.

$$\delta_y = 1/y \sum x = 1^y \delta_x \tag{4}$$

The proposed variation for γ_Y is given in the following Eqn. 5.

$$\phi_y = \beta_y + (1 + 1/y) R_y \tag{5}$$

where,

$$\beta y = 1/y \sum x = 1^y \tag{6}$$

and

$$R_y = 1/y - 1 \sum x = 1^y * \beta_x (\delta x - \delta_y)^2 \tag{7}$$

R_Y denotes the target variable for the missing data imputation. δ_x and δ_y are the change of imputations for the input and output and the β_x , $\beta + y$ are the co-efficients of the imputation. After evaluating the missing values (since the number of features is less, feature selection is not essential), we directly perform the classification using machine learning algorithms. The dataset has a multi-class target attribute. Hence we use multi-class machine learning classification models. The models which are used in the proposed work are SVM, Random Forest, Multi-nominal Naïve Bayes, Logistic Regression, and Multi-nominal Logistic Regression. The models eventually estimate accuracy, precision, recall,f1-score, sensitivity, and specificity. For the estimation of these parameters, the following measurements are required.

The four measured values help us determine these parameters such as,
T_p = True positive
T_n = True negative
F_p = False positive
F_n = False negative
T_{PR}=True Positive Rate
T_{NR} = True Negative Rate
F_{PR}=False Positive Rate
F_{NR} = False Negative Rate
The accuracy is estimated as per the Eqn. 8.

$$accuracy = T_p + T_n/(T_p + T_n + F_p + F_n) \tag{8}$$

The precision is estimated as per the Eqn. 9

$$precision = T_p/(T_p + F_p) \tag{9}$$

The recall is estimated as per the Eqn. 10

$$recall = T_p/(T_p + F_n) \tag{10}$$

The f1-score is estimated as per the Eqn. 11

$$f1 - score = 2 * (precision * recall)/(precision + recall) \tag{11}$$

After these estimations, we measure the sensitivity and specificity through the evaluation of the confusion matrix and parameters like T_{PR}, $T_{NR}q12$, F_{PR}, F_{NR}. The sensitivity is represented in the following Eqn. 12.

$$Sensitivity = T_p/(T_p + F_n) \tag{12}$$

The specificity of the models is represented by the following Eqn. 13.

$$Specificity = T_n/(T_n + F_p) \tag{13}$$

The next step is the application of the LIME XAI model to explain the prediction of the multi-nominal Naïve Bayes model. The global representation of a variable can be expressed as per the Eqn. 14. The x represents the data point and the model convergence is expressed as R with the distance d.

$$x \in R^d \tag{14}$$

However, the interpretable representation of the binary vector is represented around the data point x as per the Eqn. 15.

$$x \in (0, 1)^d \tag{15}$$

Now let us explore the model-agnostic property of LIME. Here g is a particular machine learning model that belongs to the subset of similar models G as per the below Eqn. 16.

$$g \in G \tag{16}$$

The binary vector for g is represented in Eqn. 17

$$g \in (0, 1)^d \tag{17}$$

The probability function $f(x)$ for the input value x is represented in the binary form as per the Eqn. 18.

$$x' \in (0, 1)^{d'} \tag{18}$$

The probability function $f(x).g(x)$ should be minimum for human to make the interpretable prediction. The proximity is measured for

Step	Operation
Step 1	Perform the missing value imputation δ_y and ϕy
Step 2	Estimate the outliers using correlation analysis
Step 3	Calculate the parameters T_P,T_N,F_P,F_N, T_{PR},T_{NR},F_{PR} and F_{NR}.
Step 4	Estimate the accuracy, precision, recall, and f1-score.
Step 5	Implement the confusion matrix .
Step 6	Estimate the sensitivity and the specificity for the target classes.
Step 7	Choose the appropriate classifier.
Step 8	Estimate the values g and $f(x)$ for the probabilistic functions.
Step 9	Estimate the value of the $\omega(g)$ to determine the complexity.
Step 10	Derive the explainer and provide the relevant results by minimizing L and $\omega(g)$.
Step 11	Choose the appropriate classifier.
Step 12	Select the tree explainer in SHAPEY values.
Step 13	Determine the prediction probability with dimensions of data.
Step 14	Evaluate the explainer $\pi(v)$.
Step 15	Develop the summary plot and dependency plots and estimate the risk assessment.

Table 1 Algorithm of the Classification and the Explainable Evaluations

the instance z with the locality around$x$. We define this phenomenon in the Eqn. 19.

$$\pi_x(z) \tag{19}$$

The explanation of the input instance of the model x is represented in Eqn. 20.

$$Explanation(x) = L(f, g, \pi_x) + \omega(g) \tag{20}$$

The value of g is a model that belongs to the Global model G where $g \in G$. The L is the unfaithful function, f is the complex variable, and π_x is the proximity function of g with its surrogates. $w(g)$ is a complex function of the model. For better accuracy and correctness in explanation, the L function and $w(g)$ must be minimum.

The last mathematical equation applied in the proposed work is the SHAPELY explainer. This concept is derived from the game theory, which tells about how the individual player's contribution has impact on the total payoff and how the distribution of benefits of the outcome can be done to the individual player from the overall winnings. The player's contribution is the expected value across all coalitions of the players, which does not contain this player, and there is change of prediction when this player is added to the coalition. This is represented as the probability of $f(x)$ for the value represented in the Eqn. 21.

$$\theta(v) = \sum_{s \subset Ni} |s|!(N - |s| - 1)!/N! * (v(S \cup i - V(s)) \tag{21}$$

Here θ_v is the coalition, v is the pay-off to the players, N is the total number of the players, and N_i is the possible coalitions. The first term within the sum corresponds to the corresponding time the S is available in the permutation combinations. This provides the highest weight information about the contribution of the feature. It is about a player who is isolated or a full-coalition is achieved as determined by this mathematical model.

The algorithm of the overall process is represented in the following Table 1. The various parameters of the algorithm are presented below,

T$_p$ = True positive
T$_n$ = True negative
F$_p$ = False positive
F$_n$ = False negative
T_{PR}=True Positive Rate
T_{NR} = True Negative Rate
F_{PR}=False Positive Rate
F_{NR} = False Negative Rate
g and $f(x)$= Global Variable and the activation function
$\omega(g)$= Complexity function
$\pi(v)$= Shapely Explainer

The flowchart of the proposed system is presented in Fig. 2. It shows the sequence of the steps starting from the missing data imputation and ending with the explainer model for the global surrogates. This diagram illustrates the overall processing in a detailed manner.

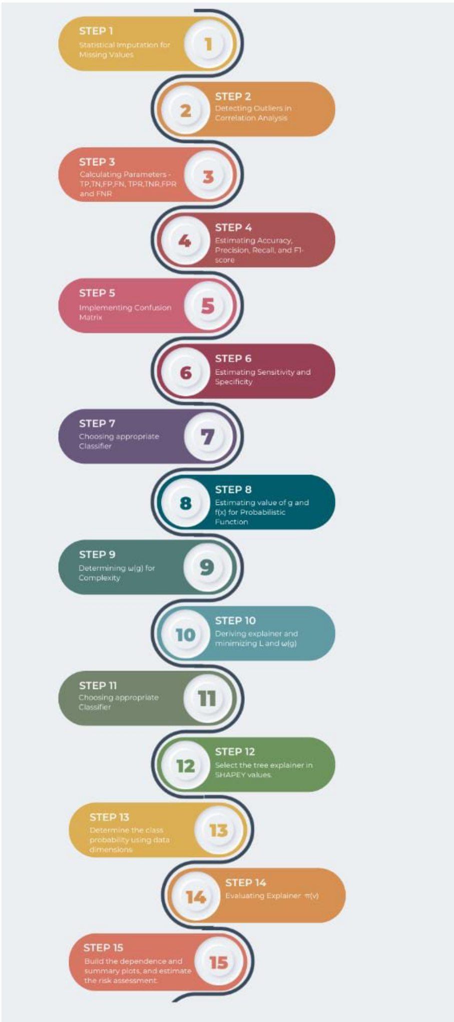

Fig. 2: Flow Chart Representation of the proposed work

4.2 *Proposed System Architecture*

The ability of hospitals, doctors, and service providers in delivering the high-quality healthcare services to enhance the patient safety, is greatly challenged by the escalation of the healthcare difficulties. This is because of the increase in the number of the chronic diseases and increase of the global population. The care must be doubled for the pregnancy related medication. The risk during maternity can be fatal.The periodical, time-bound and continuous monitoring is required for such patients, medical experts have come to the doors of cutting-edge technologies like the Internet of Things (IoT), AI, ML [37], and data analytics due to challenges imposed by such medical conditions and situations. IoMT is the one that is the real boon for the healthcare professionals and medical practitioners.

The best quality of service is achieved when the healthcare professionals meet new needs and demands caused by the increase of various healthcare related problems. IoMT has several advantages, including monitoring patients in real time, offering more sophisticated and efficient way to gather patient data and track their activities. Patients can obtain individualized care with the help of wearable devices, as shown in Fig. 1. The range of the equipment starts from the fitness bands, blood pressure ,heart rate monitor cuffs, and glucometers. These gadgets can be set to remind users to keep track of their blood [38] pressure, exercise, appointments, and much more parameters.

Electronic Health Records (EHR), wearable electronics, and RFID cards are given to the patients, which can provide data to a server or cloud storage in real-time. The data is gathered on a database system, before getting transferred to a doctor.The doctors can utilize this information for various things, such as involving with the research and development for offering the treatment for the maternity related patients. The data acquired from the pregnant

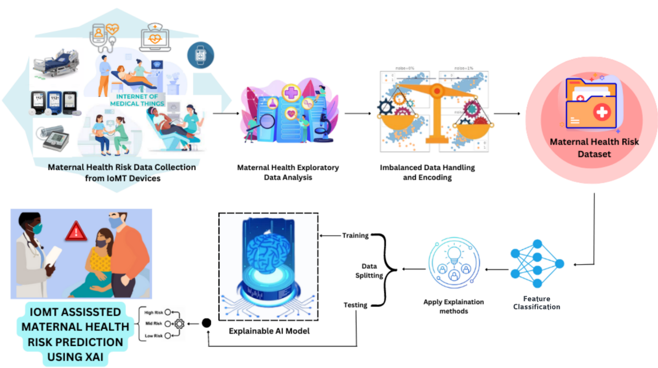

Fig. 3: Overall Architecture of Io-MT based Explainable Maternal Risk Assessment Architecture

women are periodically pushed to the cloud infrastructure, where the data is stored in JSON format and then converted to CSV. Doctors and data experts periodically monitor this data. Later the data is classified into high, medium, and low risks by the machine learning-assisted classification models. Based on the risk, doctors initiate the mitigation processes. They provide online medical assistance or bring the patient to the hospital with the available facility. Thus the classification provides support to medical experts to address the risks involved with the maternity . However, false positive values of the attributes may lead to false alarms and remains a big challenge.

Since all the machine learning implementations are model-specific, we can't interpret how a specific data value influences the categorization and identification of the risk level. Hence we apply XAI models, which provide the model-agnostic approach. This means the XAI can work around these black-box machine learning models and tries to pull out what features on the dataset and what specific values of the same influence the particular instance, which can be categorized as High, Medium, or Low.

The XAI also provides details on what features are important for making predictions of various categories, what features are interdependent, and what values of the features contribute towards the classification of the risk. It explains the classification process with the help of measurements like prediction probability. This provides classification and regression solutions with various models and explainers. In this proposed work, we also apply PDP, LIME and SHAPELY values are used in the proposed work in-order to provide explanations in both local and global scope. LIME provides the local interpretation by minimizing the complex function. SHAPELY values work on game theory, that deals with the evaluation of the model features, which are assigned with the independent weights. This criteria is understood as one of the most important one in predicting the target values. With all these outcomes obtained, the doctors would be able to understand the significance of the alarming values of the attributes and also the risks that might be addressed based on these alarming situations.

5 Results

The proposed work uses the ML algorithms such as Logistic Regression , SVM, Naive Bayes, Mutli-nominal Logistic Regression and Random Forest. The models are compared for six performance metrics, such as Accuracy, Precision, Recall, F1-Score, Sensitivity and Specificity. The model with highest performance and stability are selected for the explanation by LIME or SHAPELY values.

Classification or regression analysis of the target values is essential before proceeding with the implementation of the XAI. There are two kinds of approaches in XAI which are showcased for the implementation: model specific approach and the model-agnostic approach. The model-specific approach can be applied to a specific model and the model-agnostic approach can be applied to any generic model. The data set we acquire has the following attributes such as Bs, Systolic BP, Diastolic BP, Age, Body Temp, Heart Rate, and Risk Level is the target class.

The risk level is classified into three major categories: High, Medium, and Low, where they are transformed to numbers 2,1,0 with linear coding by Python for performing classification. The first step is checking for missing values and class imbalance in the data set. There are no missing values or class imbalances in the data set.

After the preliminary analysis, the dataset is subjected to the process of classification. The various ML algorithms which are applied in the prescribed work for the classification process are Multi-nominal Naïve Bayes, Multi-nominal Logistic Regression , Logistic Regression, Support Vector Machine, and Random Forest. Since the target function is multi-class, we used multi-classifier models to evaluate the performance metrics. The classification of these five machine learning models with the sensitivity and the specificity measurements along with the confusion matrix is given below Table 2.

The random forest provides the highest accuracy, with the highest voting acquired from the decision trees. This treated the whole data set as binary and performed the classification. The sensitivity and specificity measures for the machine learning models are presented in Tab.3.

From the above Tab.3, we understand that the specificity is good for almost all the models, which means only fewer false positives. False positives are highly undesirable. Especially, while predicting a high-risk categorical patient into a normal or low-risk is highly hazardous. In that way, from the observations performed in the proposed work, the false positive results are minimum for all the models except the multi-nominal logistic regression. The confusion matrix for all the machine learning models is represented in Fig. 4, Fig. 5, Fig. 6, Fig. 7, and Fig. 8, respectively.

From the above figures, it is evident that Random Forest performs much better than all other models regarding correctly classified instances. All models provide a decent amount of specificity, but there is a drop in sensitivity of around 65% for the multi-nominal Logistic Regression model. Since the false negatives are low for Random Forest, SVM, and multi-nominal Naïve Bayes, they can be selected for further analysis with XAI. The comparative analysis of all the models is represented in Fig. 9, with respect to the accuracy, precision, recall, and F1-score. The performance of the specificity and sensitivity is represented in Fig. 10. For further investigation and explanation, the Multi-nominal Naïve Bayes model is selected for the LIME explainer, and the Random Forest Classification model is selected for the SHAPELY values explainer for XAI implementation.

The Partial Dependency Plot explains the dependency between the heart rate and the maternal risk as per the Fig. 11. This graph

Method	Accuracy	Precision	recall	F1-Score
Logistic Regression	0.87	0.88	0.87	0.87
SVM	0.94	0.95	0.94	0.94
Multi-nominal Naïve Bayes	0.85	0.88	0.85	0.85
Multi-nominal Logistic Regression	0.78	0.80	0.78	0.78
Random-Forest	1	1	1	1

Table 2 Classification Report of the Various Machine Learning Models

Method	Accuracy	Sensitivity	Specificity
Logistic Regression	0.87	0.86	0.93
SVM	0.90	0.92	0.95
Multi-nominal Naïve Bayes	0.85	0.84	0.92
Multi-nominal Logistic Regression	0.78	0.65	0.88
Random-Forest	1	1	1

Table 3 Sensitivity and Specificity Analysis of the Various Machine Learning Models

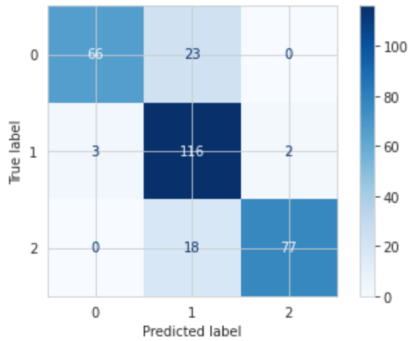

Fig. 4: Confusion Matrix for Multi-nominal Naïve Bayes

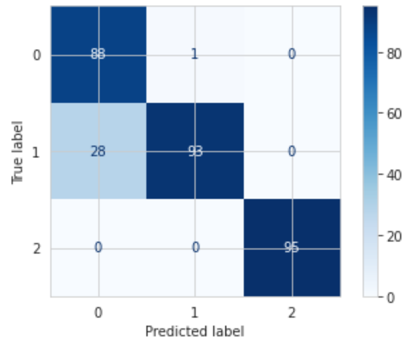

Fig. 7: Confusion Matrix for SVM

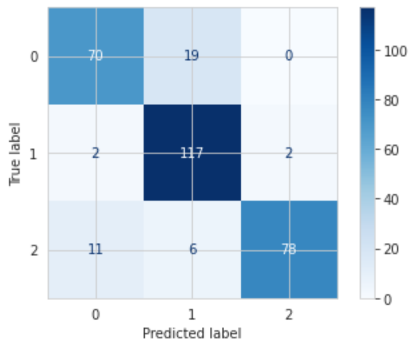

Fig. 5: Confusion Matrix for Logistic Regression

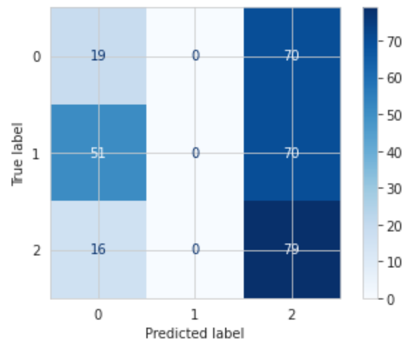

Fig. 8: Confusion Matrix for Multi-nominal Logistic Regression

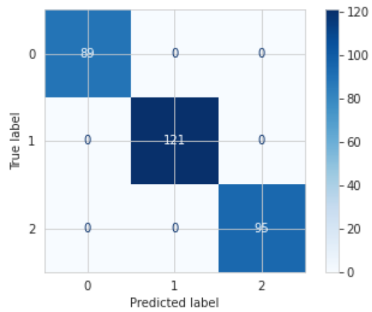

Fig. 6: Confusion Matrix for Random Forest Classification

is built using the lasso function, which provides the dependency between the heart rate and the maternal risk level. The XAI defines Maternal Risk with model-agnostic approaches and model-based approaches. We apply the classification through various machine learning models and provide the explainability using the Local Interpretable Model-Agnostic Explainer(LIME). This converts the global perception of explainability to the local perception. This explains the impact of the localized features through surrogates and illustrates the relationship between a value point and its surrogates through linear relationships using a Lasso or Linear Regression. The below-mentioned representation takes a local instance in a dataset and explains it with the LIME explainer as per Fig. 12. Fig. 12. According to this local instance, the temperature is 101, Systolic BP is 90, Age is 19, and Heart Rate is 80. In this condition, the LIME predicts and explains about these values measured in the particular local instance, and estimates the prediction score, based on the probability of the prediction of the underlying ML model. In this instance, the temperature is very high and represented with high-risk indication with a weight of around 46%. The systolic BP value is around 7% risk which is significantly close to the critical value of 95, and the age is 13 which has a 6% of risk level finally 1% risk is assessed for the heart rate; the orange color indicates a positive impact on the high-risk prediction. The green color indicates the negative impact of

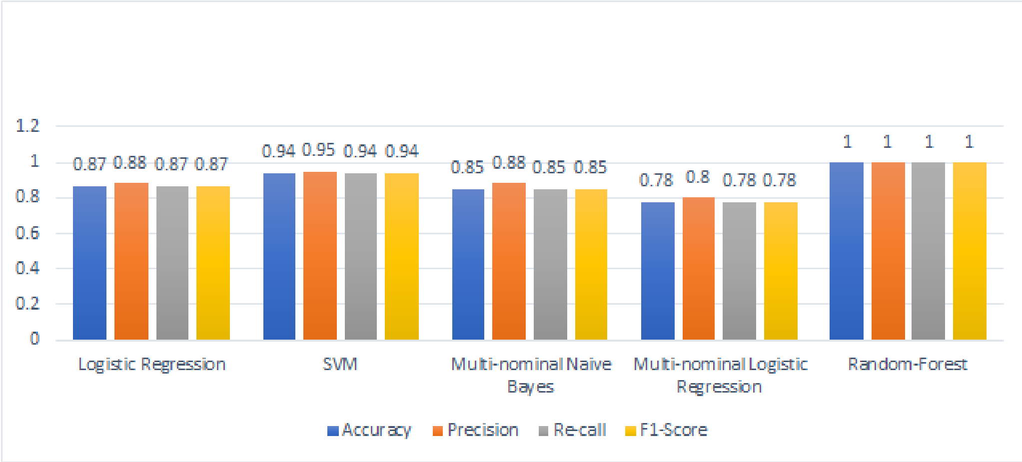

Fig. 9: Performance comparison of various machine learning models for maternal risk prediction

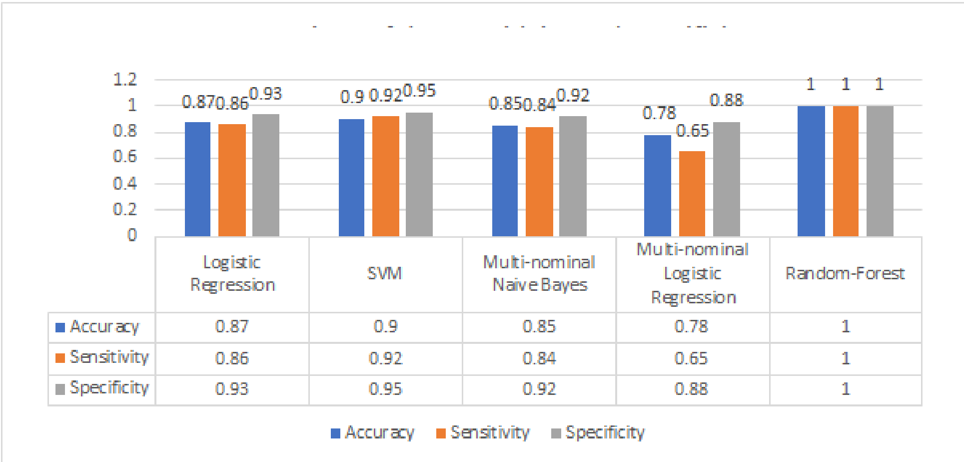

Fig. 10: Performance comparison of Sensitivity and Specificity

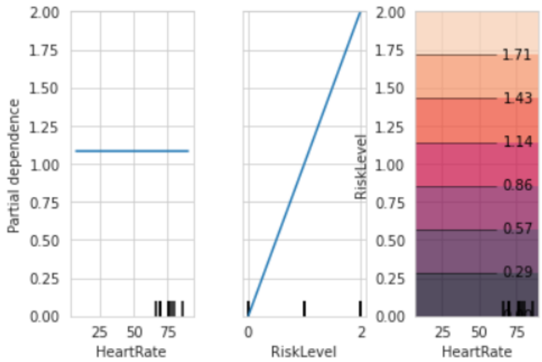

Fig. 11: Partial Dependency Plot between Heart Rate and the maternal risk

the risk assessment. This prediction is, however, for the local forecast of an instance. It does not make sense for global prediction and consideration. The same aspect is explained in the below diagram for the particular local instance in Fig. 13.

The SHAPELY values can provide global and local explanations for classification and regression. The proposed work uses the random forest classifier, which provided the highest accuracy during the classification. A sample test patch for the output values explained for all the prediction classes against all the input features. This is depicted in the below-mentioned Fig. 14. This diagram shows a point where the systolic BP has a value of 130 indicated in the high-risk category. This explains the behavior of every instance in the dataset for predicting maternal risk levels and what feature values correspond to the increase or decrease in the level of the risk at the output. Thus, it is called a test patch which gives the overall distribution of the data instances for XAI implementation.

The average impact of the total number of the features and the impact on the output magnitude is represented in Fig. 15. The Systolic BP, Body Temp are the higher impact attributes, and the Age and BS values have a lower impact on the output magnitude. The colors represent the low or high impact in the graph. The data marked around the blue colored contour represents the low impact, and the one centered around the red is the high impact point. The mixed regions are the values which are representing the medium risk category. The Fig. 14 defines the importance of every attribute and the Fig. 15 represents how each attribute predicts high, medium, and low maternal risk levels.

SHAPELY values thus explain the contribution of each attribute towards the output. The impact of features on model output is expressed in Fig. 16. The blue-colored regions indicate low impact, and the red-colored regions indicate a high impact on model output.

SHAPELY values also provide the dependency between two attributes; for example, the dependency between the two attributes, Body Temperature and the Systolic BP is explained using the dependency plot shown in Fig. 17. Finally, the Low and High-Risk decision plots for a specific local instance is explained using the Shapely values as per the Fig. 18 and Fig. 19. This model describes the input features with significant values, and estimates their impact on risk prediction. In this scenario, for example, Fig. 19illustrates

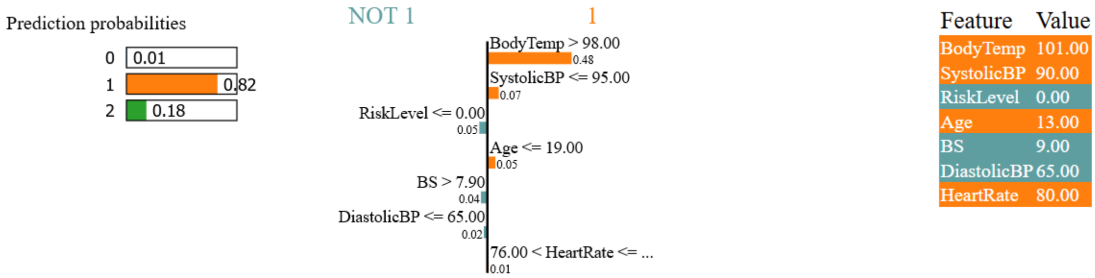

Fig. 12: LIME Explanation for a specific local instance with LASSO

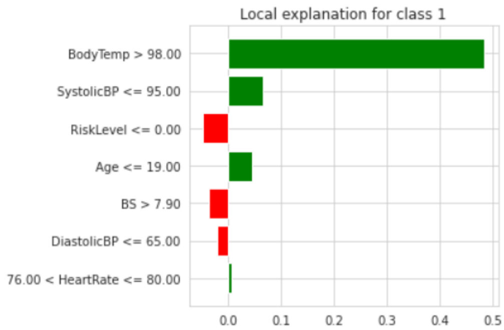

Fig. 13: LIME Explanation with PyPlot with Positive and Negative Features

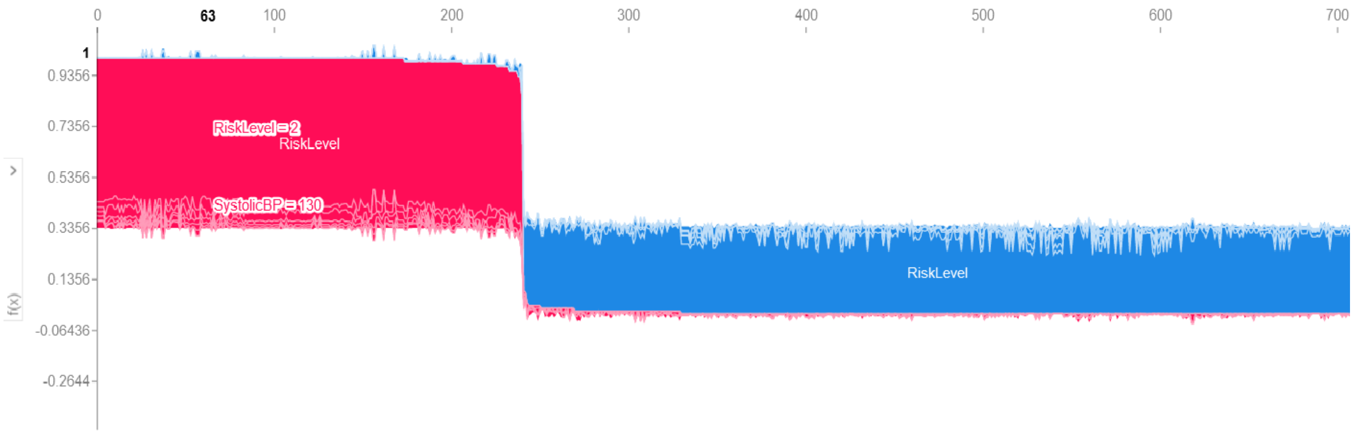

Fig. 14: SHAPELY Value Explanation for a sample test patch with local explanation

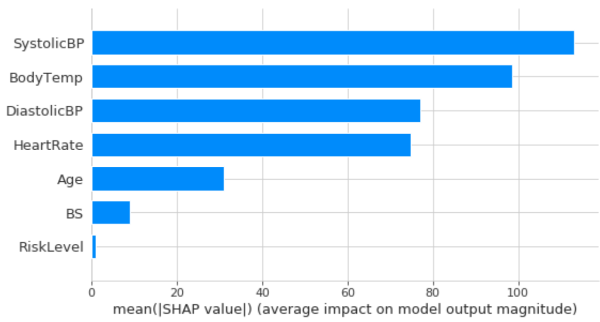

Fig. 15: SHAPELY Value Explanation Average impact of Features towards the output magnitude

an instance that has a Body Temp of 101, Heart Rate of 80, Age of 13, Systolic BP of 90, Diastolic BP of 65, and a BS level of 7. This instance is mapped to the high-risk category as the parametric values increased during the measurement . According to this instance, the Temperature, Systolic BP, and Blood Sugar levels are abnormal.

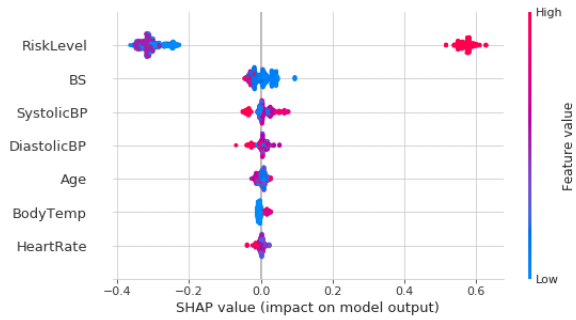

Fig. 16: SHAPELY Value Explanation Average impact of Features on the model output

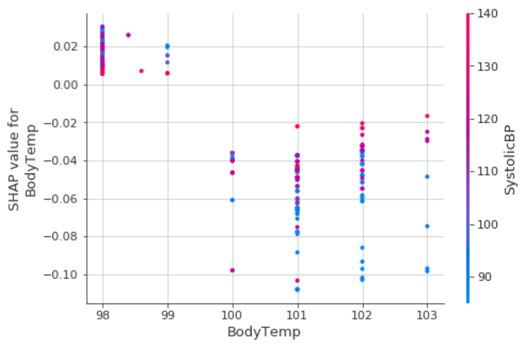

Fig. 17: SHAPELY Value Explanation for Dependency between two features

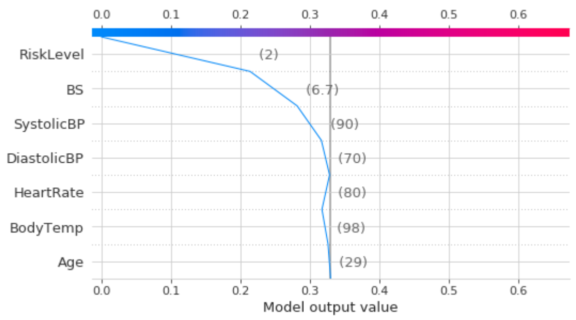

Fig. 18: SHAPELY Value Explanation using decision plot for a low-risk category between two features

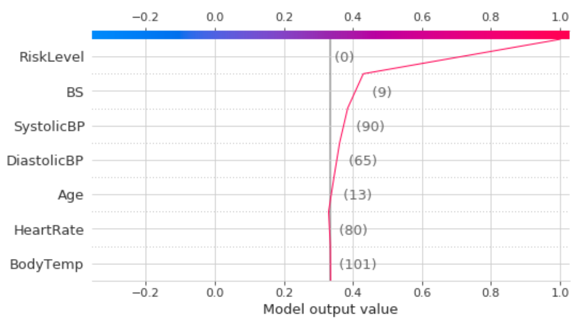

Fig. 19: SHAPELY Value Explanation using decision plot for a high-risk category between two features

6 Discussion

This section describes in detail about the implementation, how the instances are classified, what are the metrics evaluated, how the specific model is selected for the explanation and how the XAI results can help for the interpretation of the model in a detailed manner.

The results have been obtained with the explanation of the local surrogates with LIME which includes the explanations provided by the Pyplot and notebook. The output is presented in Fig.13. The feature weights of the various parameters with a corresponding impact on the target prediction are presented in Tab.4. This analysis and explanation pertain to one local instance on the dataset. Hence it doesn't provide an explanation regarding the overall dataset. The LIME is thus providing the explanation for the local surrogates with the approximation of neighboring data points through the lasso function.

The global surrogates with an explanation of the dataset for test patch validation, dependency analysis, feature importance analysis and the decision plots are done with the help of SHAPELY values. The decision parameters are tabulated and discussed as per Tab.5. The three final decisions and the respective explanations are provided in Tab.5. The three decisions such as High, Medium, and Low, are influenced by various attributes like BS, Diastolic BP, Systolic BP, Heart Rate, and Body Temperature, which is explained by the decision plot of SHAPELY values. With this, we understand what features and threshold values have an influence in determining the risk levels of maternity. Tab.5 depicts the results explained by the figures Fig.18 and Fig.19.

The dependency plots show two color densities: blue and magenta, where the blue indicates the low and the magenta indicates the high values of the specific parameter. For example, Fig.18 shows that Blood sugar level has a low impact in predicting high maternity risk, and Systolic and Diastolic BP has a high impact in predicting maternity risk, when it becomes high. Tab.6 shows the features' average impact in determining the output magnitude. The systolic BP, Heart Rate, and Diastolic BP are the significant features in predicting the output magnitude of the risk, which is also depicted in Fig.16.

6.1 *Challenges of the existing systems*

6.1.1 False Positives: False positives lead to life-threatening situations, especially when a high-risk instance is wrongly classified as low or medium risk. Medical practitioners may misunderstand a high-risk patient as a low-risk patient, and the result could be fatal. The challenge in the proposed work is to handle the false positives by reducing classification errors and imbalances.

6.1.2 Missing Data: Missing data imputation is another essential phenomenon that needs attention which lead to improper classification, generation of false positives which could further lead to life-threatening consequences. Missing data imputation can handle false positives and improve the classification algorithm's performance.

6.1.3 Sensitivity and Specificity: In majority of the studies, the evaluation metrics considered are Accuracy, Precision, Recall, and F1-Score which validate the performance of the model. But the stability of the model often lack priority wherein sensitivity and specificity should be considered. These are the most important parameters to be considered when ensuring that the performance of a model is reliable enough.

6.1.4 Lack of Interpretability: The ML models had the potential to classify the results based on different categories but they failed to provide the rationale behind the generated classification results. The importance of specific features in deriving the output's magnitude was excluded earlier from consideration. The XAI applications, using SHAPELY values help in identifying the importance of each feature towards achieving the output in the study. There also exists lack of evaluation in establishing the relationship between features and the target, which is given emphasis in XAI implementations. The conventional machine learning models were black-box, where only the processes can be tracked, but the core mapping of the significance of attributes and its contribution towards an outcome can never be tracked.

Attribute	Importance Weight	Impact
Body Temp	0.48	Positive
Systolic BP	0.07	Positive
Age	0.05	Positive
Systolic BP	0.02	Negative
Blood Sugar	0.02	Negative

Table 4 Feature Importance with Impact Analysis of LIME

Target Risk Level	Influencing Attribute1	Influencing Attribute2	Normal/Abnormal	Age
Low	Heart Rate	Body Temp	Normal	29
High	Blood Sugar	Body Temperature	Abnormal	13
Medium	Systolic BP	Diastolic BP	Abnormal	26

Table 5 Comparison of the three decisions of XAI with decision plot of shapely

Feature	Importance
Systolic BP	1
Body Temperature	2
Diastolic BP	3
Heart Beat	4
Age	5
BS	6

Table 6 Comparison of the three decision of XAI with decision plot of shapely

6.2 Lack of Model Agnostic Approach

Machine learning models are model-based, wherein the solutions depend on the model and thus often lack explainability. Thus the need for a model-agnostic explainer arises that enables interpretation of the features, determines relationships among the features, and also the contributions of the features towards achieving an output.

6.3 Solutions given by the proposed work

6.3.1 Missing Value Imputation and Performance Enhancement: The proposed work measures sensitivity and specificity for handling false positives. This enhances the model's performance and increases the prediction stability. Missing value imputation also contributes towards enhancing of the performance and reduction in the false positives.

6.3.2 Evaluation of the quality of the baseline model: The proposed work ensures that the baseline ML model is reliable and achieves enhanced performance, and stability. The models that contain maximum accuracy and minimum false positive rate are carefully chosen for explainability which ensures interpretability, reliability and dependability of the model. The proposed work performs a detailed analysis of the machine learning models before choosing the Random-Forest classifier for providing explanation.

6.3.3 Model Agnostic Approach: The model agnostic approach uses a LIME explainer that explains the positive and negative features. The notebook explainer explains the positive and negative impact of the features in predicting the risk considering feature importance weights of the contributing attributes. Thus, the model-free approach allows the model to be interpretable for any input use case, illustrating the reasoning behind the classification.

6.3.4 Evaluation of the Feature Importance: The feature importance and significance to the output prediction are done using a SHAPELY explainer. The contribution of the features and the dependency between the same are explained with the help of SHAPELY values. The decision plot of the SHAPELY explainer depicts the impact of the individual feature values on the classification process. The SHAPELY explainer performs extensive analysis considering the feature values, contributions, the magnitude of the features in determining the target value, relevant feature relationships, and the contribution of features in determining a particular classification.

7 Conclusion and Further Work

Risk mitigation and prediction of the progression of risk in pregnancy is essential considering the fact that co-morbid conditions associated with the pregnancy can be fatal. The proposed work used PDP, LIME, and SHAPELY explainers to define the attributes and their significance in determining maternal risk. These explainers used Random Forest and Multi-nominal Naïve Bayes classification models to explain the maternal risk criteria. The Random Forest generated optimum accuracy, and the Multi-nominal Naïve Bayes provided balanced sensitivity and specificity of 0.84 and 0.92 respectively. The time closer to the delivery of the baby which is known as the third trimester is considered to be extremely critical wherein the child and the mother are susceptible to multiple diseases that can adversely affect the health of the mother and the unborn. The proposed work considers various risks associated with maternal healthcare and Artificial Intelligence and Explainable AI models in predicting and classifying the risks in to three categories namely high, medium, and low. The AI models in the study had no class imbalance, missing values, and over-fitting issues while performing categorization of the risks. The model generating the best accuracy is Random Forest and hence selection for purpose of explanation. The LIME explainer provides feature importance and weights. It also categorizes positive and negative features and its contribution in predicting the results. The results of the study also provides explanations using SHAPELY values, generating correlation of the features, presents information on distribution of the data in datasets, highlights the dependencies existing across the attributes, and finally explains risk categorization using the decision plots. The integrated model thus performs classification and also provides explanation in predicting the risks associated with maternity. However, the proposed work does not include preservation of privacy or security aspects of the data. The study limits its scope in classifying and explaining the risk conditions associated with maternal health based on data collected from wearable sensors. The proposed work, which uses numeric dataset can be further extended for the complex classification of medical images. The IoMT architecture can be enhanced for better connectivity using the support of 6G technology as per the motivation from the paper [39]. The blockchain framework can be used for securing medical records as well as the IoMT architecture [40, 41]. Also, federated Learning model can be incorporated with XAI to ensure data privacy of the model. The XAI implementations can be tested and deployed in meta-verse applications to provide medical assistance through Virtual Reality and Augmented Reality interfaces.

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