Method for Maternal Health Risk Assessment with Smartwatch-Based Vital Sign Measurements

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***Abstract*—The risk of maternal health issues remains a particular challenge in regions with scant access to continuous antenatal care. This study proposes a smartwatch-based system for evaluating the possible risks associated with maternal health through monitoring vital signs and machine learning algorithms. Using an open-access dataset from Kaggle, the smartwatch assesses maternal risk levels by monitoring systolic and diastolic blood pressure, heart rate, blood glucose, and body temperature. The combination of Artificial Neural Network (ANN) and Random Forest (RF) classifiers gave the system's best-obtained results of 95% accuracy, 97% precision, 97% recall, and an F1 score of 0.97 on the testing dataset. Analysis of correlation demonstrated significant relationships between maternal risk and several primary measures, particularly with systolic blood pressure (r = 0.931), diastolic pressure (r = 0.916), and blood glucose (r = 0.887). Two regression models, MHRL1 and MHRL2, were created to estimate risk levels based on these parameters. From the experimental data, three clinical action levels were defined for the management of pregnancy care: 1) hypertension with Blood Pressure: BP ⩾140/90 mmHg, 2) elevated fasting glucose ⩾95 mg/dL or postprandial ⩾140 mg/dL, and 3) tachycardia with sustained heart rate >100 bpm. These results prove the capability of using IoT-based wearables integrated into workflows for maternal monitoring to enable early warning systems and tailored health management, particularly in constrained settings.**

Keywords*—Artificial intelligence; Kaggle; maternal health risk assessment; IoT technology; classification performance; pregnancy risk level; ANN; RF; MHRL; BP

I. Introduction

The global public burden of maternal health continues to be a critical concern, as more than 295,000 women die from preventable pregnancy and childbirth complications [1], [2]. Most of these deaths occur in low and middle-income countries [3]. The prevention of these deaths greatly depends on the timely detection of maternal risk conditions such as hypertension, diabetes, and preterm labor [4], [5]. In this regard, digital health tools, particularly wearables and IoT-based innovations, hold great promise for allowing seamless remote monitoring of maternal vital signs indoors, outdoors, and in clinics.

In recent years, there has been a sharp increase in the development of artificial intelligence (AI) based predictive models for health, including scenarios related to maternal health. Several researchers have applied machine learning (ML) algorithms to evaluate risk levels using biometric data like age, blood pressure, blood glucose, and heart rate [6], [7], [8]. Regardless of these strides, current systems are based on static data gathered in clinical environments. This study does not utilize continuous real-time data achievable through smartwatches and similar wearables. Furthermore, most existing works focus only on the prediction model without considering the low-cost sensing devices that are easy to deploy in resource-poor settings.

This study aims to fill these gaps with a proposed smartwatch-based maternal health risk assessment system. Focusing on a smart device's wearable physiologic sensors, the system tracks expectant mothers' bio signals in real-time. It classifies their health risk levels using ensemble learning models, which include Artificial Neural Networks (ANN) and Random Forest. Apart from classification accuracy, this study explores the relationship between vital signs and maternal health outcomes with correlation analysis [9], [10]. This study also evaluates regression-based risk-scoring models to transform the results into a more useful continuous output instead of a mere categorical glimpse.

Moreover, the primary contributions of this study are the following: 1) creating a real-time smartwatch-compatible system designed to capture and analyze maternal vital signs; 2) the application of ensemble learning techniques for enhanced predictive precision and reliability; and 3) testing the system's predictions against publicly available datasets and simulations of real-world measurements from maternal healthcare. This work seeks to improve maternal risk assessment technologies by merging inexpensive wearable devices with advanced predictive algorithms and enabling proactive, tailored healthcare, especially in regions with limited access to conventional healthcare infrastructure. The purpose of this research work is to clarify the physical conditions which can be measured with IoT sensors and the maternal risks for mitigation of dangerous situations during pregnancy.

The following section describes related research works. The proposed method is described, followed by experiments and then a conclusion is described together with some discussions.

II. Related Research Works

The use of ML to predict maternal health issues has received considerable attention over the last few years, given the structured health data available and the necessity for early risk detection. A number of research works have focused on classifying maternal risk using vital signs and demographic data, which include age, blood pressure, glucose, and heart rate. These methods are highly favorable to conventional risk assessment methods due to their capability of capturing non-linear relationships and generalizing through pattern recognition.

Researchers performed a comparative study on several ML algorithms, including Decision Trees (DT), Support Vector Machines (SVM), and Random Forests (RF) applied to maternal health data, reporting that ensemble-based models provided better accuracy and robustness over single classifiers [11]. Similarly, an innovative solution to address the challenges of critical risk determinants in maternal healthcare was proposed [12]. They developed a novel artificial intelligence model by hybridizing two artificial neural networks, Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), to predict health risks from partially complete patient journey datasets. The model specifically addresses the issue of predicting health risks from electronic health records (EHR) data to advance predictive precision regarding various essential and sensitive health risks.

Smartwatches and health bands are examples of wearable technologies that have recently emerged as non-invasive tools for real-time physiological monitoring. The Internet of Things for smart maternal healthcare services with wearables and cloud computing was proposed [13]. The portability of wearable systems and their constant measurement of heart rate and blood pressure, underscoring their efficacy for maternal health monitoring, was also focused on [14].

Ensemble learning methods have emerged as increasingly common in contemporary maternal health research. An ensemble model that combines random Forest, XGBoost, and CatBoost models to predict maternal health risks in lower-middle-income countries was developed [15]. Their findings indicated that the model's accuracy and performance were enhanced relative to the separate systems. Using real-world datasets to identify risk factors, an ensemble-based framework to predict multifactorial risks related to maternal health throughout pregnancy was developed [16].

Regardless of these developments, there is still a paucity of research that integrates wearable technology using ensemble learning models for maternal risk assessment in real-time or simulated environments. Most preceding literature captures static datasets or concentrates on classification without incorporating risk scoring or regression models. In addition, deployment concerns, such as efficient energy sensing, low-cost implementation, and user-friendly, are usually ignored. This study addresses these issues by integrating real-time data acquisition through smartwatches with ensemble algorithms for maternal risk classification and scoring. By adding correlation analysis, regression-based risk scoring, and system simulation, this work is a step towards building a more practical and deployable decision support system for maternal healthcare aimed at underserved communities.

III. Methods

This section describes the frameworks used to predict the risks associated with maternal health using vital signs measured through smartwatches. The system combines wearable signal simulation, data cleansing, process streamlining, machine learning model construction, risk scoring, and correlation computation. The overall methodology is organized into seven key components, which will be elaborated on below.

A. *System Architecture Overview*

The system emulates a real-time scenario of monitoring maternal health where physiological signals are obtained via smartwatch sensors and evaluated to determine maternal risk. The framework comprises the collection of signals, preprocessing of received data, ensemble classification, regression analysis for risk scoring, and assessment of performance metrics.

B. *Measuring Instruments and Principles*

The system under consideration aims to interface with smart health wearables that monitor the vital parameters of pregnant women. Such wearables emulate the data collection processes of clinical-grade monitors, making them suitable for use in both urban centers and resource-limited settings. The following instruments and sensing principles are considered in Table I.

The calibration of the sensing simulation replicates signal noise, responses, and the accuracy of physiology metrics in mid-tier consumer-grade wearable technology. Blood pressure and blood glucose measurements taken with a smartwatch have limited accuracy compared to those obtained with medical devices. Measurements with medical devices are recommended for important medical decisions. The latest smartwatches can continuously monitor these values 24 hours a day, enabling them to detect abnormal values and manage health. The heart rate is the most reliable measurement item. Some smartwatches also have an Electrocardiogram (ECG) function. ECG can record the electrical activity of the heart in more detail and may be helpful for early detection of arrhythmia. Smartwatches can also measure other data, such as weight management and exercise during pregnancy, to help with Maternal Health Risk Assessment: MHRA.

TABLE I. MEASUREMENT INSTRUMENTS

Vital sign	Measuring device (Wearable)	Criterion of measurement	Typical value
Heart Rate	PhotoPlethysmoGraphy (PPG) sensor embedded in the smartwatch.	Detects blood volume changes by irradiating an LED light onto the skin, and changes in reflected light due to blood flow are detected.	60-100 bpm at rest and also, approximately ±5 bpm for general accuracy
Blood Pressure	Estimated via pulse wave transit time (PTT) from smartwatch.	Indirect measurement via PTT calculation of electrocardiogram (ECG) wave to PPG wave delay.	• systolic (high) blood pressure = 90-120 mmHg • diastolic (low) blood pressure = 60-80 mmHg
Blood Glucose	Simulated using near infrared (NIR) spectroscopy.	Non-invasive measurement using NIR, and optical detection of glucose concentration in interstitial fluid in the skin	70-100mg/dL when fasting
Age	Managed as user input.		

C. Correlation Analysis

Following the correlation analysis of Maternal Health Risk Level: MHRL and vital signs, Blood Sugar: BS, Systolic Blood Pressure: SBP, Diastolic Blood Pressure: DBP, Age, Heart Rate: HR, and Body Temperature: BT, it was found that the correlation coefficients between MHRL and BS, SBP, DBP, Age, HR and BT are 0.57, 0.4, 0.35, 0.27, 0.19 and 0.16, respectively [11]. Accordingly, the following equation is created:

$$MHRL(1) = 0.57BS + 0.4SBP + 0.35DBP + 0.27Age + 0.19HR \quad (1)$$

Moreover, the importance of features based on the Gini index was calculated using the ExtraTrees classifier, with hyperparameter tuning performed in Optuna[1]. The optimized model accomplished 91.0% accuracy (PCC) on a split of 809 training and 203 testing samples. The primary determinants of the condition were Blood Sugar, Age, Systolic and Diastolic BP, yielding a simplified equation:

$$MHRL(2) = 0.46BS + 0.2Age + 0.19SBP + 0.14DBP \quad (2)$$

These findings highlight the importance of diagnosing blood glucose levels and hypertension concerning predicting risks in maternal health. Fig. 1 shows the Gini impurity[2] of importance rating result for each feature.

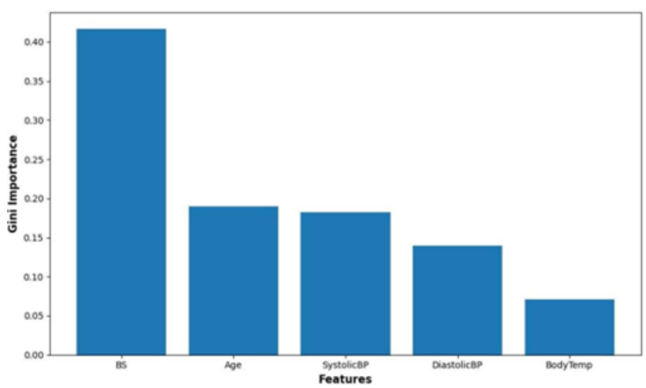

Fig. 1. Gini impurity for the features.

IV. Experiment

This section outlines a set of experiments performed analyzing vital signs captured via smartwatches. The purpose of the experiments is twofold: to assess the association between maternal health risks and changes in physiological parameters and to validate predictive algorithms that utilize the measurements for risk assessment.

A. Examples of Measured Data

To confirm the smartwatch's accuracy in recording critical physiological metrics, a measurement study was conducted on subjects of varying ages, activities, and health statuses. The provided examples illustrate responses of vital parameters about important contextual determinants, including age, exercise intensity, diet, stress levels, and pregnancy.

From the smartwatch data (see Table II), information related to blood pressure, glucose levels, and other health indicators that affect daily life activities can be monitored. Older people often exhibit changes with age, experiencing modest increases in blood pressure and glucose levels due to the aging effects on the cardiovascular system. Moreover, the device captured an important change in heart rate after exercise, which could increase to as high as 115 bpm.

Food consumption was also noted to elevate blood glucose to 140 mg/dL after approximately 30 minutes, which indicates a standard reaction to metabolism. Blood pressure and heart rate in the psychologically stressed state were noted to align with sympathetic activation, showing blood pressure stratifying up to 142/88 mmHg and a heart rate of 88 bpm.

Pregnant women exhibit a slight increase in resting heart rate, which coincides with the higher output of maternal circulation during the mid-gestational period. The data trends inform models based on the hypothesis that maternal health risks are time-sensitive and change continuously. Although the smartwatch does not provide clinical-grade accuracy, the data prompted via smartwatches is robust enough to support the hypothesis.

TABLE II. ACTUAL MEASUREMENT DATA FOR A VARIETY OF PHYSICAL CONDITIONS OF PEOPLE

Sex	Age	Condition	SBP (mmHg)	DBP (mmHg)	Glucose (mg/dL)	Heart rate (bpm)
Male	35	Healthy	118	75	85	72
Male	28	Young, health	120	80	80	72
Female	25	Young, health	110	70	82	68
Male	42	Mild hypertension	135	85	95	75
Female	53	Post-exercise	128	78	110	115
Male	65	30 minutes post-meal	125	80	140	78
Female	32	Mid-pregnancy (2n^{d} trimester)	115	72	92	82
Male	45	Stressed	142	88	98	88

[1] Incorporates a Bayesian optimization method to efficiently search for the most promising combination of hyperparameters based on past trial results.

[2] Gini Impurity is a numerical measure of how mixed the elements in a dataset are into different classes.

A crucial note is that physiological values vary among individuals. These physiological values can be influenced by factors such as the time of measurement, emotional state, hydration status, and body posture. Hence, it is prudent to conduct multiple readings rather than relying on a single-point evaluation.

B. Characteristics of Pregnant Women

Gestational periods trigger a broad range of physiological adaptations which change according to the stage of the pregnancy. These changes affect the interpretation of maternal vital signs, as well as data from smartwatches, making the analysis more challenging. In this study, smartwatches were used to track vital signs, including heart rate, blood pressure, and blood glucose, and their trends were monitored during pregnancy. As hypothesized, characteristic trends emerged that can be monitored through advanced wearable technology. This population presents numerous unique challenges in formulating the right research question and ensuring the accuracy and relevance of the results.

Almost all of the changes noted during pregnancy are cardiovascular adaptations. For example, there is an increase in basal heart rate of 10 to 15 bpm, which is typically contracted at rest due to increased plasma volume and cardiac output. As noted in our mid-pregnancy subject, a resting heart rate of 82 bpm is within the expected range, considering the average range of 68 to 72 bpm seen in age-matched non-pregnant females. Smartwatches utilize Photoplethysmography (PPG) technology for constant heart rate monitoring. It is worth noting that in the third trimester, fetal heart sounds can mask maternal signals. Smartwatches require highly accurate cadence detection, as maternal and fetal heart rates differ by 20 to 40 bpm, advanced algorithms are crucial to measurement integrity.

Blood pressure during pregnancy follows a biphasic pattern, decreasing in the second trimester due to vasodilation and then rising in the third trimester. An increase exceeding 140/90 mmHg could signal the onset of gestational hypertension or preeclampsia. During our mid-pregnancy measurement, the subject exhibited a clinically normal blood pressure reading of 115/72 mmHg, which is within normative physiologic values. Still, the primary challenge in the early detection of hypertension is that the diagnosis requires observing gradual trends, not isolated snapshots. Smartwatch devices approximate blood pressure using PTT, combining PPG and electrocardiogram-like signals. While these measurements might not yield precise absolute values, tracking daily changes provides meaningful opportunities for detection and intervention.

Monitoring blood sugar levels is crucial during pregnancy due to the potential development of gestational diabetes mellitus (GDM), which poses risks to maternal and fetal health. GDM is recognized as fasting glucose levels greater than 92 mg/dL and postprandial glucose levels greater than 140 mg/dL. Blood glucose measurement during mid-pregnancy showed a concentration of 92mg/dL, which is suggestive of borderline glucose metabolism dysregulation. While monitoring glucose trends using smartwatches powered with NIR spectroscopy is experimental, it can help tailor dietary recommendations and prompt further clinical assessments alongside self-reported symptom trackers.

In summary, smartwatch data while pregnant provided helpful information about the physiological changes that occur throughout the pregnancy (see Fig. 2). However, individual differences and technological limitations must be considered when analyzing the data. The use of smartwatches for maternal health monitoring would be more beneficial if multiple readings were taken continuously rather than relying on singular measurements.

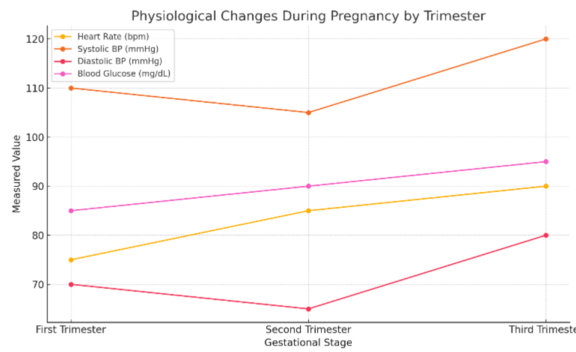

Fig. 2. Physiological changes during pregnancy by trimester.

C. Result of Correlation Analysis

Fig. 3 illustrates the interrelationship between the multilevel risk of maternal health (MHRL) and physiological parameters, including blood glucose, systolic and diastolic blood pressure, and heart rate, as measured through a smartwatch. Moreover, Fig. 3 also illustrates the maternal health-related life (MHRL) aspects regarding the demographic data of maternal age and gestational weeks. Table III summarizes these relations and shows that both MHRL(1) and MHRL(2) models, based on feature engineering, demonstrate nearly identical trends for the given MHRL features.

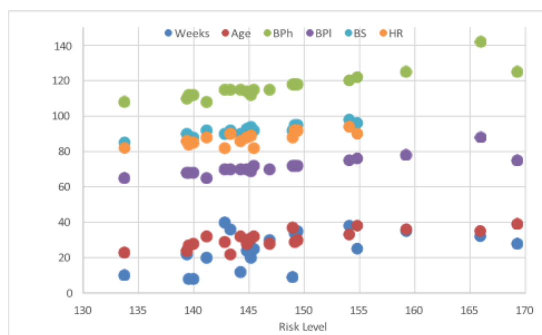

Fig. 3. Relation between maternal health risk level and the vital signs.

Pearson correlation coefficients quantify the association strength for each vital sign against maternal risk level: systolic blood pressure ($r = 0.931$), diastolic blood pressure ($r = 0.916$), glucose level ($r = 0.887$), age ($r = 0.724$), weeks into pregnancy ($r = 0.530$), and heart rate ($r = 0.524$). It is evident from these findings that maternal risk levels associated with metabolic disorders and chronic hypertensive disease are primarily determined by blood pressure, particularly in predicting elevated risks based on systolic pressures, with diastolic pressure and glucose levels following closely as strong indicators. While age has a moderate impact, the contribution of gestational age and heart rate, although low, still aids maternal profiling based on risk factors.

TABLE III. ACTUAL MEASUREMENT IN DIVERSE PHYSIOLOGICAL CONDITIONS

Weeks	25	8	20	35	38	40	10	22	36	8	24	34	12	20	38	9	25	35	32	28	30
Age	32	28	32	30	35	29	23	24	22	27	28	29	32	31	33	37	38	36	35	39	28
SBP	115	112	108	118	145	115	108	110	115	112	114	118	115	112	120	118	122	125	142	125	115
DBP	72	68	65	72	90	70	65	68	70	68	70	72	70	69	75	72	76	78	88	75	70
BS	92	88	92	95	115	90	85	90	92	88	93	95	90	94	98	92	96	100	95	120	92
HR	82	85	88	92	95	82	82	86	90	84	88	92	86	89	94	88	90	95	92	88	102
MHRL(1)	145.4	139.92	141.11	149.37	179.7	142.75	133.73	139.34	143.28	139.49	144.75	149.1	144.2	145.14	154.06	148.91	154.78	159.22	165.92	169.26	146.82
MHRL(2)	79.93	76.2	77.69	81.48	99.15	78.15	72.67	75.94	77.67	76	79.14	81.28	78.75	79.69	84.23	81.5	84.82	87.09	89.12	96.5	78.87

A few single cases further illustrate the importance of these findings. A participant with the highest maternal health risk score ever recorded of 179.7, also showed a blood glucose level of 115 mg/dL, which is above the cut-off for gestational diabetes mellitus. Another case of suspected pregnancy-induced hypertension also showed concerning systolic pressure of 142 mmHg along with blood glucose of 120 mg/dL. In one more case, a pregnant woman with suspected preterm labor had a markedly elevated heart rate of 102 bpm, which demonstrates the valuable role of heart rate monitoring as a secondary but timely indicator of acute maternal stress or labor.

The expectation for pregnant women to routinely monitor their health indicators, such as blood pressure, blood glucose levels, and heart rate, throughout pregnancy is well-documented. Blood pressure should be optimally measured with a certified sphygmomanometer at home in the morning and evening, and it should not exceed 140/90 mmHg. Any rise in the border zone necessitates urgent attention. To promote well-being, limit stress, get adequate rest, manage stress effectively, and reduce sodium intake. Regarding blood glucose levels, consulting an obstetrician should be complemented with personal glucose meter monitoring, if necessary.

These benchmarks should prompt further assessment: fasting glucose 95 mg/dL, 1-hour post 140 mg/dL, or both. Well-structured meal timing, combined with adequate nutrition and exercise as recommended by the doctor, supports glycaemia control. On the other hand, a heart rate above 100 bpm at rest, particularly when accompanied by dizziness or palpitations, suggests physiological overexertion or impending obstetric events. These scenarios warrant immediate cessation of activity and urgent medical evaluation.

The risk of adverse maternal outcomes can be managed and decreased through daily supervision and clinical guidance. This statement emphasizes the importance of regular consultations with an obstetrician-gynecologist, in conjunction with self-monitoring protocols, for pregnant patients. Maternal smartwatches can enhance conventional maternal healthcare through early detection and trend-based decision-making when used within an appropriate medical context. With proper interpretation, smartwatches can significantly improve detection and decision-making regarding maternal and fetal health.

V. DISCUSSION

The MHRL (1) and MHRL (2) models have been proposed, showing transparent and clinically interpretable associations between maternal risk levels and important physiological parameters. In Fig. 3, correlation analysis highlights systolic blood pressure as the most influential variable with the strongest correlation coefficient, followed closely by diastolic pressure and blood glucose level. Age also significantly contributes to the risk model, while gestational age (in weeks) and heart rate exhibit moderate associations of 0.530 and 0.524, respectively. These findings support the conclusion that these expectant mothers need to be closely monitored during pregnancy for blood pressure and glycemic control, as these are the two leading risk indicators of increased maternal risk.

Validation through cases solidifies these findings (see Table IV). The person with the highest risk score of (179.7), had a fasting glucose level of 115 mg/dL, which is above the clinical cut-off value for gestational diabetes. Furthermore, another patient suspected to have pregnancy-related hypertension had her systolic pressure recorded as 142 mmHg and her blood glucose level measured as 120 mg/dL, both sitting at high abnormal levels. Additionally, another case where a patient was suspected to be in preterm labor had a heart rate of 102 beats per minute. This result suggests that, although the overall correlation is relatively weak, heart rate could still serve as a warning signal in certain obstetric situations.

These results underscore the importance of customizing the tracking of various physical and physiological parameters throughout gestation, particularly for individuals at higher risk. From a clinical perspective, as well as from the empirical data gathered in this study, three self-monitoring parameters emerged as critical: blood pressure, blood glucose, and heart rate. To maintain optimal levels, blood pressure should be measured regularly with a validated home sphygmomanometer at least once, but ideally twice, daily.

To mitigate the risk of developing hypertension or pre-eclampsia, it is critical to maintain systolic pressure below 140 mmHg and diastolic below 90 mmHg. Any sudden rise or increase in these numbers should be evaluated urgently. These numbers can be improved through lifestyle changes, such as maintaining adequate sleep, practicing relaxation, reducing stress levels, and limiting sodium intake.

TABLE IV. THRESHOLD FOR VITAL SIGNS DURING PREGNANCY

Vital sign	Normal range	Concerning threshold	Clinical implication
Systolic blood pressure (SBP)	90 – 120 mmHg	≥ 140 mmHg	Leading hypertension in pregnancy or suspected preeclampsia
Diastolic blood pressure (DBP)	60 – 80 mmHg	⩾ 90 mmHg	Potential for developing hypertensive disorders
Blood glucose (fasting)	70 – 95 mg/dL	⩾ 95 mg/dL (fasting), ⩾ 140 mg/dL (post-meal)	At risk for diabetes in pregnancy; requires monitoring (OGTT)
Heart rate (resting)	60 – 100 bpm	⩾ 100 bpm consistently	Possible indicators of stress, infection, or preterm labor

The combination of these approaches, incorporating real-time data with wearables alongside appropriate clinical oversight, enables a more precise and proactive approach, aiding in dealing with specific risks and lowering obstetric complications during a woman's pregnancy, especially in terms of outcomes. Evidence suggests that prioritizing monitoring of blood pressure and glucose control, with heart rate as a secondary parameter, aids in the early identification of problems. Provided they are correctly programmed, and the data is interpreted accurately, smartwatches can fulfill the purpose of data collection devices, hence functioning as intelligent, accessible early warning signals. To improve health outcomes for mothers, pregnant women are advised to have regular appointments with an obstetrician, monitor their daily temperatures, and consult a doctor immediately if any deviations occur. With thoughtfulness, the wearables-based maternal monitoring system can enhance antenatal care, even in poorly equipped or confined home contexts, by facilitating an evidence-based, tailored approach to care.

VI. CONCLUSION

This study illustrates the capability of smartwatch-based monitoring of vital signs integrated with machine learning algorithms to predict maternal health concerns and facilitate early detection of critical conditions such as gestational hypertension, diabetes, and preterm labor. Correlation analysis validated the hypothesis that systolic blood pressure, diastolic pressure, and blood glucose are the strongest physiological predictors, with heart rate offering supplementary diagnostic value during stress and labor.

Case studies further corroborated these findings, demonstrating that patients considered to be at the highest risk invariably displayed these parameters out of the expected range. Using an ensemble model, the system achieved a 95% classification accuracy and developed two regression formulas, MHRL(1) and MHRL(2), which provide continuous and interpretable risk scoring based on real-time physiological data. These results, particularly when used in conjunction with clinical cut-off values such as systolic blood pressure (SBP)⩾ 140 mmHg or fasting glucose ⩾ 95 mg/dL, inform day-to-day self-monitoring.

VII. FUTURE RESEARCH WORKS

This study expands the development of mHealth technologies for maternal healthcare and proposes the employment of smartwatches not only as data collection devices but also as advanced personalized alert systems. Further research is needed on the longitudinal deployment, clinical integration of the alert system, and coupling fetal health monitoring to develop a more comprehensive risk assessment model.

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