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Contextual Framework for Remote Intelligent Monitoring and Detection System for Prediction of Pregnancy Complications

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Abstract
Maternal health disorders can cause complications and harmful incidents in women during pregnancy. To minimize risks, this research developed a platform powered by a supervised machine learning model (SMLM) to support remote intelligent monitoring and prediction of pregnancy complications caused by hypertensive disorder, gestational diabetes, and related indicators. The study used real-world datasets with six UCI Machine Learning Repository features to identify and predict Maternal Health Risk (MHR) factors. A Support Vector Machine (SVM) algorithm was applied to construct the classifier model, which was trained and evaluated using StratifiedKFold cross-validation (k=10). The model achieved 80% accuracy with a precision, recall, and F1-score of 77%. The outcome of this work is the P-Health mobile application, designed to record and track blood pressure, blood sugar, heart rate, body temperature, and weight, while predicting the risk level of pregnancy complications through inference from the integrated machine learning model. Developed with Kotlin and Android Studio, the application enables healthcare practitioners to remotely monitor patients' vitals in real time. This innovation addresses the challenge of early detection of pregnancy complications and provides continuous monitoring and assessment. The findings suggest that P-Health can improve early detection and timely intervention, helping medical specialists minimize maternal health risks. The system also has the potential to raise public awareness of maternal health issues, thereby contributing to the prevention of complications during pregnancy.

Keywords: *P-Health. SMLM, MHR, Webserver API.*

I. INTRODUCTION

Pregnancy or gestation is a period during which a woman's uterus grows one or more children. A few gynecologists describe each trimester as lasting around 14 weeks, which adds up to about 42 weeks of pregnancy. Maternal sepsis, maternal hemorrhage, complications from abortions, and high blood pressure throughout pregnancy (Hurt et al., 2012), gestational diabetes, and weight gain during pregnancy are the most frequent causes of complications and fatalities during this time. The most serious and avoidable pregnancy complications are anomalies in Blood Pressure (BP), Blood Glucose Levels, and Weight Gain.

Gestational hypertension, which affects certain pregnant women, is high blood pressure. Low birth weight and premature delivery can result from high blood pressure, which can also damage the mother's kidneys and other organs. Preeclampsia, also known as toxemia of pregnancy, occurs in the mother and can endanger both the mother and the baby by raising blood pressure and increasing the amount of protein in the urine. According to (Vousden et al., 2019), due to

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hypertensive disorder leading to the incidence of eclampsia and preeclampsia, in 2015, about 42,000 women died.

The lack of knowledge on maternal health care throughout pregnancy and after delivery contributes to the high rate of pregnancy-related disorders that cause death in pregnant women. It typically affects the lower middle classes and rural areas of emerging countries, (Ahmed et al., 2020). Pregnancy is a complex and dynamic process that involves significant physiological changes in a woman's body. While most pregnancies are uneventful, several complications can arise. During pregnancy, some women have health issues. These issues may affect the mother's health, the health of the fetus, or perhaps both. Complications might arise even in pregnant women who were in good health before. These issues might turn the pregnancy into a high-risk pregnancy.

A pregnancy complication refers to any condition or situation that arises during pregnancy that may negatively affect the health of the mother, the baby, or both. Complications can range from mild to severe and may occur at any time during pregnancy, childbirth, or in the postpartum period. There are common pregnancy complications that have been at the center of medical research; some of such include gestational diabetes, hypertension, preeclampsia, placenta previa, preterm labor, and miscarriage, among others. These complications can be caused by a variety of factors, including pre-existing medical conditions, genetic factors, lifestyle choices, or environmental factors.

In Nigeria, gestational diabetes is becoming an increasingly common complication of pregnancy, with an estimated prevalence of 3-10%, according to (Onyenekwe et al., 2019). Gestational diabetes can increase the risk of adverse outcomes for both the mother and the baby, including preterm delivery and fetal macrosomia. In recent years, the application of machine learning techniques in medicine has increased significantly. One common approach that plays a significant role in many medical diagnoses is classification.

Classification techniques can aid in the integration of computer technology into the healthcare setting to allow effective and high-quality diagnosis of medical issues. Essentially, hypertension is a serious medical disorder that can jeopardize the health of your heart, brain, kidneys, and other organs. It is a leading cause of death in the globe, affecting 1 in every 4 men and 1 in every 5 women, affecting over a billion people. Low- and middle-income countries bear a disproportionate share of the burden of hypertension. Two-thirds of cases are found in those populations, owing to increased risk factors in recent decades (Minja et al., 2022).

Pregnancy in women with underlying health conditions can be challenging. Women who already battle the severity of an illness who wish to become pregnant encounter several risks that could have of negative impact on the health of their unborn baby. These underlying health conditions may lead to foetal loss in the form of a spontaneous abortion (before 20 weeks of gestation) or there could be an intrauterine foetal death (still birth after 20 weeks of gestation) (Mahmood et al., 2024; Turesheva et al., 2023), the work focus on the use of electrocardiography (ECG) to predict the development of hypertension in the general population who are not hypertensive for early syndromic evaluation and prediction for minimization.

II. LITERATURE REVIEW

With machine learning's quick development, it now provides several benefits over conventional methods for data prediction and categorization. As a result, it is being used progressively in healthcare. Time signals in the healthcare industry are strongly supported by the study carried out by Feifei Li's group. Two-level data compression utilizing machine learning in time series databases was proposed by (Mahmood et al., 2024). Strong temporal correlations exist in time-series data. This technique, which has several applications in the healthcare industry, drastically compressed time-series data; however, no remote application for monitoring patients was developed.

(Liu et al., 2024) research on the design and implementation of an Intelligent Labour contraction monitoring system based on wearable Internet of Things, a machine learning technique was deployed for smart and intelligent prediction and monitoring of labour contraction by pregnant women who have entered 37 weeks of their pregnancy. In the work, a deep learning model, LSTM, was used to classify, collect data, and identify types of labour contraction using the IoT. The model had an accuracy of 93.7%. The result of the model was stored and accessed using the WeChat applet application. In this work, there was no remote monitoring of the model results by physicians except by the user. This therefore shows the need for further research on the incorporation of remote monitoring of pregnancy complications.

In (Elbatanouny et al., 2024), the work used the K-nearest neighbor algorithm (KNN) to identify Freezing of Gait (FoG) in Parkinson's disease patients (PD). Pre-FoG, no-FoG, and FoG were the three types of occurrences into which the gait was divided. The information obtained by the accelerometers on the patient's body was sent to the mobile phone. Data vectorization and a transformation matrix were used to process the data once it had been received. They then trained the KNN classifier before entering it. The model's accuracy was eventually 94.1 percent. This work was limited to predicting freezing gait in people living with Parkinson's disease. Two research gaps were identified in this work: a lack of remote monitoring by health professionals, and the use of wearable and sensing devices was limited to the monitoring of Parkinson's disease

In the field of healthcare, many great deep learning algorithms have been suggested. Convolutional neural networks (CNNs) were proposed by (Cerundolo et al., 2025) for the detection of breast ultrasonography abnormalities. To categorize and quantify emphysema, (Onyenekwe et al., 2019; Peng et al., 2019) developed a multi-scale residual network. They created their own emphysema database and had 93.74 percent classification accuracy. Convolutional autoencoders were employed by (Shastry et al., 2022) to understand the complex structure of Alzheimer's disease, and they were successful in diagnosing the condition with a classification accuracy of more than 80%.

The paper published by (Lestari et al., 2023), researched Machine Learning for Perinatal Complication Prediction: A Systematic Review. This systematic review aimed to assess the utilization of machine learning in predicting pregnancy complications through an exhaustive examination of published literature. The research drew upon data from reputable scientific journals indexed in major databases like PubMed and Scopus. The key findings indicate the successful application of machine learning in predicting pregnancy complications across multiple studies. Various algorithms, including decision trees, random forests, logistic regression, and neural networks, were identified as effective tools in this context. Despite the positive outcomes, the research highlights certain limitations associated with the use of machine learning for predicting pregnancy complications. Challenges include a dependency on the quality of available data and a lack of transparency in the prediction process. These limitations underscore the need for careful consideration and validation when implementing machine learning technologies in this domain.

The work of (Kopanitsa et al., 2023), proposed a work on Prediction of Pregnancy Complications Using Machine Learning and Deep Learning Algorithms. This research explores the potential of machine learning (ML) and deep learning (DL) algorithms in predicting pregnancy-related complications to enhance early detection and reduce maternal mortality. The study systematically evaluates existing literature on pregnancy risk prediction, focusing on three ML algorithms (SVM, DT, extra tree classifier) and two DL algorithms (LSTM and Bi-LSTM). These models aim to categorize pregnancy risks into low, medium, and high levels. The proposed method involves three key steps: data selection and pre-processing, implementation of ML and DL algorithms, and evaluation of model performance using standard metrics. The findings reveal that the Bi-LSTM model stands out, achieving an impressive accuracy of 94.34%, surpassing the performance of other models. This research suggests the promising potential of utilizing advanced machine learning techniques, particularly the Bi-LSTM model, in accurately predicting pregnancy-related risks, which can contribute significantly to improving maternal outcomes.

This research, presented by (Feduniw et al., 2022), considers a comprehensive overview of the application of artificial intelligence, particularly machine learning, in predicting perinatal complications within the medical field. With the increasing use of machine learning in healthcare for prediction, diagnosis, and prioritization, this study focuses on summarizing the various machine learning techniques employed to predict perinatal complications. The objective of the review was to identify the applicability and performance of machine learning methods in identifying pregnancy complications. A thorough search yielded 98 articles from scientific databases, such as PubMed, Scopus, and Web of Science, using relevant keywords.

Following the PRISMA method, 31 articles were selected after applying the inclusion and exclusion criteria. The features used for predicting perinatal complications were diverse, including electronic medical records (48%), medical images (29%), biological markers (19%), and other types of features such as sensors and fetal heart rate (4%). The primary complications considered were pre-eclampsia and prematurity, with a total of sixteen complications predicted across the studies. The precision metric employed in most studies was the AUC (Area Under the Curve). Noteworthy results include the prediction of prematurity from medical images using the support vector machine technique, achieving an accuracy of 95.7%, and the prediction of neonatal mortality with the XGBoost technique, boasting an accuracy of 99.7%.

In (Lee et al., 2023), the research focuses on developing interpretable prediction models for adverse perinatal outcomes in nulliparous pregnant individuals at different points during pregnancy. The study, based on data from the Nulliparous Pregnancy Outcomes Study, employs L1-regularized logistic regression for model development at three pregnancy visits. The models aim to predict a composite adverse perinatal outcome, incorporating factors like stillbirth, neonatal death, low Combined Apgar score, and preterm birth. The interpretable machine learning models showed varying predictive performance across visits (visit 1: AUC 0.617, visit 2: AUC 0.652, visit 3: AUC 0.673).

Notably, the placental biomarker inhibin A consistently emerged as a valuable predictor, significantly improving predictive accuracy at all visits. Additional predictors contributing to model performance included endoglin, fbHCG, uterine artery pulsatility index, and cervical length at specific visits. The study concludes that, despite advancements in predictive modeling in obstetrics, accurately predicting adverse perinatal outcomes remains challenging. While interpretable machine learning aids in understanding predictions, barriers hinder widespread clinical adoption. The research emphasizes the need for a better understanding of evolving risk factors throughout pregnancy for effective intervention development.

The work of (Irfan et al., 2024) emphasizes the significant risks associated with pregnancy complications for both mothers and babies, underscoring the importance of early detection to improve health outcomes. The authors propose an Internet of Things (IoT)-based system that utilizes machine learning to identify pregnancy complications. The system employs various sensors, including those for blood pressure, heart rate, foetal heart rate, and temperature, to collect data from pregnant women. Machine learning algorithms, specifically supervised learning algorithms for classification and regression analysis, are then applied to analyze the collected data. The study's findings highlight the system's efficacy in recognizing pregnancy complications with high levels of accuracy, sensitivity, specificity, and AUC (Area Under the Curve). The suggested IoT-based system holds significant potential for enhancing maternal and fetal health outcomes by enabling early detection and intervention in high-risk pregnancies.

The work presented by (Shamshuzzoha & Islam, 2023), focuses on predicting labor and delivery complications using machine learning techniques, aiming to identify determinants and enhance early intervention to prevent health challenges for both mothers and babies. Data were collected from Ayder Comprehensive Specialized Hospital in Ethiopia, and machine learning models (KNN, SVM, random forest, DT, and XGB) were employed to develop predictive models. The synthetic minority oversampling technique (SMOTE) was used to balance the training dataset. Results indicate that 16% of mothers experienced labor and delivery complications. The developed models demonstrated varying accuracy levels (KNN: 82%, SVM: 82%, random forest: 80%, DT: 82%, XGB: 85%), with the XGB model performing the best. Determinants of complications included age, history of hypertension, preeclampsia, abortion, vaginal bleeding, diabetes mellitus, fetal presentation, and Rh status. This methodology aligns with NLP-driven classification in various domains, including those where semantic processing significantly improved categorization and decision-making (Thong et al., 2022).

The concepts of (Perera et al., 2023), underscores the significance of specialized care for pregnant women, recognizing the critical period during which various physiological changes occur. The study emphasizes the importance of early detection and management of complications like gestational diabetes, hypertension, pre-eclampsia, and preterm labor to ensure the safety of both mother and baby. In this context, the chapter explores the potential of machine learning-based devices as tools to enhance maternal and fetal health outcomes during pregnancy. The overview aims to contribute valuable insights into the application of machine learning technologies in improving the overall care and well-being of pregnant women.

The proposed work of (Milosevic Stevanovic et al., 2024), delves into the intricate dynamics of the maternal immune system and fetal immune systems during pregnancy, emphasizing the potential for serious complications when this delicate balance is disrupted. Gestational diabetes mellitus (GDM), pre-eclampsia, preterm birth, and low birth weight are identified as significant threats to maternal and fetal health. The study aims to identify early biomarkers through an indepth analysis of 47 proteins related to inflammation, chemotaxis, angiogenesis, and immune system regulation. Using a prospective cohort of 1,049 pregnant women, the research employs Bayesian linear regression models to examine associations between biomarkers, maternal and neonatal health outcomes, and baseline characteristics.

Machine learning models are then utilized to evaluate the predictive value of these biomarkers, with Shapley additive explanation (SHAP) scores identifying key predictors (Taufik et al., 2025). The results reveal associations between specific inflammatory markers and pre-existing conditions, such as maternal age, pre-pregnancy BMI, chronic diseases, and previous pregnancy complications (Sholekhah & Noviar, 2025). Smoking during pregnancy significantly affects certain biomarkers, and distinct biomarker patterns are observed across different ethnicities. The study identifies correlations between biomarkers and obstetric complications, providing insights into the pathophysiology of conditions like pre-eclampsia, GDM, and severe postpartum hemorrhage.

Predictive modeling using biomarkers demonstrates promising accuracy for GDM and pre-eclampsia prediction, as presented by (Zainudin & Siswanto, 2024). This research chapter highlights the significance of machine learning in the healthcare sector, particularly for predicting and diagnosing diseases, ultimately aiming to save lives. It emphasizes the application of machine learning in addressing pregnancy complications, with a specific focus on preeclampsia. The section explores various machine learning algorithms, particularly regression algorithms, to analyze their effectiveness in predicting and preventing preeclampsia. The overarching goal is to identify the most efficient predictive techniques that can provide early warnings and allow for timely interventions to safeguard the health of pregnant women.

The techniques presented by (Gómez-Jemes et al., 2022), focuses on developing an intelligent application for early risk pregnancy prediction using machine learning techniques. The study analyzes data from 997 patients with 114 attributes from electronic medical records in a primary health care cohort. Eight attributes, aligned with the Indonesian Ministry of Health guidelines, are chosen as classifier attributes. The research explores decision tree C4.5, random forest, and naive bayes algorithms for their suitability, with accuracy values of 98.01%, 98.51%, and 68.81%, respectively. Random forest outperforms the other algorithms and is used to build a web-based application. All three algorithms achieve high AUCs (0.95 to 0.99), indicating excellent prediction accuracy.

The study highlights the potential of machine learning in intelligent applications for early risk pregnancy prediction, contributing to self-checking and early detection of pregnancy risks. The proposed work by (Latif & Rafique, 2025) presents an ML framework for predicting patients'

LOS following implementable treatment pathways for efficient and robust ED resource allocation. The adaptation of big data analytics also facilitates precise categorization that helps determine the correlations, hidden patterns, and other valuable insights from the vast amount of data with varied properties through the classification process. Overall, combining machine learning with big data shows great promise in making healthcare services more efficient and effective.

III. RESEARCH METHOD

A. Overview of Proposed Framework

Some of the limitations of the system under review are addressed in the proposed system as follows:

a. Most of the systems considered for review lack the functionality for remote monitoring of pregnancy complications. Nevertheless, the proposed system, through the incorporation of cloud data storage with integration of cross-platform for both patients and medical professionals, can make patients' data, such as glucose level, heart rate, blood pressure, etc., accessible in real time by the patients and doctors remotely.
b. The development of a user-centered Android application as proposed in the research will enhance usability by pregnant women in terms of recording of data, storage of data, continuous monitoring, and prediction of pregnancy complications, as well as provide for seamless real-time monitoring by health professionals.
c. The use of local and cloud data storage facilities, as indicated in the proposed system, will enable pregnant women to take their daily records of blood pressure level, blood glucose, and other parameters used for the assessment of pregnancy complications. This feature is not available in the existing system.
d. The proposed system integrates provision for management and monitoring, including advice, changing medication, or establishing of diagnosis remotely by health professionals into the software. This feature was lacking in the existing system since there was no user software developed in the project. The proposed system architecture is presented in Figure 1. The system architecture is subdivided into three sections:

Section One: This section covers the design and implementation of an intelligence system, starting from data collection, data preprocessing, model training, and testing. A complete explanation of the key components in this section is presented in Figure 1. Section Two: Section two of the proposed system covers the application development part of this research work. This section comprises of design and implementation of the user endpoints, user interface, and application programming interface for the interaction with data and prediction model. In this section, mobile

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applications are used as the main endpoints for users. Section Three: This section is considered as data storage section and consists of the design and implementation of the Room database for local storage, as well cloud database management system show in Figure 1.

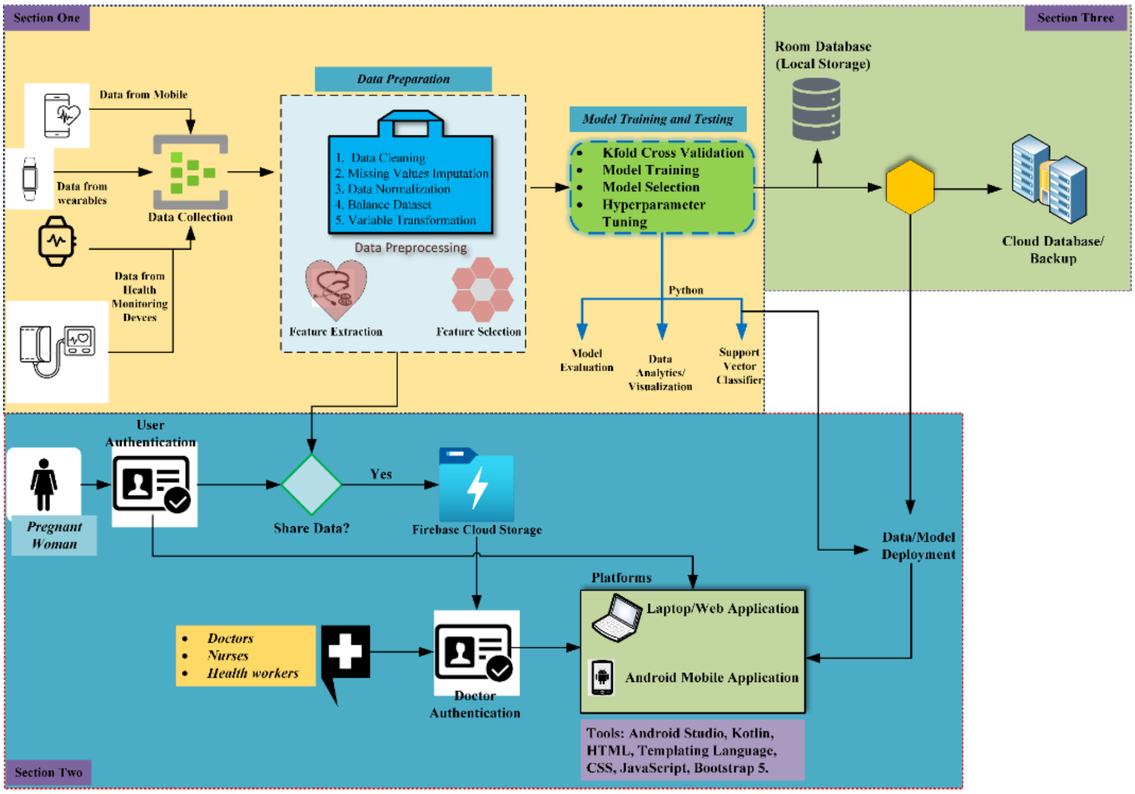

Figure 1. Proposed Remote Intelligent Monitoring and Detection System Architecture for Pregnancy Complications

B. Sample Dataset

Secondary data collection and the dataset are used in this research. The dataset used in this work was obtained from an online UCI Machine Learning Repository and was first used by (Mohi Uddin et al., 2023). The data was collected from different clinics, maternity wards, and hospitals using IoT IoT-based pregnancy risk monitoring system. The dataset consists of 1014 observations with six feature variables, including age, diastolic blood pressure, systolic blood pressure, blood sugar (glucose) level, heart rate, and body temperature. The dependent variable is the level of risk of pregnancy complication and was classified as low risk, mid-risk, and high risk. 272 observations belong to the class of high risk, 336 observations were classified as mid risk, while 406 data points were grouped as low risk samples. A snapshot of the dataset is shown in Figure 2.

	Age	SystolicBP	DiastolicBP	BS	BodyTemp	HeartRate	RiskLevel
2	25	130	80	15	98	86	high risk
3	35	140	90	13	98	70	high risk
4	29	90	70	8	100	80	high risk
5	30	140	85	7	98	70	high risk
6	35	120	60	6.1	98	76	low risk
7	23	140	80	7.01	98	70	high risk
8	23	130	70	7.01	98	78	mid risk
9	35	85	60	11	102	86	high risk
10	32	120	90	6.9	98	70	mid risk
11	42	130	80	18	98	70	high risk
12	23	90	60	7.01	98	76	low risk
13	19	120	80	7	98	70	mid risk
14	25	110	89	7.01	98	77	low risk
15	20	120	75	7.01	100	70	mid risk
16	48	120	80	11	98	88	mid risk
17	15	120	80	7.01	98	70	low risk
18	50	140	90	15	98	90	high risk
19	25	140	100	7.01	98	80	high risk
20	30	120	80	6.9	101	76	mid risk
21	10	70	50	6.9	98	70	low risk
22	40	140	100	18	98	90	high risk
23	50	140	80	6.7	98	70	mid risk

Maternal_Health_Risk_ Dataset

Figure 2. Sample Dataset

C. *Data Preprocessing*

1. Missing Values

Missing values checking is a preprocessing step applied to identify whether the dataset contains null or empty entries. In this research, the detection was carried out using the Pandas `.isnull()` function, which is capable of scanning all columns and rows of the dataset. The procedure ensures that each attribute in the dataset is examined systematically without leaving gaps in the observation. By applying this technique, the structure of the dataset can be verified before continuing with other preprocessing operations.

2. Outlier Detection

Outliers are data points that significantly differ from the majority of the data points in a dataset. They can arise due to various reasons, such as errors in data collection, measurement noise, or rare but valid extreme events. Outliers can have a significant impact on the results of data analysis and machine learning models, and therefore, it is important to address them appropriately. In this project, detecting outliers was done using the interquartile range (IQR). The IQR of the predictive variables was calculated to identify data points that fall below Q1 (1.5-IQR) or above Q3+1.5. Q1 = quantile(0.25) and Q3 = quantile(0.75), therefore, IQR = Q3 - Q1. The lower bound was then obtained using the following formula (1).

$$lower\ bound = Q1 - (1.5 \times IQR) \quad (1)$$

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where Q1 is the first quartile, and IQR is the interquartile range obtained by subtracting Q1 from Q3. Any value below this threshold is considered a lower-end outlier. The upper bound, on the other hand, is used to flag unusually high data points. It follows a similar logic to the lower bound and is calculated as shown in equation (2).

$$upper\ bound = Q3 + (1.5 \times IQR) \tag{2}$$

where Q3 is the third quartile, and the constant 1.5 defines the acceptable spread of the data. Values above this upper bound are treated as upper-end outliers.

3. Data Standardization

A technique for transforming data such that its mean and standard deviation are both equal to one is called data normalization. This is usually done to ensure that all characteristics in a dataset are on an equal scale since some machine learning algorithms are sensitive to the size of the input data. The Python StandardScaler library was used in this project to standardize the data. The mathematical expression used for data standardization is given as follows (3):

$$X_{std} = \frac{x - \bar{x}}{standard\ deviation} \tag{3}$$

Where x is the data point, $\bar{x}$ is the mean of the feature variable, and X_{std} is the standardized value of x. The result, X_{std}, represents the standardized value of x, indicating how many standard deviations the original value is from the mean.

4. Correlation Analysis

A correlation matrix was used to examine the relationships among variables in the dataset. This technique is useful for identifying strongly associated features and selecting predictors relevant to model training. To calculate the correlation between two continuous variables, the Pearson correlation coefficient was used. The formula used in this project is shown in equation (4).

$$corr = \frac{N\sum xy - (\sum x)(\sum y)}{\sqrt{[N\sum x^2 - (\sum x)^2][N\sum y^2 - (\sum y)^2}} \tag{4}$$

where x and y are the two variables being compared, and N is the number of data points. This formula measures the strength and direction of the linear relationship between two variables, resulting in a value between -1 and 1.

D. Support Vector Machine (SVM)

A support vector classifier is trained using support vector machines, a distance-based technique. By maximizing the distances between the instances (for either class) or the boundary, the approach establishes a decision boundary between examples represented as vectors. Multiple continuous and categorical variables are both supported by SVM. According to studies, the technique frequently results in models that perform better than alternative classification algorithms, such as decision trees and traditional statistical approaches. Regression is used by this classifier to identify and create hyperplanes in a multidimensional space that best distinguish cases of various class labels, in this case, three labels. One can be more certain about a forecast for a spot the further it is from the dividing line. Radial, polynomial, and linear kernels are often used in SVM. The linear kernel, which makes use of the inner product of two observations, is shown in Figure 3. The linear kernel and the support vector classifier are the same.

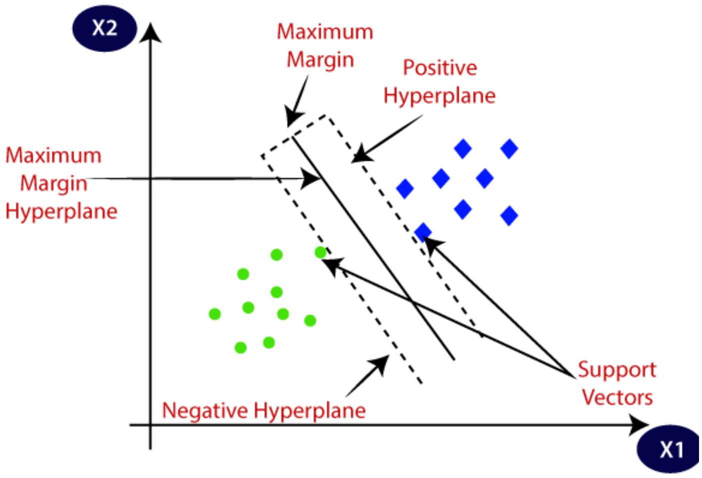

Figure 3. SVM Linear Kernel model, Javapoint (2022)

By utilizing the power function, the polynomial kernel creates nonlinear boundaries. This kernel can map input data into a higher-dimensional space where separation becomes possible. It helps in handling data distributions that are not linearly separable. Figure 4 displays an illustration of a polynomial kernel for an SVM.

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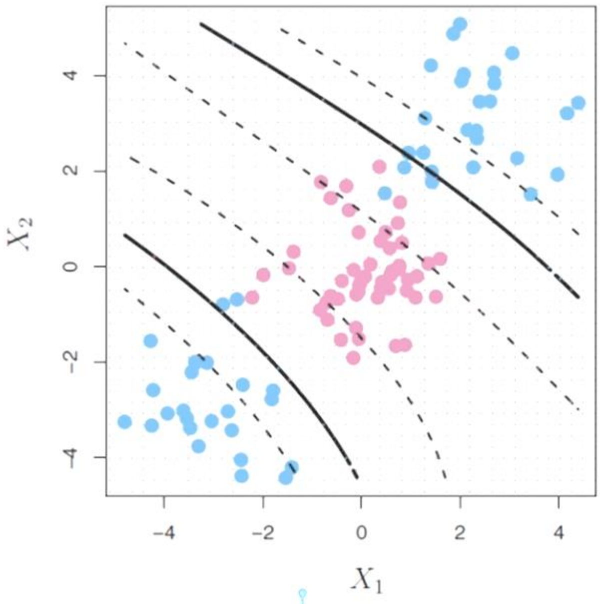

Figure 4. SVM Polynomial Kernel Model

Radial kernels that employ radial functions generate radial boundaries. These kernels operate based on the distance between two input vectors in the feature space. The influence of a data point decreases as the distance from it increases. An example of a radial kernel is shown in Figure 5.

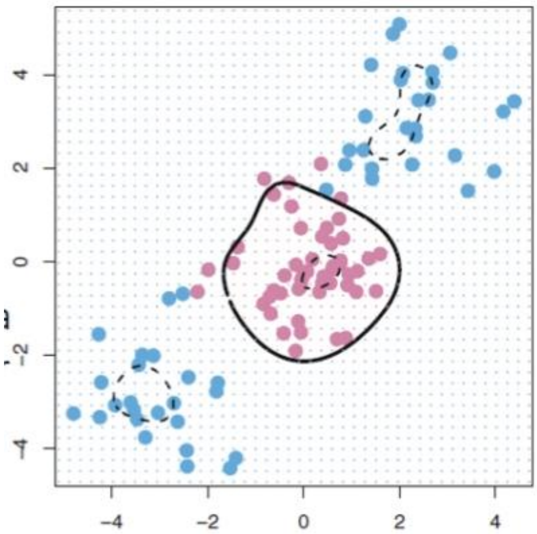

Figure 5. SVM Radial Kernel

E. *Model Training and Testing*

Model training refers to the process of training a machine learning model using a dataset to learn patterns, make predictions, or perform specific tasks. It involves feeding input data into the model, allowing it to process and learn from the data, and adjusting its internal parameters to optimize its performance. Training a machine learning model involves feeding the training data into the model and iteratively adjusting its parameters to minimize the difference between its predictions and the actual target values. This process was using a support vector machine algorithm, which updates the model's parameters based on the computed error or loss.

Cross-validation was a technique used to assess the performance and generalization ability of the Support Vector Classifiers (SVC). It helped to evaluate how well the model was able to generalize to unseen data and provided an estimate of its performance. The type of cross-validation technique used in this work is known as K-fold cross-validation. It involves the division of the training dataset into K equally sized subsets or folds, where *k* was taken to be 5. During the training of the model, a series of iterations is performed. In each iteration, we trained the SVC on K-1 folds of the training set and validated its performance on the remaining fold. This process is repeated K times, with each fold serving as the validation set once. With cross-validation, a more robust and reliable estimate of the performance score of the SVC is obtained compared to using a single train-test split approach.

F. *Model Evaluation and Performance Analysis*

Model evaluation was done using the StratifiedKFold cross-validation. The StratifiedKFold cross-validation model evaluation approach divides the dataset into k equal, mutually exclusive stratified subsets. The model is then trained using K-1 folds, and the prediction performance of the model is tested using each subset precisely once. The model performance results for each k-fold are then pooled after this procedure has been performed (iterated) k times. The generalization outcome according to the model assessment measure is the mean (average) value. When utilizing unbalanced data, StratifiedKFold CV is a well-known model assessment technique.

Since no one measure can adequately capture all a model's performances, research supports the use of numerous metrics to evaluate and assess model performance. Model accuracy, F-score, precision, recall (sensitivity), and the area under the receiver operating characteristic curve are strategies used in the analysis of the performance of the SVC model implemented in this research. Each metric provides different insights into the model's behavior in terms of classification quality. The use of multiple metrics allows for a more comprehensive understanding of the strengths and limitations of the model.

G. *Research Toolset and Techniques*

The models in this work were built, trained, and tested using the Python programming language framework. Scikit-learn was used in Python. Because of their wide library support, researchers are growing increasingly interested in Python and R, which provide easier, more effective, and more efficient ways to perform machine learning research. Additionally, these libraries aid researchers in carrying out several data-related tasks quickly and simply, including data pretreatment. Android Studio using Kotlin programming language was used in the development of the mobile application, while template language, HTML, JavaScript, CSS, Bootstrap 5 web framework were toolsets deployed for the development of the software part of the proposed system.

H. Pseudo Code for the Proposed Algorithm

```
Inputs: Electronic health records of pregnant women
Output: Data Visualization, Data stored in the server, Prediction of pregnancy risk
condition
Start
Read electronic records from csv file row by row
While True:
      i. Check for missing values from each feature of each row.
     ii. Standardize feature set by subtracting the mean from each feature and dividing
         it by the standard deviation.
    iii. Extract new attributes from the row based on the setup extraction rule.
     iv. Add a new feature as a column to the feature row.
      v. Choose the importance of the feature with respect to the contribution to the
         accuracy and loss.
     vi. For other feature contribution, go to step 1.

Update and compare data stored in the server.
If (user requests classification of risk level)
       Classify and predict the level of risk
Else:
       Show data on the app dashboard
End
```

I. Ethical and Clinical Deployment Considerations

Deploying machine learning in maternal healthcare introduces ethical and clinical responsibilities:

a. **Data Privacy & Security:** Patient data must be handled with strict adherence to data protection laws such as HIPAA or GDPR. Data encryption, secure APIs, and anonymization protocols should be enforced to protect sensitive health information.
b. **Bias and Fairness:** The training dataset must be scrutinized for biases to prevent skewed predictions that may disproportionately affect certain demographic groups. Continual model re-evaluation and updates are essential.
c. **Clinical Validation:** The predictive model should undergo rigorous clinical testing and validation against real-world cases before deployment. Collaboration with certified medical professionals is critical.
d. **Informed Consent:** Patients must be informed about how their data will be used and must consent to data collection, storage, and predictive usage.

e. **Decision Support, Not Replacement:** The system is designed to support, not replace, professional clinical judgment. Clear disclaimers must communicate that predictions are advisory and not diagnostic.

IV. RESULT

A. Dataset Overview

To select the appropriate data preprocessing methods that will be applied to the project dataset, it is critical to gain some insight into how the data samples are distributed. This is done using a Python function for a general overview of the data. This function lists all the columns of the dataset, including their data type. Our dataset consists of 1014 observations in all 7 columns. From the CSV file, it was observed that the 7th column was designated as the risk level column, which indicates the risk of pregnancy complications. The column contains categorical values (low risk, mid risk, and high risk). Figure 6 shows a snapshot of a general overview of the project dataset using the Python pandas library.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1014 entries, 0 to 1013
Data columns (total 7 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Age          1014 non-null   int64
 1   SystolicBP   1014 non-null   int64
 2   DiastolicBP  1014 non-null   int64
 3   BS           1014 non-null   float64
 4   BodyTemp     1014 non-null   float64
 5   HeartRate    1014 non-null   int64
 6   RiskLevel    1014 non-null   object
dtypes: float64(2), int64(4), object(1)
memory usage: 55.6+ KB
```

Figure 6. General Overview of Project Dataset Showing Types of Null Values

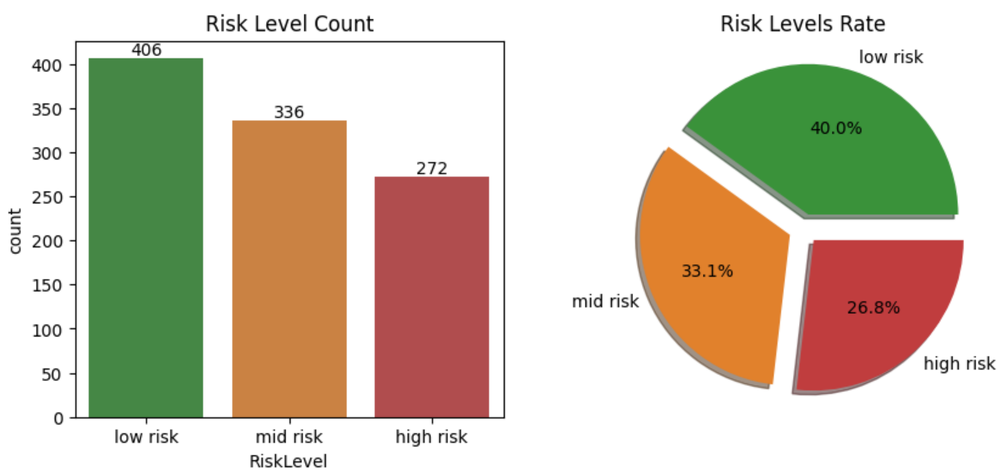

Figure 7. Dataset Count Based on Risk Level

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As shown in Figure 6, it is observed that the dataset consists of 1014 samples and does not contain null values. Also, the total number of samples of the dataset was grouped based on the risk factors as shown in Figure 7. This indicates that the dataset has already undergone basic cleaning and preparation before analysis. Grouping data by risk levels can help highlight patterns that may not be visible in the raw data alone.

In Figure 7, it is observed that 406 samples (40%) of the dataset belong to the class of low risk, 336 (33.1%) belong to mid risk, while 272 (26.8%) belong to high risk. This distribution shows that the data is not perfectly balanced across the risk categories. The variation in class size may influence the performance of classification models. It is important to consider this distribution during the training and evaluation stages of the modeling process.

B. Missing Values Result

The application of the missing values check produced an output that shows every attribute of the dataset with its corresponding status. The generated result indicated that none of the seven variables contained null or empty entries. This verification was displayed in Figure 8, where the summary of the check is shown in tabular format. The figure presents all dataset columns with their respective counts, confirming that the data used for subsequent preprocessing steps is complete.

2.3.Missing values

```
[6]:  df.isna().sum()

t[6]:
      Age            0
      SystolicBP     0
      DiastolicBP    0
      BS             0
      BodyTemp       0
      HeartRate      0
      RiskLevel      0
      dtype: int64
```

Figure 8. Missing Values

C. Outlier Detection and Removal Result

The result of the calculation of Q1, Q3, IQR, upper, and lower bound for detecting outliers is shown in Figure 9. Furthermore, the total number of outliers detected in the project dataset is shown in Figure 10. These statistical measures help identify data points that lie far from the central tendency of the data. Using these bounds ensures that the detection process is consistent and based on standard criteria.

	Age	SystolicBP	DiastolicBP	BS	BodyTemp	HeartRate
q1	19.0	100.0	65.0	6.90	98.0	70.0
q2	39.0	120.0	90.0	8.00	98.0	80.0
iqr	20.0	20.0	25.0	1.10	0.0	10.0
lowerFence	-11.0	70.0	27.5	5.25	98.0	55.0
upperFence	69.0	150.0	127.5	9.65	98.0	95.0

Figure 9. Outlier Detection

```
Total number of outliers: 433
Percentage of outliers: % 0.427
```

ut[22]:

	Feature	Number of Outliers
0	Age	1
1	SystolicBP	10
2	DiastolicBP	0
3	BS	210
4	BodyTemp	210
5	HeartRate	2

Figure 10. Total Number of Outliers

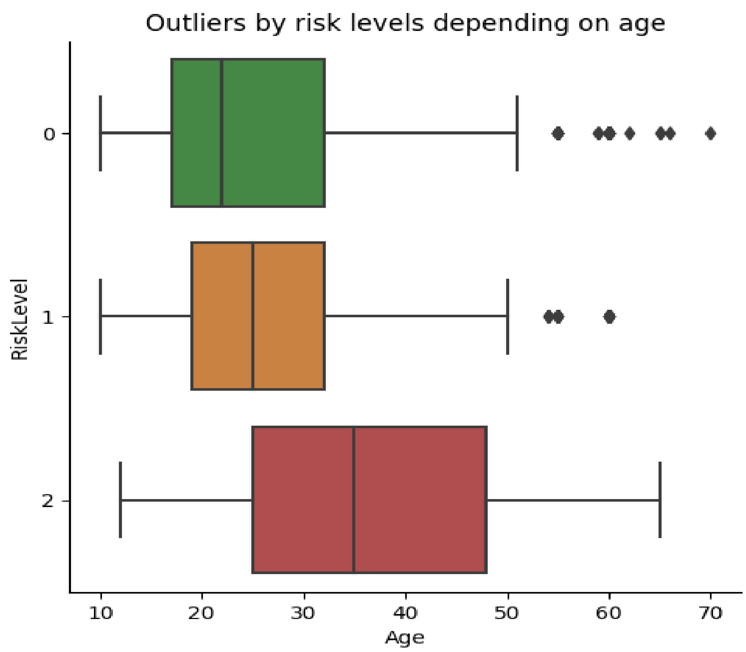

Figure 11. Outliers by Risk Depending on Age

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It can be observed from Figure 10 that 0.43% of the project dataset are outlier' samples, while a closer examination of the dataset using a box plot is also illustrated in Figure 11. Outliers by risk levels depending on the age of the patient are shown in Figure 10, by blood sugar in Figure 12, and by body temperature in Figure 13. Box plots provide a visual representation that highlights the spread and concentration of data points. They are useful tools for identifying variability within different risk groups.

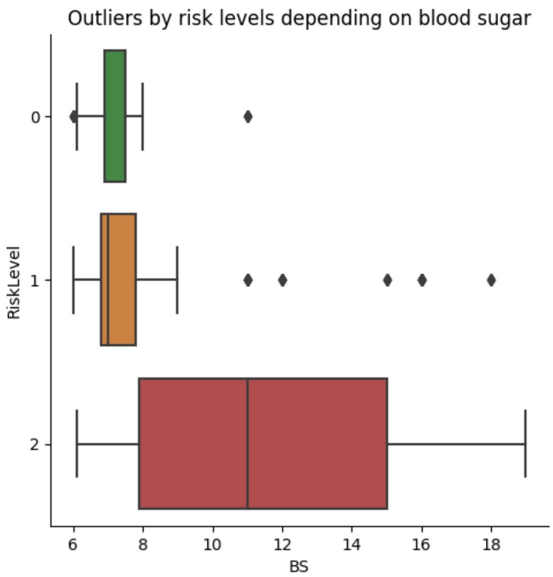

Figure 12. Outliers by Risk Level Depending on Blood Sugar

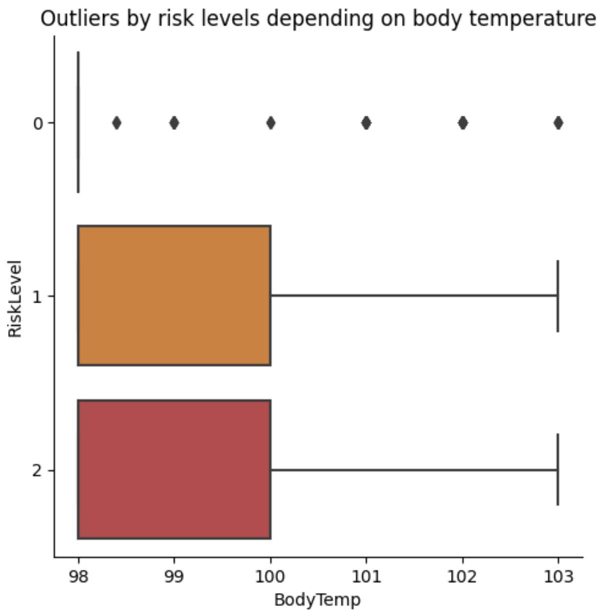

Figure 13. Outliers by Risk Level Depending on Body Temperature

After removing the outliers detected, a total of 895 observations were obtained without outliers. Therefore, the preprocessed dataset showing the distribution of samples based on risk level is shown in Figure 14. After removing outliers, it can be observed that 333 samples (37.2%) belong to low risk, 290 samples (32.4%) to mid risk, while 272 samples (30.4%) belong to high risk. This distribution helps to better understand the characteristics of the dataset after the cleaning process.

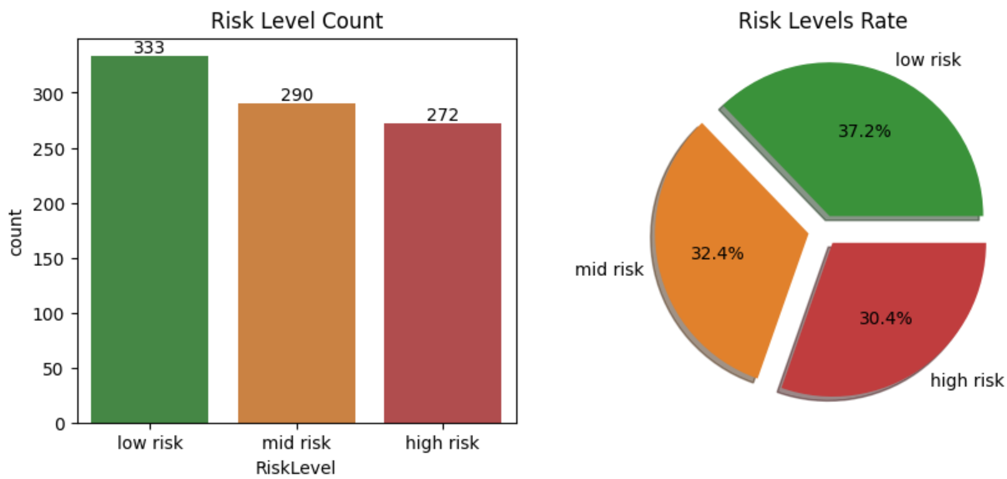

Figure 14. Preprocessed Dataset without Outliers

D. Standardization Result

After applying the standardization procedure, the dataset values were rescaled to have zero mean and unit variance. Standardization is a common preprocessing step to prepare data for machine learning models. This process helps to bring all features to a comparable scale, reducing bias caused by different units. Figure 15 shows the standardized dataset snapshot.

```
38]:
     (array([[-1.3383836 , -1.31134824, -0.85472073,  0.09781741,  1.9409914
     7,
               0.72194873],
             [-0.73345354,  0.32294202, -0.14697579, -0.3553627 , -0.4555778
     8,
              -0.59796922],
             [ 0.73566232,  0.32294202,  0.91464163,  0.70205755, -0.4555778
     8,
               1.77788309],
             ...,
             [-0.30136064,  0.32294202,  0.20689669, -0.50642273, -0.4555778
     8,
              -1.1259364 ],
             [-1.42480218, -1.31134824, -1.20859321,  0.70205755,  2.7398479
     1,
```

Figure 15. Standardized Dataset

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E. Correlation Analysis Result

The correlation matrix of the dataset is presented in Figure 16. The analysis shows that diastolic and systolic blood pressures are significantly correlated. Risk level is strongly influenced by blood sugar, followed by age and blood pressure readings, while heart rate and body temperature show weaker associations. Correlation analysis provides insight into the relationships between different variables in the dataset.

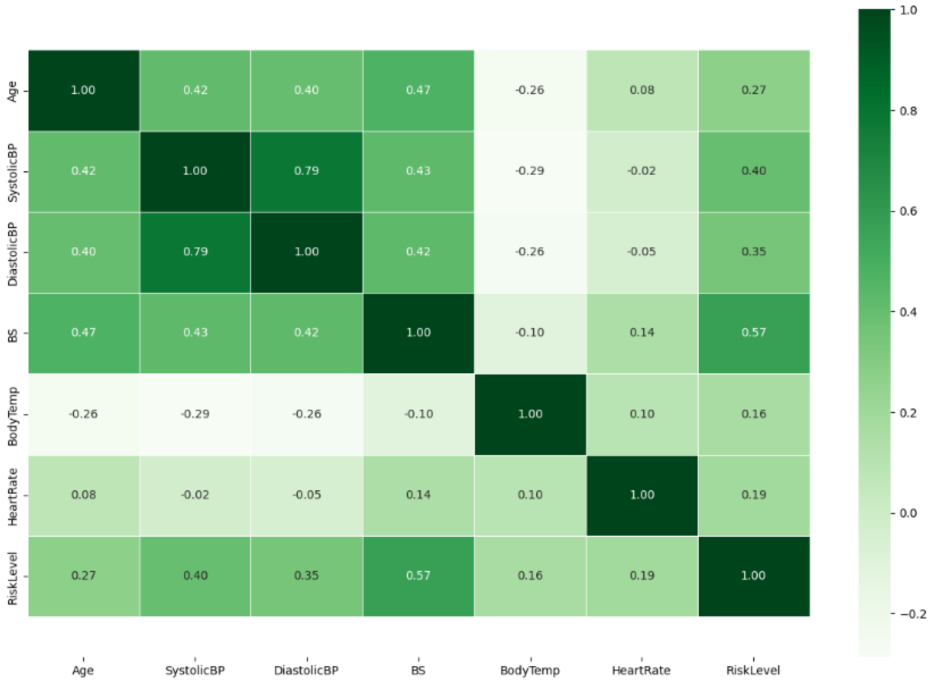

Figure 16. Correlation Matrix

V. DISCUSSION

The findings of this study demonstrate that the Support Vector Machine (SVM) model achieved an accuracy of 80%, with balanced values of precision, recall, and F1-score at 77%. This indicates that the proposed model is effective in predicting maternal health risks using multiple clinical features such as blood pressure, glucose level, heart rate, and body temperature. These results confirm that a data-driven approach can support remote and intelligent monitoring of pregnancy complications, which aligns with the overall aim of reducing maternal health risks.

When compared with earlier studies, the outcome reinforces the results in (Cerundolo et al., 2025), which emphasized the role of IoT-based systems in detecting maternal complications. The findings are also consistent with (Hossain et al., 2023), which highlighted the usefulness of machine learning for analyzing pregnancy-related health indicators, and with (Onyenekwe et al., 2019; Peng et al., 2019), which showed that SVM classifiers achieved competitive performance in clinical risk prediction tasks. However, this study goes beyond those works by integrating multiple risk factors simultaneously rather than focusing on a single condition, thereby offering a broader perspective on maternal health risk assessment.

The correlation analysis further shows that blood glucose and blood pressure levels are the strongest predictors of pregnancy complications, which aligns with (Thong et al., 2022; Turesheva et al., 2023). Interestingly, the relatively weaker influence of age in this dataset contrasts with (Mahmood et al., 2024), which considered maternal age a dominant factor. This suggests that while age remains important, its effect may be moderated when multiple physiological indicators are included, thus providing a more nuanced understanding of maternal health risk prediction.

VI. CONCLUSION AND RECOMMENDATION

Pregnancy complications to improve pregnancy management and healthcare for pregnant women. The primary goal of remote monitoring and intelligence classification of pregnancy risk complications was to create a platform to provide access for self-management and monitoring of pregnancy conditions by patients and remote monitoring by medical healthcare providers. The Pregnancy Health (P-Health) application provides a mobile application for both patients and doctors. Medical Doctors can use the application to monitor the state of pregnancy-related complications of their clients remotely without physical presence for individual medical examination.

Meanwhile, pregnant women can self-monitor their pregnancy, analyse clinical data, and predict the risk of developing pregnancy complications. The system platform will have a tremendous positive impact on the reduction of the maternity mortality rate, reducing pregnancy complications due to high blood pressure disorder, gestational diabetes. This will be achieved through real-time monitoring and classification risk level of developing pregnancy complications. Furthermore, to strengthen the practical value of the proposed P-Health platform, a real-world pilot usability test could be conducted with a small group of pregnant women and healthcare professionals in a clinical or community health setting.

Participants would use the app over a set period to monitor vital signs and receive risk predictions, while researchers observe interactions, gather feedback through interviews or surveys, and track system responsiveness and user comprehension. Metrics such as task completion time, user satisfaction, accuracy of input data, and clarity of risk feedback would be evaluated. This pilot test would provide valuable insights into how effectively the system supports real-time monitoring, early detection, and communication between patients and practitioners, ensuring that the final product is both user-friendly and clinically relevant.

Although this study provides valuable insights into maternal health disorders that can cause a series of complications and harmful incidents in women during pregnancy. Several avenues for future research could build upon our findings to improve pregnancy management and healthcare for pregnant women. Firstly, our sample consisted solely of a prototype, so it would be beneficial to extend this research to actual deployment. Additionally, the study focused on the development of the Pregnancy Health (P-Health) System for the provision of a mobile application to monitor the state of pregnancy-related complications of their clients remotely without physical presence for individual medical examination.

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