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A Medical Cyber-physical system for predicting maternal health in developing countries using machine learning

Mohammad Mobarak Hossain [a,*], Mohammod Abdul Kashem [a], Nasim Mahmud Nayan [b], Mohammad Asaduzzaman Chowdhury [c]

[a] Department of Computer Science and Engineering, Dhaka University of Engineering and Technology (DUET), Gazipur, 1707, Bangladesh
[b] Department of Computer Science and Engineering, University of Information Technology and Sciences (UITS), Dhaka, 1212, Bangladesh
[c] Department of Mechanical Engineering, Dhaka University of Engineering and Technology (DUET), Gazipur, 1707, Bangladesh

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ABSTRACT

It is essential to monitor any health issues during pregnancy to ensure a safe delivery because pregnancy is crucial for both mother and child. However, developing countries have poor access to healthcare, making managing possible health risks during pregnancy challenging. An Internet of Things (IoT)-based Medical Cyber-Physical System (MCPS) can offer a valuable and affordable solution for anticipating and controlling health hazards during pregnancy to solve this issue. This paper presents the design and development of an MCPS for recognizing health risks in pregnant women in developing countries. The system collects key health metrics using temperature, blood pressure, glucose levels, and heart rate sensors. It automatically considers risk factors to predict health risks using Machine Learning (ML) and sends them to the nearest clinic or hospital. Patients can manually enter their risk factors into the program and talk with a doctor through it. The efficacy of the proposed MCPS is evaluated using a dataset of pregnant women, and the results demonstrate that the system can accurately detect health issues during pregnancy. Medical experts can.

enhance maternal and fetal health outcomes using the systems real-time data collecting and processing capabilities. Despite restricted access to healthcare in developing countries, the proposed MCPS provides a valuable and economical method of addressing pregnancy-related health risks. The MCPS can assist medical personnel in making quick and informed choices, enhancing the level of care provided to expectant mothers and their unborn children.

1. Introduction

Information technology (IT) is crucial for risk management, clinical decision support, and healthcare [1]. While IT has enabled the gathering, processing, and transmitting of data from sensors and wearables, there still needs to be a gap in its practical application for maternal health, especially in developing countries.

This research addresses this gap by introducing a novel Medical Cyber-Physical System (MCPS) tailored for predicting and monitoring maternal health risks. It allows medical professionals to remotely monitor the health of pregnant patients, identify issues, and treat them as soon as they arise.

During a woman's pregnancy, it is essential to guarantee the welfare of both the mother and fetus. According to the World Health Organization, 94 % of all maternal deaths occur in low-income and lower-middle-income countries, where.

810 women per day perish from complications during childbirth and pregnancy [2]. Despite technological advancements, more access to quality maternal health monitoring systems must be needed, especially in resource-limited settings. By combining the strengths of MCPS, the Internet of Things (IoT), and ML for efficient maternal health monitoring, this article intends to close the gap. Women experience difficulties with their maternal health during pregnancy, childbirth, and the postpartum period [3]. Due to geography, economics, or healthcare infrastructure, it is challenging to obtain pregnancy monitoring systems [4]. Pregnant women should have equal access to care and monitoring options to receive adequate compensation and care [5]. Clinical usage validation is essential, so the dependability and precision of the

* Corresponding author.
E-mail addresses: mobarak.hossain@uits.edu.bd (M.M. Hossain), drkashemll@duet.ac.bd (M.A. Kashem), smnoyan670@gmail.com (N.M. Nayan), asadzmn2014@yahoo.com (M.A. Chowdhury).

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wearable technology, sensors, and other technologies utilized in pregnancy monitoring systems may vary [6]. It may be difficult to develop practical clinical decision support tools and algorithms for assessing and interpreting the data generated by pregnancy monitoring devices [7]. Pregnant women are more likely to experience health problems that may lead to miscarriage or even mortality. Confirming a healthy pregnancy is a lifealtering and emotionally significant event for a married woman [8]. The welfare of women is essential for both the mother and the infant. Therefore, lifestyle choices and overall health should be considered prior to pregnancy. Pregnant women must receive high-quality care to ensure their health [9]. Women must experience a healthy pregnancy and postpartum period in order to protect the health of both mothers and infants. Regarding infancy, adolescence, and maturity, it is likely that these women will maintain their health in old age [10]. However, it can be challenging to anticipate pregnancy-related health issues, and prompt action could mean the difference between an uncomplicated and a complicated birth [11]. Providing equal access to pregnancy monitoring systems, developing dependable clinical decision support tools, and emphasizing women's health throughout pregnancy and postpartum are essential for the health of mothers and neonates, with potential long-term effects on the general health of older adults. Using an integrated communication core, CyberPhysical Systems (CPS) integrate computational control methods and tangible components [12]. CPS consists of a patient's body, software for medical devices, and networks. Multiple medical conditions, including airway-laser surgery and patient-controlled analgesia (PCA) [13,14], have demonstrated the efficacy of Medical Cyber-Physical System (MCPS) [15]. On the other hand, it is a new system created by synchronizing various medical devices with the physiologic dynamics of the patient [16]. In MCPS, IoT devices such as wearables, sensors, and smart home appliances can collect real-time patient health data, such as vital signs, activity levels, and medication adherence, allowing for detecting and tracking early health issues [17]. MCPS combines elements of the natural world and the internet with dynamic, completely customizable systems for decisionmaking and other healthcare applications [18]. IoT solutions in the medical field create a seamless environment by keeping track of remote patients and dispatching medical aid to distant regions [19]. ML algorithms evaluate and interpret data from peripheral devices, EHRs, and other health databases for remote patient monitoring. ML-based predictive analytics, risk assessment, and individualized therapy recommendations facilitate early intervention and enhanced patient care [20]. Using wearable sensors is a potential, non-invasive, and patient-friendly strategy to facilitate the early diagnosis of intraamniotic infection in women with Preterm Premature Rupture of Membranes (PPROM) [21]. Managing key risk factors in a timely and effective manner by a care provider located in a remote location is made possible by using MCPS, which is an exciting development in information technology [22]. IoT, MCPS, and ML can potentially transform pregnancy health monitoring and enhance the results for both mother and child health. While recent technical improvements have led to a decrease in maternal mortality, it is still difficult to ensure the safety of both mother and baby throughout pregnancy [23]. Compared to women who are not pregnant, pregnant women have a higher risk of health problems. For instance, bleeding is the primary factor in maternal mortality, responsible for almost 27 % of fatalities [24]. Risking the lives of the mother and the child by doing Severe maternal problems can arise from unfavorable delivery conditions, such as significant blood loss, failure to progress (FTP) labor, atypical fetal presentation, and preterm birth [25]. Due to the development of IoT-based MCPS and ML algorithms, healthcare systems now have additional options for detecting and treating pregnancy-related health issues. In Developing Countries, where access to healthcare is limited in many areas, a practical means for tracking pregnancy-related health issues is essential. Consequently, it is preferable to monitor expectant women at home. With the aid of MCPS, a monitoring system for maternal health during pregnancy and delivery can be developed, allowing for early detection of health hazards and prompt intervention. This research aims to develop an ML-based pregnant health risk prediction system using MCPS to monitor and regulate pregnancy-related health issues in developing countries. This research aims to develop an ML-based pregnant health risk prediction system using MCPS to monitor and regulate pregnancy-related health issues in developing countries. Our preliminary results have shown an accuracy measure of 99 % in predicting maternal health risks, showcasing the potential of our approach. Connected wearable devices will gather real-time data on health indicators, including blood pressure, pulse rate, glucose levels, and body temperature. Then, these data will undergo analysis through ML algorithms. This approach not only offers a technological solution but also has the potential to revolutionize maternal healthcare in regions where traditional healthcare infrastructure may be lacking. This study's outcomes could enhance maternal and infant health by facilitating early health issue prediction, informing public health policies, and eliminating healthcare barriers. The proposed research makes three significant contributions to the field of maternal health care in the context of an MCPS.

- Firstly, We present a unique real-time dataset on maternal health care, paving the way for future prediction models and health risk monitoring.
- Secondly, Our research introduces a standardized interface for medical devices, enhancing their interaction with the MCPS.
- Finally, Our system offers continuous monitoring of pregnant women, emphasizing early detection and intervention.

Overall, the study advances maternal health care by integrating machine-learning techniques, medical device integration, and long-term monitoring to enhance the prediction and monitoring of maternal health hazards in a medical CPS environment. The remaining portions of this paper are as follows: Part 2 is a Literature Review of relevant literature and studies, providing a comprehensive overview of current knowledge and research in the field. The third section expands on the instruments and procedures used in the study to collect and analyze data by describing additional materials and techniques. Section 4 of the manuscript contains the findings and discussion. Section 5 concludes the paper by summarizing the main findings, highlighting the research contributions, and identifying potential areas for future study.

2. Literature Review

Numerous research endeavors acknowledge the potential of IoT technology to enhance patient outcomes, resulting in a significant increase in its utilization in healthcare facilities [26,27]. One such application employs custom-built devices and IoT concepts to monitor and manage chronic diseases such as diabetes and hypertension [28]. More research is needed to apply this innovative maternal health risk assessment approach. Using multiple data collectors, Sarhaddi et al. [29] propose a system to monitor the mother's health, including her stress levels, sleep patterns, and physical activity. They implemented the system and used real human subjects to study expectant women in southwest Finland. Their findings indicate that the system in place is viable for nine months. Artizzu et al. [30]identified the variables associated with preterm birth utilizing a deep convolutional Neural Network (NN) approach. Rawashdeh et al. [31]used Decision Tree (DT), Random Forest (RF), K Nearest Neighbors (KNN), and NN to predict the probability of preterm delivery. This study employed multiple ML methods with variable results. Javaid et al. [32]demonstrated that ML is utilized extensively in numerous fields. Classification and prediction are the primary applications of ML algorithms in medical diagnosis and pandemic forecasting. Cluster analysis secures the web by identifying abnormal traffic, cancer cells, and client segmentation. Other functions of natural language processing include sentiment analysis, language translation, and speech recognition. Islam et al. [33]utilized multiple supervised ML algorithms to predict the optimal delivery method for vaginal, cesarean, forceps, and vacuum delivery. Usharani et al. [6] proposed a wireless accelerometer sensor and deep learning-based wristband framework for inexpensive vital sign monitoring. Their technologyenabled remote monitoring and recording were precise, portable, and stable.

Sam et al. [34]demonstrated that using a new invention in remote patient observation systems allowed for patient observation outside of clinical contexts, enabled complete access for healthcare institutions, and reduced operational costs for social insurance. Sharma et al. [35] developed the Enhanced Binary Bat Algorithm (EBBA) and refined it to outperform other methods for selecting features. This innovative bio-inspired optimization algorithm reduces computational costs through precise dimensionality reduction, facilitating proper feature selection. Akter et al. [36]proposed a CPS-based system to collect real-time values from the community using ML models to predict the onset of cardiovascular disease. Learnability is explored in Ref. [37] and a framework is proposed in Ref. [38]. According to Kadhim et al. [39], the health monitoring system computes ECG, blood pressure, and temperature monitoring results in less than 1 min. Due to the consolidation of multiple medical data sensors onto a single component, the scope is also reduced compared to the conventional approach. Consequently, time-cost complexity is reduced. Miah et al. [40] concludes that MCPS are necessary to incorporate a medical device network in the healthcare industry. Levonevskiy et al. [41]demonstrated that Health status monitoring, patient interaction, data collection and visualization, and problem-solving are all possible withMCPS. Jimenez et al. [42] addressed the use of WBAN in cloud environments and IoT networks, in addition to the security and privacy concerns that MCPSs and digital twins present. According to Sony and his colleague [43], MCPS will favorably influence the healthcare service delivery's comprehensiveness, accessibility, coverage, continuity, quality, person-centeredness, coordination, accountability, and efficiency dimensions. Using questionnaires, Shi et al. [44] conducted experimental research with 315 expectant women. The findings indicate that several factors influence expectant women's recognition and acceptance of wearable IoT devices. In another study, Marzia et al. [45] developed a method to monitor and predict the level of risk pregnant women in Bangladesh encounter. It analyzed expectant women's health information and risk factors using analytic instruments and ML algorithms. The Modified DT (DAlgorithm has the most excellent numerical accuracy at 97 %. They developed a web application to collect user feedback. Wakschlag et al. [46]provided a method for estimating the stress level of expectant women in real-time, with the possibility of integrating the suggested model into an edge-based architecture. Duatt et al. [47] provided an integrated solution for high-risk monitoring of obstetric patients by IoT network-based sensors in which features are recovered from the observed signal using the feature extraction approach, and then a deep DCGAN-based Classification system is used to predict the health of the mother and fetus. Emergency Diagnostics Section is where Venkata Subramanian et al. [48] develop a system of inferential principles that can provide an area under the curve more significant than 80 % for fetuses, expectant women, and emergencies. Chen al [49]. MCPS, a medical field Cyber-Physical System, is crucial in strengthening national healthcare systems by ensuring secure identity verification, access control, and the efficient exchange of extensive medical data. Paul et al. [50] demonstrate that socio-demographic factors, including education, household wealth, urbanization, caste, religion, women's age, marriage age, media exposure, and regional location, notably impact maternal healthcare utilization. Marques et al. [51] proposed a comprehensive strategy for continuous high-risk patient surveillance in hospitals based on a network of IoT sensors and devices. According to Islam et al. [52], ML has substantially improved the best method to deliver a baby and the identification of numerous complications during delivery. Li et al. [53] presented an innovative, cutting-edge, and distinctive paradigm for smart maternal healthcare services that employ wearable technology and its core technologies. The obstetrics departments of hospitals also investigated its uses, monitoring, and home management techniques. Sachian et al. [54] describe how the Raspberry Pi-based prototype will measure air quality metrics in hospital rooms via a TLS/SSL MQTT connection, enabling real-time data transmission and protecting against outside attacks. From April 2017 to June 2018, Dutta et al. [55] collected data through verbatim transcription of recorded interviews conducted in a single subdistrict in Bangladesh. They reveal the need to increase service user knowledge and develop guidelines for community-level service providers to address maternal mental health issues among expectant women in rural Bangladesh. By utilizing MCPS, we create an IoT-based device that predicts maternal health risks, such as high-risk, moderate-risk, and low-risk pregnancies. This device would use ML algorithms to analyze this data in real-time to discern patterns and identify potential health risks, enabling healthcare providers to intervene early and improve outcomes for both mother and fetus.

3. Materials and methods

This paper describes the dataset, procedures to sanitize the raw data, and exploratory data analysis. In our paper, we discussed and utilized the techniques of data set knowledge acquisition, careful characteristic selection, and experimentation. Fig. 1 demonstrates the block diagram of the Proposed Research Methodology.

3.1. Demographics

We used Bangladesh as a case study for emerging nations, with the possibility of extrapolating our findings to other developing nations and populations in future studies. This paper examined the age, monthly income, education level, technological aptitude, and status of expectant women who participated in a health surveillance program utilizing IoT devices for real-time data collection.

Age: The participants' ages varied from fifteen to forty-five, with a mean of twenty-seven. Most participants (56 %) were between 20 and 29. Gender: The research focused on pregnant women and solely included female participants. As a result, only women were included in the gender variable for this study. Education: The participants' levels of education varied, although the majority (66 %) had at least finished elementary school. Monthly Income: The participants' monthly incomes were divided into four categories and expressed in Bangladeshi Taka (BDT). Ability to Utilize Technology: Participants' self-reported comfort levels with cellphones, internet-enabled gadgets, and health monitoring apps were used to gauge their capacity to use technology. Most participants said they were generally comfortable with technology rather than IoT devices. The majority of respondents with more than 60 % live in cities. On the other hand, 40 % of the respondents now reside in rural regions. Comprehensive information on the demographic and socioeconomic circumstances of the respondents is provided in Table 1.

3.2. Pregnancy data collection

We constructed our MCPS by integrating a Raspberry Pi 4 Model B single-board computer with various detectors, including heart rate, blood pressure, glucometer (HbA1c, Fasting hour-m), and temperature sensors (see Table 2). Alongside this, we primarily used a sphygmomanometer to measure Blood pressure (systolic and diastolic). Body mass index (BMI) was manually taken from the patient. This system automatically captures sensor data and transmits it to the cloud. The server in the cloud automatically receives data via a wireless connection. The data was converted to a CSV file and then downloaded for evaluation. The system was strategically positioned in various locations, including clinics, hospitals, and the homes of expectant women, to collect a vast array of data. Once every 30 min, the device was configured to collect data from the sensor at regular intervals throughout the day. Patients were instructed to wear the device.

to record measurements at specific periods throughout the day. This

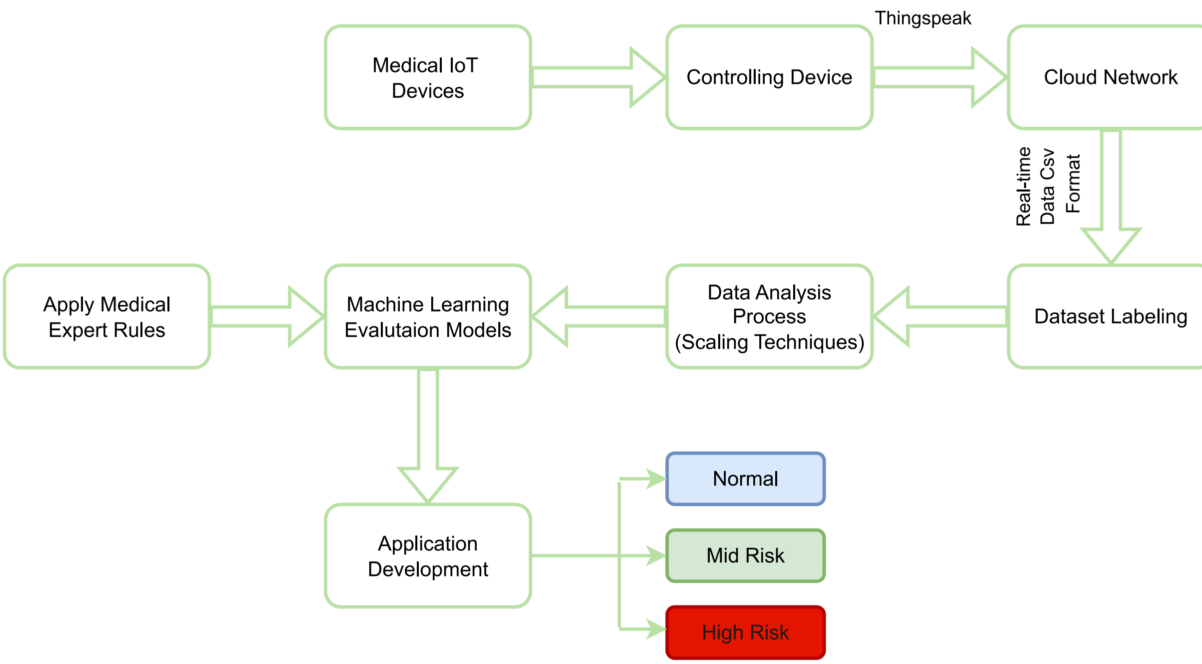

Fig. 1. Proposed methodology architecture.

Table 1
Demographic data.

Factors	Values	Percent	Mean Average
Age	Less than 20	8	25
	20–29	56	
	30–39	34	
	older than 40	2	
Gender	Female	100	100
Educational Status	No formal education	2	25
	Completed primary	66	
	education	23	
	Secondary education	9	
	Tertiary education		
Household monthly income in (BDT)	Less than 10,000	38	25
	10,000–20,000	34	
	20,001–30,000	25	
	More than 30,000	3	
Ability to use technology in general	Low proficiency	4	33.3
	Modest proficiency	20	
	High proficiency	76	
Ability to use IoT device	Low proficiency	84	33.3
	Modest proficiency	18	
	High proficiency	8	

Table 2
List of Maternity clinic and hospital for data collection.

Hopital Name	Contact And Address	Period
Alhaj Sufi Mohammed Dayem Uddin Hospital	Charpara Er Pase, Rupganj, Dhaka	February 17, 2021 January 02, 2022 February 25, 2023
Dr. Jhumu Khan's Laser Medical	121/C, Shariatullah Bhaban, Gulshan Ave, Dhaka 1212	May 04, 2021 August 19, 2022
Senior Citizen Hospital - Baridhara	Senior Citizen Hospital, House# 8, Road# 8, Baridhara Block# J Dhaka, 1212	18-05-2022
US-Bangla Medical College	Kornogop, Tarabo, Rupgonj, Narayangonj, Dhaka.	February 28, 2022
Green Life Medical College	MAK Khan Tower 31 and 31/1, Bir Uttam K.M. Shafiullah Sarak (Green Road) Dhaka	September 01, 2022
Snehaloy	41/2 Shiddeshwari Kalimondir Road, Dhaka 1217	November 19, 2022
BACC Womens & Children Hospital (Pvt.) Ltd.	R Panthapath, Dhaka 1205	August 16, 2022
Rahima maternity	H- 1, R- 5 A, Dhaka 1216, 1216	July 07, 2022 12.01.2022
Pabna Shishu Hospital and Mattriseba	Meril Bypass Road, Shalgaria, Pabna 6600	22.01.2023

paper's dataset comprises over 6000 data elements from multiple sources. Our system collected four hundred twenty-three data points. Before use, demographic information was collected from individuals who agreed to participate in the study and wore the device. The remaining data points were collected from private residences, hospitals, and clinics. Our collected data was compared to hospital data for cross-validation. While accumulating data, we discussed our findings with surgeons, obstetricians, and gynecologists from various hospitals. Drs. Sharmin Afroz, Mahbooba Akhtar, and Rifat Sultana deserve special recognition. Below 2 is a list of prestigious hospitals and institutions from which we gathered data on patients admitted with the device. In addition, it included the information of patients previously admitted to that hospital. We chose the most significant risk variables to predict the patient's risk status. This Table 3 provides succinct descriptions of eleven attributes of our dataset.

Fig. 2 Plot three classes (low, high, and medium risk) to demonstrate their relationship. The datasets contain a total of 6103 patient records, 2059 of which are high risk (class 0), 2043 are medium risk (class 2), and 2001 are low risk (class 1).

3.3. Data pre-processing

To ensure the quality and integrity of our dataset, the initial stage of our research consisted of meticulous data preparation methods. To address potential issues of missing and duplicate values, we employed Python's built-in functions. Specifically, we used the isnull (). sum () method to identify any missing values across all columns and the

Table 3
Attribute Details of our Dataset.

Attribute	Attribute Type	Attribute Details
Patient Id	Integer	Id Number of Patient
Patient Name	Object	Name of Patient
Age	Integer	Age of Patient
Body Temperature	Float	Body Temperature of a Patient
Heart Rate	Integer	Heart Rate of a Patient
Systolic Bp	Integer	The top number is the maximum pressure the heart exerts while beating
Diastolic Bp	Integer	The bottom number is the amount of pressure in the arteries between beats
BMI	Float	weight in kilograms divided by height in meters squared
Blood Glucose (HbA1c)	Float	our average blood sugar levels over the past 3 months
Blood Glucose (Fasting hour-mg/dl)	Float	blood sugar after an overnight fast
Comment	Object	Status of a patient (Low risk, High risk, Mid risk)

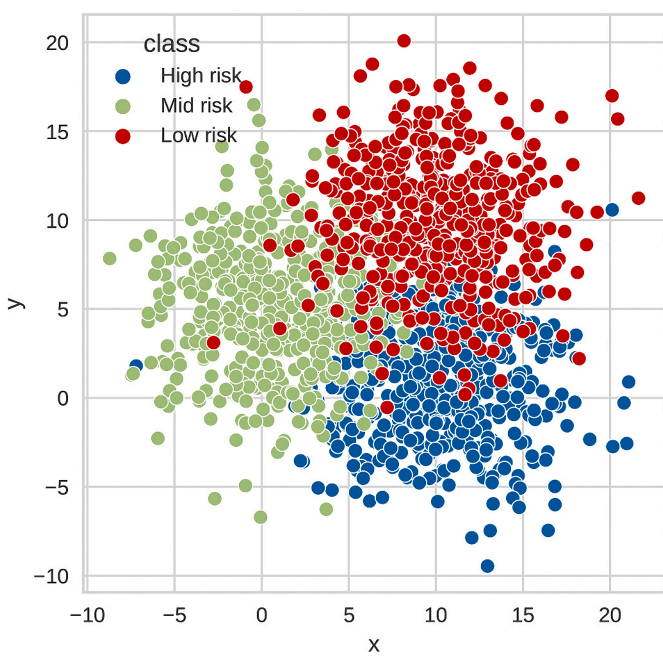

Fig. 2. Visualizing the overlap between classes in the dataset.

duplicated (). sum () method to detect any duplicate rows. After running these checks, we found that our dataset contained no missing or duplicate values. This rigorous validation ensured we worked with accurate and complete information. During data conversion, we used label encoding to convert categorical variables into numeric values. This method facilitated subsequent analysis and modeling by representing categorical data numerically. We employed the Pearson coefficient correlation to assess the linear relationship.

between variables in our dataset. This statistical test allowed us to determine the strength and direction of any linear relationships, aiding in our subsequent analyses. To address the concern regarding data standardization, we utilized the StandardScaler method, represented by the simple equation (1):

$$X_{std} = \frac{X - \mu}{\sigma} \tag{1}$$

This method effectively scales each feature with a mean of 0 and a standard deviation 1. Doing so guarantees that all features contribute equally to the distance metric in subsequent analyses. This data standardization process ensures that all characteristics are measured consistently, facilitating meaningful comparisons and ultimately leading to more accurate and reliable results in our analysis. Fig. 3 depicts this paper's overall preprocessing and model evaluation phase.

Heat map depicts coefficients to illustrate the significant correlation between various elements. Its stated purpose is to illustrate straightforwardly how various elements interact. A heat map is a form of data visualization that simultaneously displays the row and column hierarchical cluster structure in a data matrix [56]. Heatmap displays the most significant and tiniest values in the matrix. Fig. 4 illustrates the relationship between the data attributes.

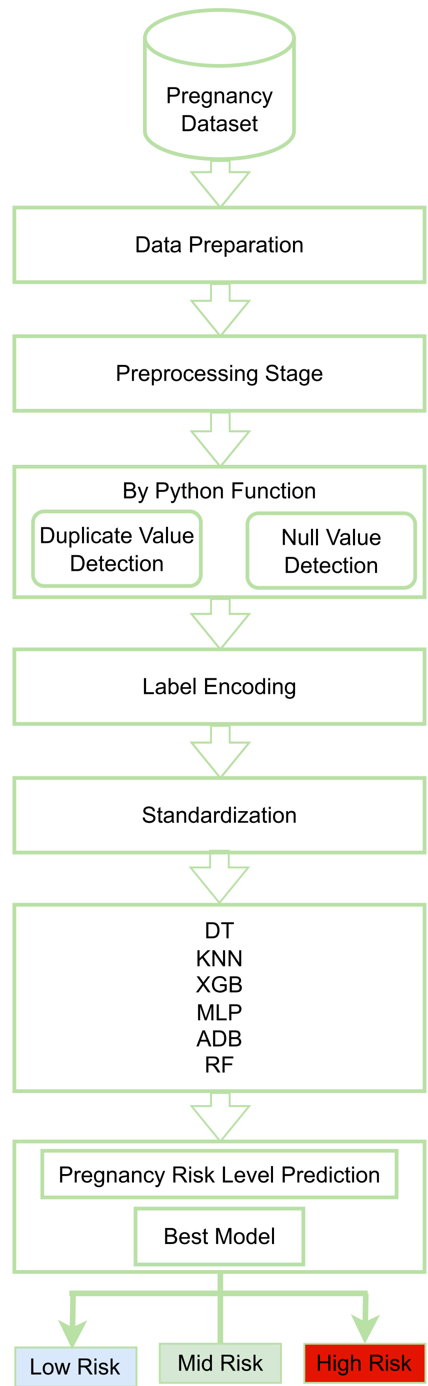

Fig. 3. Preprocessing step and model evaluation.

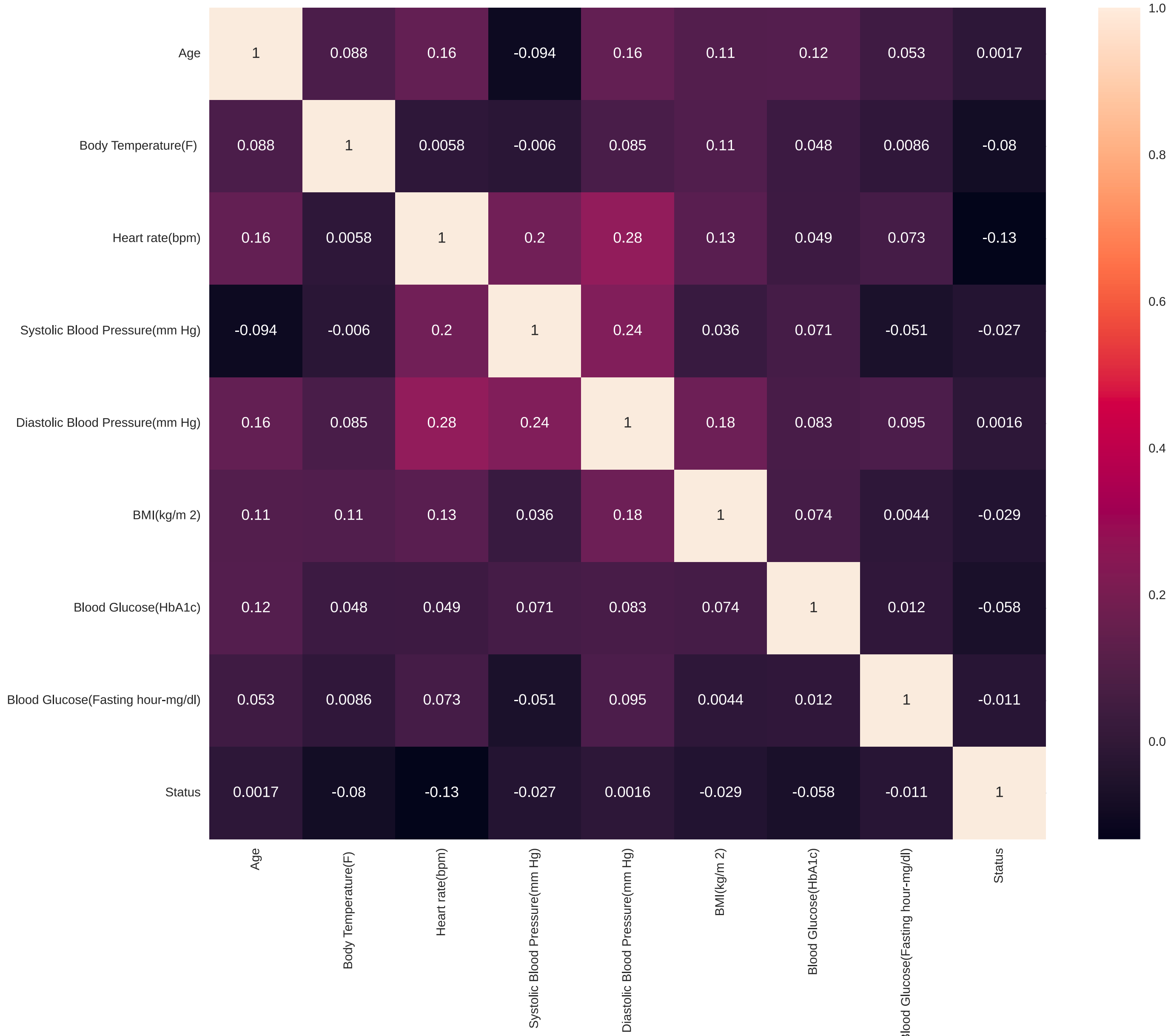

Fig. 4. Heat map for checking correlated columns.

3.4. Workflow

The workflow of the paper is shown in Fig. 5 which provides a comprehensive overview of our entire process, starting from the beginning and ending at the conclusion. Our work begins with a well-defined research proposal that outlines what we aim to achieve. Next, we gather real-time data from various sources using IoT devices. Once we have our data, we put it through a series of processes to clean and prepare it for analysis. We apply six different algorithms to analyze and make predictions based on the data. To ensure our models are reliable, we use various evaluation metrics and employ k-fold cross-validation to test their robustness. To make our results more understandable, we use Explainable AI (XAI) techniques to create visualizations that show how our models make decisions. Then, we deploy.

applications or systems using the Streamlit framework. Finally, we wrap it all up by summarizing our key findings and future work.

3.5. Simulation environment

1. Hardware Specifications:
   (a) Central Processing Unit (CPU): Intel Core i5-9600K 3.6 GHz.
   (b) Memory (Random-access memory):16 GB DDR4.
   (c) Storage: 1 TB SSD for faster data access.
2. Software & Libraries:
   (a) Operating System: Windows 10.
   (b) Programming Language: Python 3.9.
   (c) Key Libraries & Frameworks:
      i. Machine Learning: scikit learn 1.3.1. ii. Data Processing: Pandas 1.2, NumPy 1.2.
      iii. Visualization: Matplotlib 3.8.0, Seaborn 0.13.
3. Dataset Specifications:
   (a) Size: 6103 records.
   (b) Features: 11 features, including target feature.
   (c) Dimension: (6103,11).
   (d) Preprocessing: Data was normalized using StandardScaler, and data transformation was done by labe encoding.

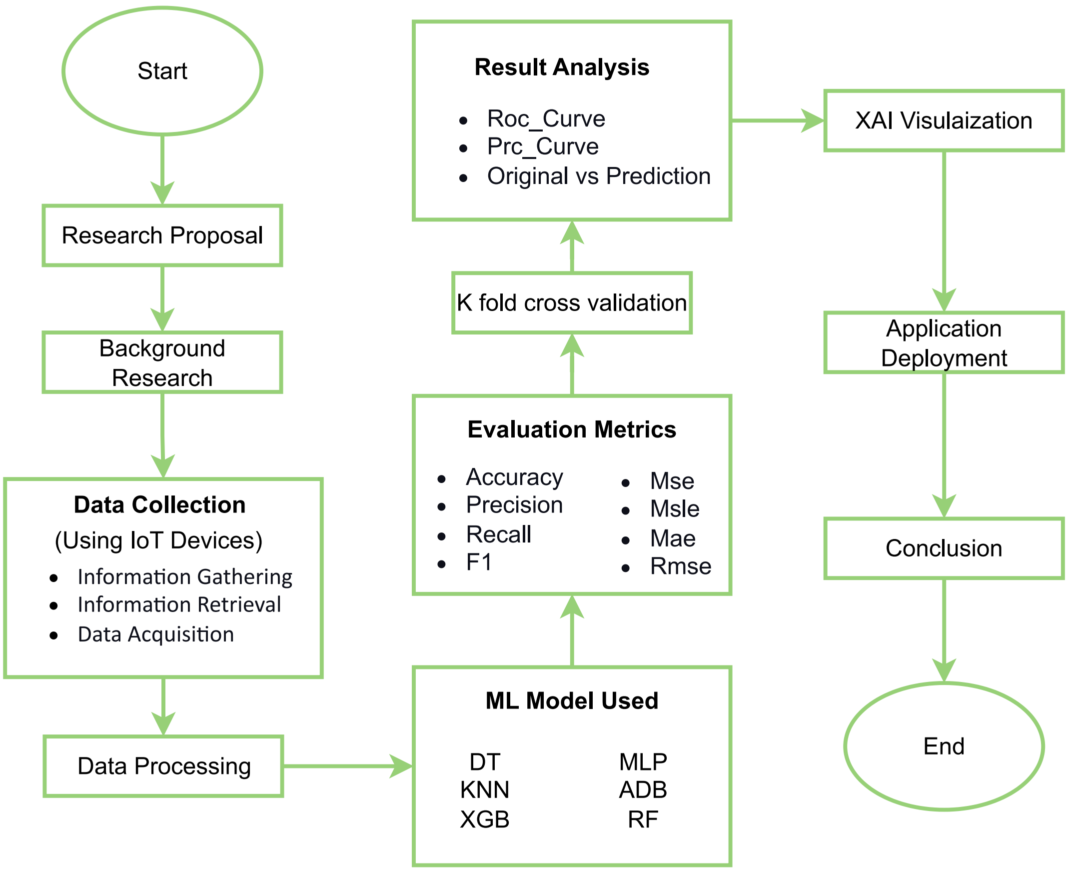

Fig. 5. Overall workflow chart for our paper.

4. Model & Algorithm Configurations:
   (a) MLP Configuration: Learning rate was set to 0.001.
   (b) DT Configuration: The maximum depth was set to 5. The criterion used was Gini impurity.
   (c) 7. KNN Configuration: Used Euclidean distance metric with K set to
   (d) XGB Configuration:Learning rate of 0.01, max depth of 3, and n estimators set to 100.
   (e) ADB Configuration: Used a base estimator of a decision tree with a depth of 1 and n estimators set to 50.
   (f) RF Configuration: Utilized 100 trees, the maximum depth of each tree was set to 10, and used the Gini impurity criterion.
5. Real-time Application Development:
   (a) Framework: The application was developed utilizing the Streamlit framework.
   (b) Development Environment: All coding and debugging tasks were carried out within the Spider IDE.
   (c) Version Control: We Used GitHub to store code.
   (d) Deployment: The final application was deployed and made accessible to users via Streamlit sharing.

3.6. *Machine learning algorithms*

3.6.1. *Decision tree*

Historically, DT has been recognized as a strategic and highly effective technique in various fields, including ML, image processing, and pattern recognition.

The DT model compares a numerical feature to a threshold value during each

test. The conceptual principles that regulate how nodes in a neural network connect are much simpler to develop than the numerical weights [57]. Equation.

1 represents the equation for the DT method.

$$H(T) = -\sum_{i=1}^{c} p_i \log_2 p_i \tag{2}$$

where c represents the number of classes and p_i represents the percentage of samples that belong to each class i, and $H(T)$ represents the entropy of the DT. Using this formula, entropy, a measure of the impurity or randomness of a dataset, is calculated for DT.

3.6.2. *K nearest neighbors*

The conventional KNN algorithm is a supervised machine-learning technique predominantly used for classification. k represents the quantity of "nearest neighbors" in an algorithm. The KNN technique locates the adjacent data point or neighbors for a query from a training dataset [58]. The method is founded on the similarity between instances in a dataset. It locates the K training dataset instances most similar to a new instance.

Equation (2) below provides an equation for the KNN method.

$$\hat{y}(\mathrm{X}) = \arg\max_y \sum_{i=1}^{K} \mathbf{1}(y_i = y) \tag{3}$$

Where $\hat{}y(\mathbf{x})$ is the predicted class for $\mathbf{x}$, y_i is the class of the ith nearest neighbor, and 1 $(y_i = y)$ is an indicator function that equals 1 if $y_i = y$ and 0 otherwise. The equation employs the 'argmax' and 'sum' operators to identify the class label that maximizes the number of instances.

3.6.3. *Extreme Gradient Boosting*

This ML paradigm enhances the learning effect by combining multiple poor learners. In addition to its many other advantages, the Extreme Gradient Boosting (XGB) concept is highly adaptable and scalable [59]. This ensemble approach uses multiple DTs to make predictions.

The following equation, 3 represents the XGB method.

$$\hat{y}_i = \sum_{k=1}^{K} f_k(X_i), f_k \in f \tag{4}$$

Based on the sum of the outputs of K trees, indicated as f_k ($\mathbf{x}_i$), where f_k is a member of the function space F, the predicted target variable value for the i-th instance is $\hat{}y_i$.

3.6.4. Multilayer perceptron

Multilayer perceptrons (MLPs) are the basic architecture of artificial neural networks (ANN), reflecting the human brain's organization. They have multiple hidden layers between input and output, connected to neurons in the nextlayer [60]

Equation (4) demonstrates how the MLP classifier forecasts class probabilities.

$$y\hat{} = f\,(W_2 \cdot \sigma\,(W_1 \cdot x + b_1) + b_2) \tag{5}$$

Where: $\hat{}y$ is the predicted class probabilities. x is the input feature vector. W_1 and b_1 are the weights and biases of the first hidden layer. W_2 and b_2 are the weights and biases of the output layer. σ represents the activation function in the hidden layer. f represents the output activation function, often softmax for.

classification.

3.7. Adaptive boosting

Adaptive boosting (AdaBoost) methods combine multiple weak classifiers to generate a robust classifier by adaptively determining the weights of the weak classifiers. Sample weights vary based on whether the categorization results were accurate or inaccurate [61]. The following equation, 5 represents the Adb

method.

$$f(x) = \sum_{m=1}^{M} \alpha_m h_m(x) \tag{6}$$

Where the final classifier is represented by $f(x)$, there are M weak classifiers in total, and the weight given to the classifier with the mth position is *alpham*, where $hm(x)$ is the result of the mth classifier for the input instance x.

3.7.1. Random Forest

As a general-purpose method, the RF algorithm has achieved considerable success in classification and regression. When there are many more variables than observations, it has been demonstrated that the technique performs well in certain situations. In the RF technique, some decision trees are trained using random subsets of the training data and features, and then their predictions are combined by voting or averaging [62]. RF improves the model's overall accuracy by reducing variance and preventing the overfitting of specific trees. The equation for the RF algorithm is shown in Equation 6.

$$F(x) = \frac{1}{N} \sum_{i=1}^{N} f_i(x) \tag{7}$$

Here, $fi(x)$ is the prediction of the i-th hlDT for the input instance x, $F(x)$ is the ultimate prediction for the input instance x, and N is the total number of hlDT.

3.8. Evaluation metrics

A confusion matrix, a table, is utilized to assess the efficacy of a classification model. It indicates the proportion of accurate and inaccurate predictions the model made based on a particular data set compared to the actual outcomes. Numerous performance indicators, such as accuracy, precision, recall, and F1score, are frequently calculated using the matrix.

- True positives (TP): The number of instances in which the model predicted the positive class precisely.
- False positives (FP): The number of times a model predicted a positive class when the actual class is negative.
- True negatives (TN): The number of instances in which the model pre-
  dicted the negative class correctly.
- False negatives (FN): The number of cases in which the model predicted a negative class when the actual class was positive.

These are terms used to compute evaluation metrics. The percentage of all predictions that the model produced that were accurate. A number between 0 and 1, with one denoting perfect accuracy and 0 denoting no accuracy, represents the accuracy score.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

The proportion of optimistic predictions generated by a precise model. A model's forecasts are evaluated based on their precision. It determines the ratio of accurately predicted favorable outcomes to all favorable results. In contrast to low precision scores, which indicate an overwhelming number of erroneous optimistic predictions, high precision scores indicate that the model provides reliable optimistic predictions.

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

The proportion of positive data points that the model correctly predicted. Recall score, also known as sensitivity, is a statistical metric used to evaluate how well an ML model can recognize each relevant occurrence in a dataset. When a

model's recall score is high, it is effective at locating all relevant instances in the dataset, whereas a low score indicates that it may be omitting essential cases.

$$Recall = \frac{TP}{TP + FN} \tag{10}$$

The F1 score, which combines accuracy and recall into one statistic, is used to assess the effectiveness of a binary classification model. It is characterized as the harmonic mean of recall and precision.

$$F_1 = 2\bullet\frac{precision \bullet recall}{precision + recall} \tag{11}$$

Mean Absolute Error (MAE) measures the average absolute difference between predicted and actual values in a regression problem. The average absolute differences between the expected and actual values characterize it.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{12}$$

The mean squared error is the variance between the expected and actual value's squared deviations.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{13}$$

The units of the response variable are also used to represent the Root Mean Squared Error, which quantifies the average difference between predicted and actual values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{14}$$

in statistical analysis, the R-squared measure, also known as the coefficient of determination, indicates the proportion of the variation in a dependent variable that independent variables can explain. This value fluctuates between 0 and 1, with larger values indicating a more significant correlation with empirical data.

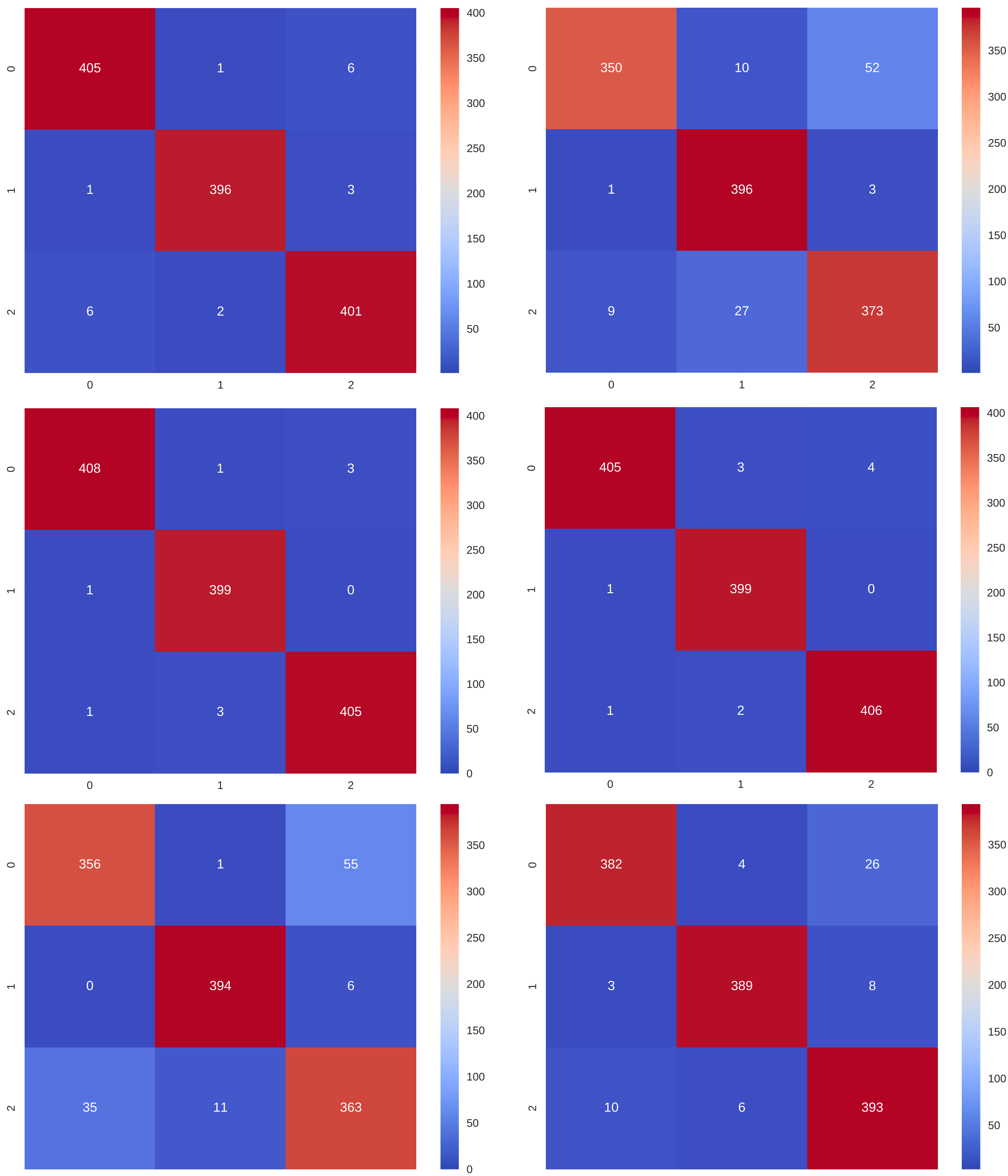

Fig. 6. Confusion matrix for a classification model, a) DT, b) KNN, c) XGB, d) RF, e) ADB, f)MLP.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \widehat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \overline{y}\right)^2} \tag{15}$$

4. Results and discussion

The entire dataset was split into two groups by us. While the second is for testing, the first is for training. The model was trained using 80 % of the total data and tested using the remaining 20 %.

4.1. Confusion matrix

The confusion matrix, as shown in Fig. 6, visually represents each model's performance metrics. It makes it simple for readers to understand and evaluate the model's performance metrics.

4.2. Classification evalutaion

This Table 4 compares the efficacy of six distinct machine-learning algorithms. The table includes three typical evaluation metrics for classification tasks: precision, recall, and F1 score. A comparison of the findings indicates that the XGB algorithm receives the highest aggregate score across all performance metrics. The XGB algorithm has outperformed the other algorithms in.

correctly identifying data points for three classes with high precision (Low risk.

99 %, Mid risk 99 %, and High risk is 100 %), recall (Low risk 99 %, Mid risk 100 %, and High risk is 99 %), and F1 (Low risk 99 %, Mid risk 99 %, and High risk is 99 %). It is essential to remember that the efficacy of different algorithms may vary depending on the application and dataset being used.

4.3. Regression evaluation

The MAE, MSE, and RMSE regression error measures for six distinct methodologies are included in Table 5. Mean squared error (MSE), mean absolute error.

(MAE), mean squared logarithmic error (MSLE), and root mean square error (RMSE) are used to evaluate the model's performance. Among these algorithms, the XGB method performs the best for this specific regression task due to its low error rate. We obtain MSE (0.01), MSLE (0.004), MAE (0.009), and RMSE (0.11) using the XGB model. On average, it has the lowest error when estimating numerical values, which is relatively low and suggests strong

Table 4
Experimental result of performance metrics.

Model	Class	Precision	Recall	F1
DT	Low risk	0.99	0.99	0.99
	Mid risk	0.98	0.98	0.98
	High risk	0.99	0.98	0.99
KNN	Low risk	0.91	0.99	0.95
	Mid risk	0.87	0.91	0.89
	High risk	0.97	0.85	0.91
XGB	Low risk	0.99	0.99	0.99
	Mid risk	0.99	1.00	0.99
	High risk	1.00	0.99	0.99
RF	Low risk	0.99	1.00	0.99
	Mid risk	0.99	0.99	0.99
	High risk	1.00	0.98	0.99
ADB	Low risk	0.97	0.98	0.98
	Mid risk	0.86	0.89	0.87
	High risk	0.91	0.86	0.89
MLP	Low risk	0.97	0.93	0.95
	Mid risk	0.97	0.97	0.97
	High risk	0.97	0.93	0.95

Table 5
Regression error value table.

Algorithm Name	mse	msle	mae	rmse
DT	0.03	0.01	0.02	0.19
KNN	0.23	0.06	0.13	0.48
XGB	0.01	0.004	0.009	0.11
RF	0.02	0.006	0.01	0.14
ADB	0.03	0.09	0.16	0.55
MLP	0.13	0.04	0.07	0.36

predictive capabilities.

4.3.1. Cross-validation

Six models' k-fold cross-validation results are presented in Table 6. The data was divided into five segments, as indicated by the fact that the crossvalue validation of k was five. Cross-validation is employed to determine how well each method performs on fictitious data. The average results from each of the five folds are used to compute the mean cross-validation score for each method, which is then displayed in the table. The mean score comprehensively evaluates the algorithm's performance on the data. XGB achieved the highest mean accuracy of 99.12 % out of the six algorithms.

Fig. 7 describes the accuracy of the following ML algorithms to determine which ML technique is the most effective. This graph displays the accuracy ratings for six distinct algorithms. Three of the algorithms have accomplished a remarkable 99 % accuracy. Nevertheless, the XGB method outperformed the other algorithms marginally when other crucial parameters such as recall, F1, and accuracy score were considered. According to the regression error metrics MAE, MSE, MSLE, and RMSE, the XGB model performs this task best. Even after k-fold cross-validation, XGB was determined to have the highest mean accuracy score. The XGB model is the optimal algorithm for this assignment due to its superior balance of precision and other crucial parameters (see Fig. 8).

4.4. Experimental result analysis

Using a micro-average ROC curve and precision-recall curve analysis, this paper evaluated the overall performance of our classification model across all classes in the dataset. The receiver operating characteristic and precision-recall curves are valuable performance indicators for classifiers [63]. The micro-average.

ROC curve represents the model's overall performance by integrating the true positive and false positive rates across all classes into a single curve. Our investigation's micro-average ROC curve yielded an AUC value of 1.0, indicating 8 that our model can perfectly discriminate between all classes. This result indicates that our model can distinguish between positive and negative samples regardless of the specific class identifier.

The precision-recall curve assesses the performance of our classification model. The precision-recall curve illustrates Fig. 9 the trade-off between precision and recall for various threshold values used to classify samples as positive or negative. As a result of our investigation, we determined that our model's average precision (AP) value is 0.99,

Table 6
K fold cross validation.

Algorithm Name	iter1	iter2	iter3	iter4	iter5	Mean Accuracy
DT	0.989	0.980	0.981	0.981	0.982	98.31 %
KNN	0.919	0.904	0.918	0.911	0.928	91.6 %
MLP	0.949	0.949	0.956	0.947	0.953	95.12 %
XGB	0.992	0.9888	0.993	0.990	0.990	99.12 %
ADB	0.912	0.905	0.959	0.952	0.926	93.12 %
RF	0.989	0.987	0.988	0.988	0.989	98.87 %

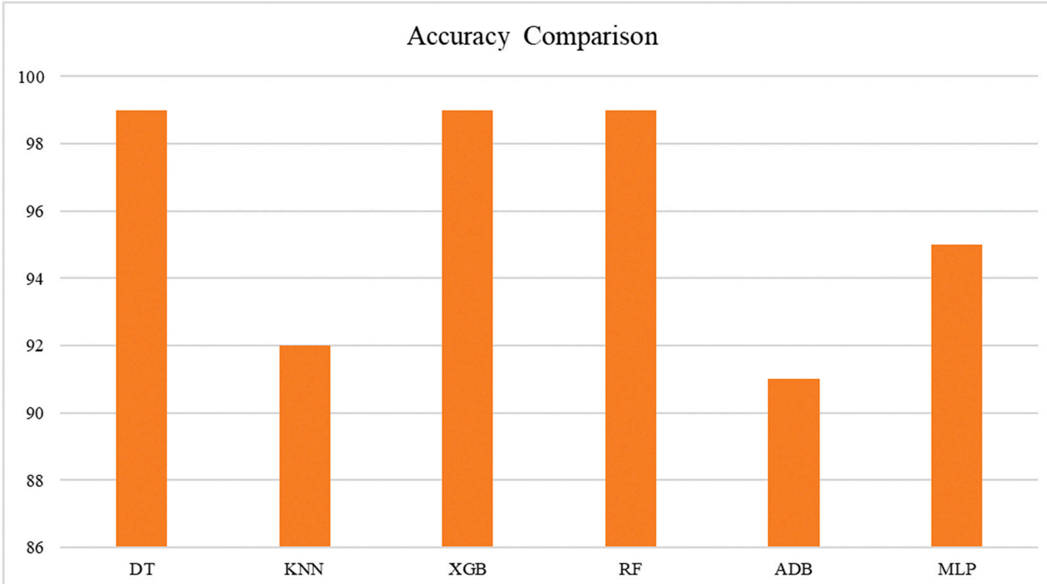

Fig. 7. Algorithm comparison for ML.

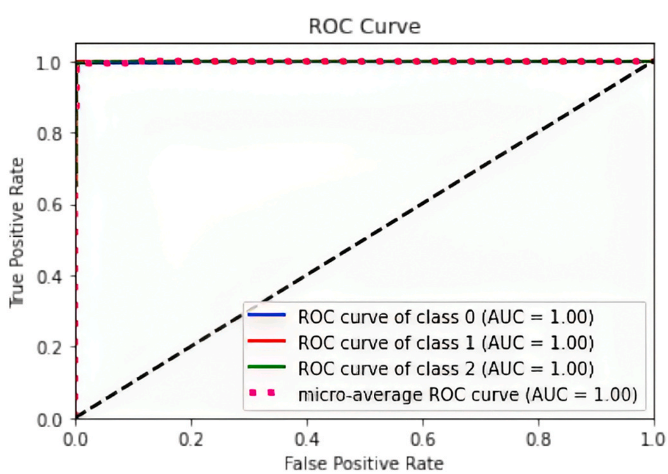

Fig. 8. ROC curve for best result.

demonstrating its high precision and recall for classifying positive samples. A score of 0.99 indicates that our model is exceptionally effective at recognizing genuine positive data, with few false positives and false negatives. Notable because an AP score of 1.0 would indicate flawless precision and recall, the AP score of 0.99 indicates that our model's performance is highly.

close to optimal. This finding suggests that our model is optimal for tasks requiring high recall and accuracy, such as fraud detection and medical diagnosis.

We could evaluate our model's performance by comparing the projected data (in orange) to the actual data (in blue). As shown in Fig. 10, the pattern of the projected data is identical to that of the actual data, demonstrating that our model effectively depicts the underlying structure of the data. This result demonstrates that our model can accurately identify and reproduce the underlying data structure in the predicted data. This discovery is important because it demonstrates that our model can generate new data that closely resembles the original data or make accurate predictions.

4.5. XAI visualization

We evaluate the efficacy of all algorithms and methods and select XGB based on its overall accuracy, precision, and recall. Medical imaging researchers are increasingly utilizing XAI to elucidate the outcomes of their algorithms. XAI has played a crucial role in visualizing and comprehending black box models [64]. This section discusses model precision, fairness, and transparency, as well as the outcomes of AI-supported decision-making. This study employed Shapley Additive Explanations (SHAP) to investigate the predictive value of several characteristics for health hazards among pregnant women. The SHAP bar diagram is shown in Fig. 11format. This Figure illustrates the significance of each characteristic. By examining this graph, we can see that systolic blood pressure is the most likely risk factor for pregnancy. It is responsible for rates of high-risk cardiac conditions that are roughly twice as high. Heart rate is another significant risk factor during pregnancy.

4.6. Virtual platform

A virtual platform (mobile application) has been developed to make it simpler for expectant patients to contact physicians. It allows for direct communication between patients and doctors and the generation of test results and physician feedback. The goal and objectives that we kept in mind while developing the application is reiterated below.

- Provide a user-friendly interface so expectant women can easily access accurate, up-to-date medical information.
- Facilitate and expedite the process of locating medical professionals who specialize in treating specific symptoms or diseases for expectant mothers.
- Provide a secure and convenient platform for expectant patients to communicate with their physicians via messaging, video conferencing, and other means.
- Permit patients to provide feedback on their interactions with their physicians in order to aid others in selecting the best physician for their needs and to aid physicians in enhancing their services.
- Provide a virtual platform that allows pregnant women to procure medical services from the comfort of their residences, such as remote monitoring and virtual consultations.

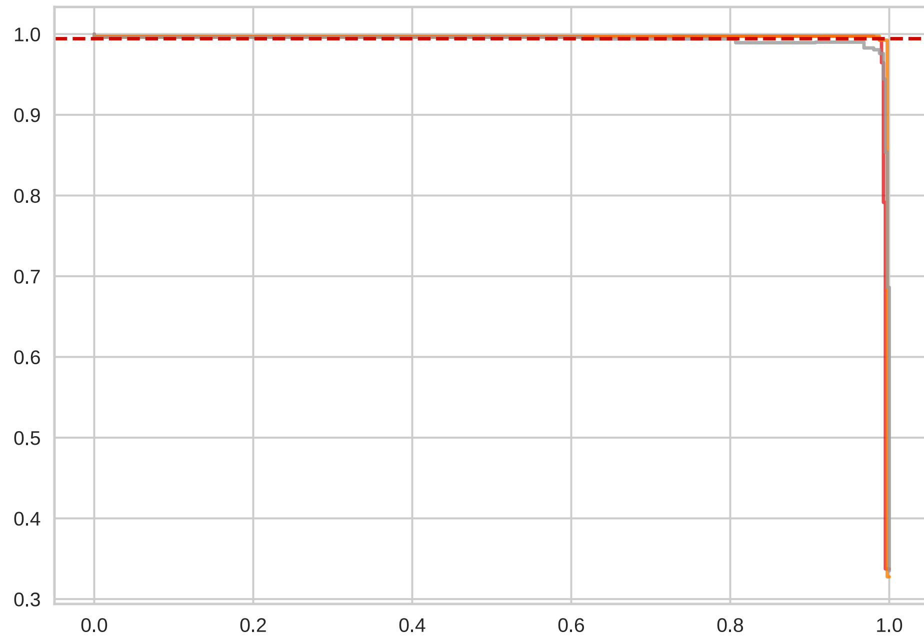

Fig. 9. PRC curve for best result.

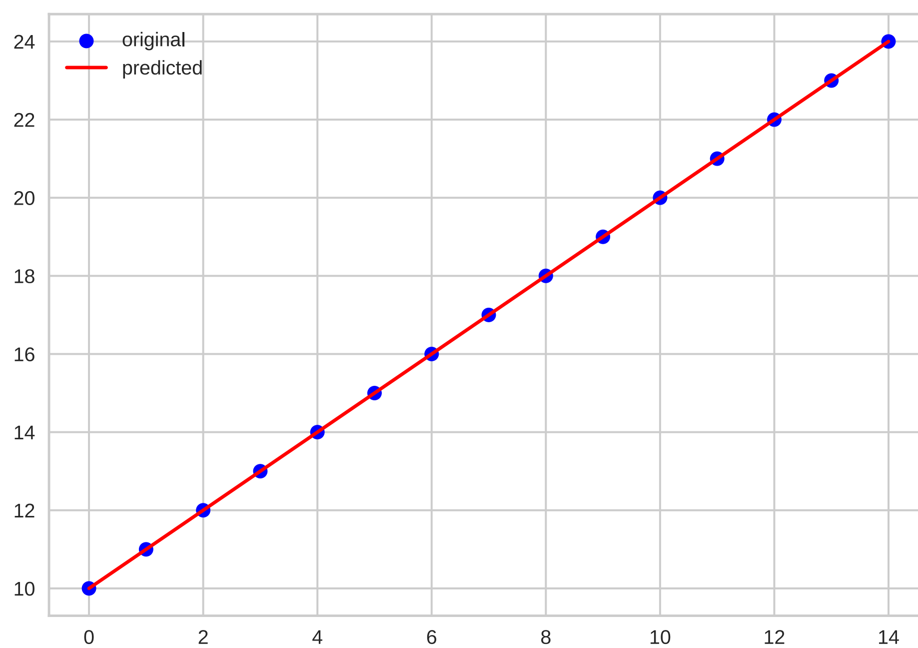

Fig. 10. Comparison of original data and predicted data.

A pictorial description of the developed platform for symptom identification and management is provided in Fig. 12.

5. Conclusion and future works

This research has demonstrated the potential of integrating MCPS with machine learning algorithms to predict maternal health outcomes with real-time data collection and cutting-edge algorithms. Due to the lack of all necessary sensors for capturing health metrics, we had to use a specific device to measure a particular metric. Utilizing comprehensive evaluation metrics such as precision, recall, and F1 score. Remarkably, our predictions using the XGB classifier reached an accuracy of 99 %, outperforming other algorithms, and had the lowest error rates. The research incorporates XAI to enhance interpretability and trust among medical professionals, ensuring accuracy, reliability, and trustworthiness. Our Proposed systems provide real-time, data-driven insights for maternal and child safety during pregnancy, collect vital health metrics, predict risks, and facilitate patient-doctor communication, paving the way for future innovations. Our findings imply that this technology might benefit the nation's healthcare system, giving doctors and other medical personnel more precise and timely information to make knowledgeable decisions on patient treatment. Ultimately, this may improve maternal and fetal health outcomes and reduce Developing countries' maternal death rates. The study plans to use MIT-engineered wearable blood pressure sensors for improved monitoring, focusing on robust security mechanisms to protect sensitive pregnancy data. Future studies will examine the system's effectiveness in reducing maternal and newborn mortality rates, disease prevalence, access to care, and overall

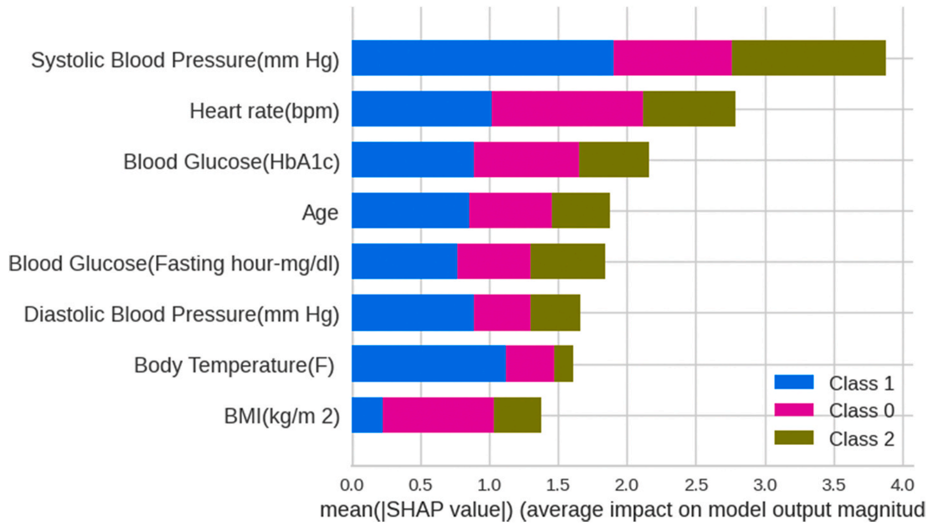

Fig. 11. SHAP bar plot.

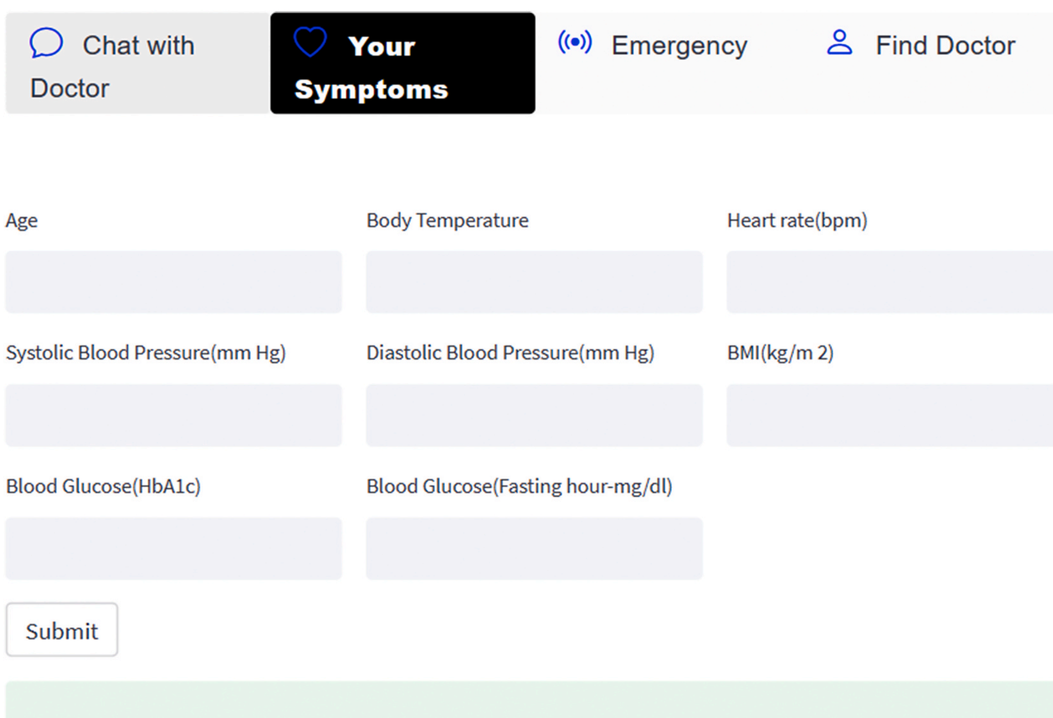

Fig. 12. Platform for symptom identification and management.

health outcomes.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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