DMPedia Lecture Notes in Computer Science & Engineering
Volume 1, pp. 299-308, 2026

International Conference on Multidisciplinary Perspectives in Advanced Computing and Technology (IMPACT 2026)
G. B. Pant University of Agriculture and Technology, Uttarakhand, India. Jan. 10-11, 2026

# A Smart Pregnant Women Health Care System for Risk Level Prediction Using Machine Learning

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## Abstract

Pregnancy is essential for mother and child, thus it is important to keep an monitor on any health concerns to ensure a safe delivery. Given that it compromises the mother's health as the long-term development of the baby, early risk tagging is essential for maternal health. Mothers would receive additional treatment before during, and after pregnancies if high-risk pregnancies were assigned, which would lower the chance of difficulties. However, the lack of access to healthcare in developing countries makes it difficult to manage any possible health risks during pregnancy. Medical systems can generate data-driven decision support models automatically with machine learning techniques, removing the requirement for explicit rule development by utilizing real-world data inputs. In this analysis, A Smart Pregnant Women Health Care System for Risk Level Prediction Using Machine Learning is presented. The Support vector machine (SVM) is used to predict the risk levels and health condition of pregnant woman. This model predicts the risk levels into Low, Mid and High levels. The accuracy, precision, recall, and F1-score of the model is used to evaluate its performance. When a patient is in a high-risk, this system informs registered family members and medical professionals.

**Keywords:** *Pregnant, Maternal Health (MH), Machine Learning, Risk and Support Vector Machine (SVM).*

## I. Introduction

The condition of a woman's health during her pregnancy, childbirth, and postnatal period is referred to as maternal health. Maintaining the health and well-being of both mother and child is the goal of MH (Maternal Health). Insufficient awareness of MH care can have fatal effects during pregnancy and lead to negative results in low- to middle-class families and rural areas [1]. Compared to men, women tend to report higher levels of stress and are more significantly affected by family duties. Pregnancy is recognized as a sensitive time with an increased risk for psychosocial symptoms and poor oral health, and a woman's lifestyle at this time can have long-term effects on her general health [2].

MH is an important issue that requires care and prioritization. Simply making it through pregnancy and delivery is not considered MH success. Acute kidney diseases, pulmonary edema, heart failure, and placental abruption are among the maternal complications related to preeclampsia [3]. It has been mentioned that most of these deaths can be avoided with the right MH care. High BP (Blood Pressure) in pregnant women is linked to antepartum period death, acute kidney damage, pulmonary edema, stroke, and disseminated intravascular coagulopathy. In addition to reducing the chance of maternal death, a safe pregnancy and birth ensure the child's normal growth, development [4].

In low and middle-income nations with limited access to high-quality healthcare, the majority of maternal deaths occur. Excessive blood loss, high blood pressure, infections, unsafe abortion, diabetes, thyroid disease, heart and blood disorders, poorly managed asthma, and unsafe abortion are the most frequent primary causes of complications for women. Pregnancy risk factors can include alcohol consumption, illegal drug use, and cigarette smoking. Enhancing maternal health is essential to preserving the lives of women who pass away each year due to difficulties during pregnancy and childbirth. Factors that raise the risk of maternal death include poverty, illiteracy, and inadequate nutrition [5]. The rate of maternal death and childbirth is affected by a number of factors, such as location, time, and distance, as well as the lack of doctors and nurses.

Ensuring the health of both maternal and fetal health requires the identification of high-risk pregnancies, but this can be a challenging task because of the complexity and variability of the factors involved. The chance that a woman would have adverse health outcomes during her pregnancy or childbirth is known as the maternal health risk during pregnancy [6]. Pregnancy problems can be classified as low, moderate, or high risk depending on risk factors that have been demonstrated to increase the possibility of these events. High-risk pregnancies can pose a risk of perinatal complications, perinatal asphyxia, congenital defects, and even adult cardiovascular abnormalities. These conditions, which include preeclampsia, cesarean section delivery, and gestational diabetes mellitus, can affect the mother [7].

Medical care providers utilize a range of tools and evaluations, such as blood tests, physical examinations, and medical histories, to identify women who might be highly susceptible to adverse effects. Early detection of risk factors in the early stages of pregnancy, effective risk management and mitigation, preventative measures, adverse perinatal outcomes challenges for mother child can be greatly decreased with adherence management [8].

To achieve the best predictive performance, numerous screening procedures have been developed over time. Therefore, the Uterine Artery Pulsatility Index (UTPI), which is evaluated in the first trimester of pregnancy, serum biomarkers, maternal features, and Mean Arterial Pressure (MAP) have all been used by researchers as important screening processes [9].

A high-risk pregnancy carries a greater danger to the mother's health, the health of the unborn child, or both. All pregnancies involve some risk, but some are higher than others; some may require extra care before, during, and after the pregnancy. Furthermore, some pregnancies turn high-risk as they go along, and other women are increased to problems for a number of reasons even before they get pregnant. As a result, many women benefit from early and regular prenatal care, which helps them have safe pregnancies and easy deliveries [10].

Artificial Intelligence (AI) has been increasingly used in the medical and health sectors in recent years. Specifically, ML has several applications in this area, including tracking the mother's and the fetus's health, identifying risk factors during pregnancy, detecting pathological abnormalities early, and detecting preterm births [11]. Pregnancy supports the health and well-being of both the maternal and the fetal, and the application of ML can be a powerful tool. More and more research indicates that Machine Learning (ML) can be useful as a predictive and detection tool, particularly for preventing maternal risks during pregnancy [12]. Predictive analytics supported by machine learning, risk evaluation, and individualised treatment suggestions enable timely intervention and improved patient care [13].

This analysis presents a Smart Pregnant Women Health Care System for Risk Level Prediction Using Machine Learning. The following is the arrangement of the remaining work: The Literature Survey is discussed in Section II. Section III presents A Smart Pregnant Women Health Care System for Risk Level Prediction Using Machine Learning. The result of the analysis is assessed in Section IV. Section V presents the conclusion.

## II. Literature Survey

Krisnanik E., Tambunan K. and Irmanda H. N. et. al., [14] explain the analysis of pregnancy risk factors for pregnant women using expert system-based analysis data. Four degrees of pregnancy risk factors were identified during this study of observation at Panimbang Health Centre: 1) accompanied by the disease, 2) poor obstetric history, 3) poor maternal condition, and 4) complicated pregnancies. The data analysis approach used in the development of the system includes descriptive, predictive, and prescriptive analysis, which are each utilized to provide advice after an examination of the symptoms that pregnant women experience. According to the results of the research, midwives could use this method to estimate the risk level of pregnant women by advising them to be ready for any situation, which could decrease the possibility that the mother or the fetus would die during pregnancy.

Ahmed M. and Kashem M. A. et al. [15] present a risk-level prediction model for maternal health care based on the Internet of Things in the context of Bangladesh. Using respective analytical tools and machine learning algorithms, this study aimed to determine the risk level based on pregnancy risk variables. An IoT (Internet of Things) device, a web portal, and Bangladeshi hospitals are among the sources from which data on maternal health have been collected for this study. This dataset has also been stored locally on the server and, as is typical, in the cloud as a CSV (comma-separated values) file. Depending on the level of danger, many approaches to categorization and classification have been used for the examination of risk variables. After evaluating several sets of machine learning algorithms, it is clear that the Modified Decision Tree Algorithm performs well in terms of categorization and risk level prediction.

Lakshmi B. N., Indumathi T. S and Ravi N. et. al. [16] describe A unique technique for monitoring pregnant women's health. In order to predict risk during pregnancy, the C4.5

classifier's accuracy is affected by the standardization process, which is discussed in this work. The aim of this paper is to demonstrate that parameter standardization affects the prediction accuracy achieved in the present study. The report also examines the performance of the C4.5 decision tree classification method chosen for this study in terms of accuracy when applied to a collected and standardized pregnant data set.

F. Oktaviana, M. N. Widyawati, K. Kurnianingsih and N. Kubota et. al., [17] provide advice for identifying pregnant women who could be at risk of stunting early for the purpose of early detection of pregnant women's stunting risk and suggestions. An android-based application has been developed. When a pregnant woman is at high risk of giving birth, they offer advice and utilise forward chaining procedures to detect stunting. They achieved an accuracy of 89% with the proposed forward-chaining stunt detection method.

J Pintye, Kinuthia J, Drake AL, Unger JA, Matemo D, Heffron RA, McClelland RS, Barnabas RV, Kohler P, John-Stewart G et al., [18] explains A Risk Assessment Tool for Determining Women Who May Benefit from Preexposure Prophylaxis and Are Pregnant or Postpartum. To generate a risk score, multivariate Cox (Cyclooxygenase) proportional hazards models and standard clinical prediction techniques were applied. The Brier score and the Area under the receiver operating characteristic (ROC) curve (AUC) were used to evaluate the tool's predictive ability for maternal HIV (Human Immunodeficiency Virus) acquisition. An AUC of 0.76 (95% CI,.67–.85) was obtained from a simplified score that eliminated candidiasis and bacterial vaginosis; (7.3 vs. 1.1 per 100 person-years, respectively; P <.001), the incidence of HIV was higher among women with risk scores >6 than in those with scores ≤6. While comprising 16% of the population, women with simplified scores greater than 6 were responsible for 56% of HIV (Human immunodeficiency virus) acquisitions.

LC Martins, CM Freire, CA Capuruçu, C Nunes Mdo, CA Rezende et al. [19] explain that pregnant patients with heart disease are at increased risk of cardiovascular complications. From January 2005 to July 2010, they examined 132 pregnant patients with cardiac disease in an outpatient clinic for high-risk pregnancies. The following factors were chosen because they were thought to have an impact on the mother-fetal outcome: parity, age, smoking, heart disease etiology and severity, history of heart problems, cyanosis, New York Heart Association (NYHA) functional class > II, arrhythmia, left ventricular dysfunction/obstruction, treatment change, when to begin prenatal care, and the number of prenatal visits are all relevant factors. At the start of prenatal care, patients were divided into three risk categories based on the maternal-fetal risk index determined retrospectively by the Cardiac disease in pregnancy (CARPREG).

B.N. Lakshmi, T.S. Indumathi, and Ravi N. et al. [20] compare different classification systems for predicting pregnancy risk. This research uses two classification algorithms, the C4.5 Decision Tree Classification Algorithm and the Naive Bayes Classification Algorithm, to predict the health problems that pregnant women are likely to face at this moment. The chosen algorithms are strong, well-established tools for data mining tasks such as prediction and classification.

These two algorithms predicted a woman's current health status and any related health issues based on pregnancy data collected from women at various stages of pregnancy. The goal of this study is to determine which of the two categorisation algorithms is most effective at predicting each pregnant woman's health state and potential complications.

## III. A Smart Pregnant Women's Health Care System

In this section, A Smart Pregnant Women Health Care System for Risk Level Prediction Using Machine Learning is presented. The block diagram of the presented system is shown in Figure 1.

Firstly, this system collects the patient's details, including age, Pregnancy month, weight, Blood Pressure, Temperature, heart rate, Blood Sugar, and laboratory results. An important variable to consider is age, as it appears that pregnant women's health risks begin to increase from age 25. BS (Blood Sugar) will have a relatively strong positive connection with High Systolic BP, Diastolic BP, and high Age. Must be careful. Records related to clinical and laboratory procedures are gathered, and they are primarily classified into six time periods that also change according to conditions. First trimester: ≤13 weeks and 6 days of gestation; second trimester: ≥14 weeks and ≤127 weeks and 6 days of gestation; third trimester: ≥28 weeks of gestation. (1) Pre-pregnancy: within six months before pregnancy. Pre-delivery: no later than 24 hours following admission for delivery; post-delivery: no later than 3 months.

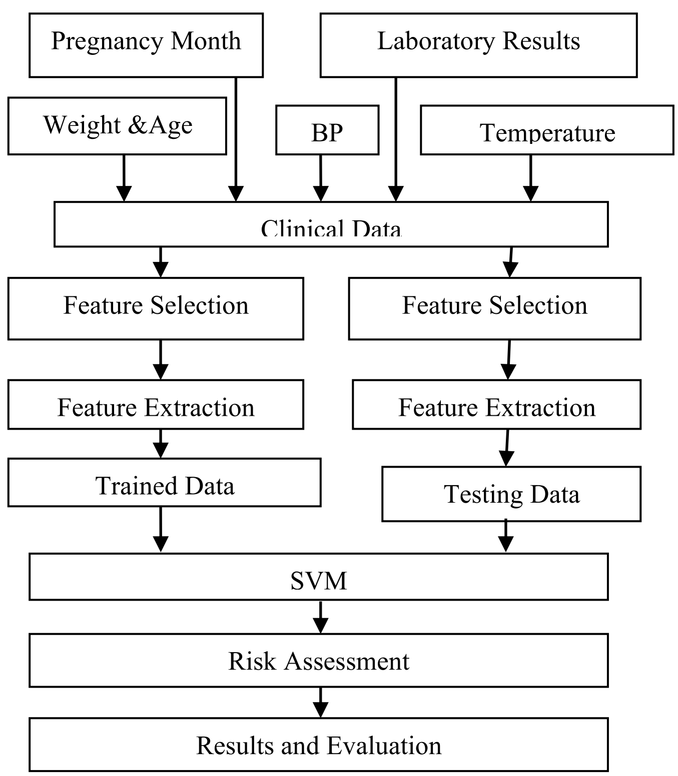


**Figure 1:** Block Diagram of Smart Pregnant Women Healthcare System

Heart Rate is the least relevant variable in the feature selection process that uses the data. Selected features are those that are available in a dataset; this process is known as feature selection. Before applying ML techniques, feature selection is a crucial data preparation step that can speed up processing and increase prediction accuracy. Feature selection is the process of determining which features are most suited to accurately predict the classification's results. The method of evaluating and visualizing data to obtain understanding, recognize underlying patterns, and identify relationships between variables is known as exploratory data analysis, or EDA. It supports variable evaluation, outlier detection, and understanding of the data structure.

An essential step in deriving new features from the original data in any prediction or classification system is feature extraction. Because the attributes and abilities of pregnant working women significantly impact learning outcomes, this is an essential phase in the classification process. Keystrokes, other actions, average idle time, total activities, and average time are the five features extracted from the normalised data. For simpler training and testing, these data are separated into two sets. Pregnant women's risk levels are predicted using SVM with training and testing data used.

The gathered data is analysed using the SVM machine learning algorithm to find patterns and correlations between risk factors and possible health risks. Support Vector Machine (SVM), for classification or regression analysis, maximises the separation margin, which is a binary linear classifier that establishes a decision boundary between two classes, allowing for the prediction from one or more feature vectors. By transforming the training data into a high-dimensional feature space, the model produces a linear optimal solution by dividing the decision boundary into points that have the smallest distance between them and the highest margin between the classes.

Each pregnant woman would be assigned a risk level by the system based on the study, which predicted the possibility and severity of potential health risks into three categories: low, mild, and high. A risk-level assessment method helps assign high-risk cases as a priority for additional, urgent medical care. When a patient's risk level exceeds a predetermined threshold, the system can send alerts and notifications to registered family members and medical professionals. Equations (1), (2), (3), and (4) express the performance of the proposed system in terms of accuracy, precision, and F1-score.

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 - score = 2 \times \frac{precision \times recall}{precision + recall} \quad (4)$$

## IV. Result Analysis

In this section, the result analysis of A Smart Pregnant Women Health Care System for Risk Level Prediction Using Machine Learning is presented. Table 1 shows the performance metrics comparison.

**Table 1:** Performance Comparison

| Metrics/ Model | Decision Tree (DT) | SVM |
|---|---|---|
| **Precision (%)** | 90.3 | 94.8 |
| **Recall (%)** | 91 | 95 |
| **Accuracy (%)** | 90.6 | 95.3 |
| **F1-score** | 90 | 94.7 |

A comparison is made between the accuracy, precision, recall, and F1-score of the SVM model and the DT model. Figure 2 shows the three risk levels of pregnant women.

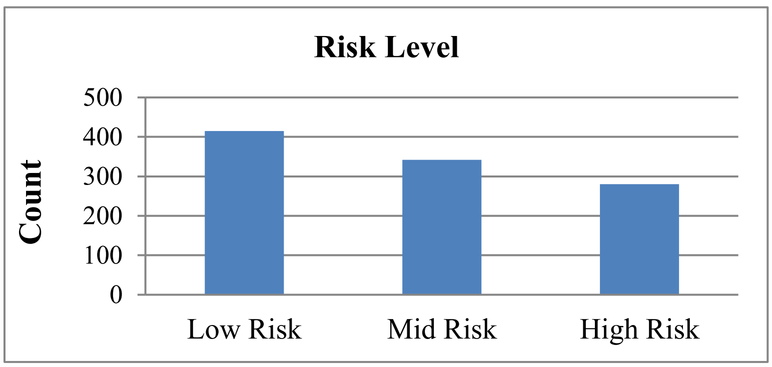


**Figure 2:** Risk Level Comparative Graph

In Figure 2, the y-axis shows the number of patients and the x-axis shows the risk levels. From Figure 2, it is clear that most pregnant women have a low risk. Figure 3 shows the Recall and Precision Comparison.

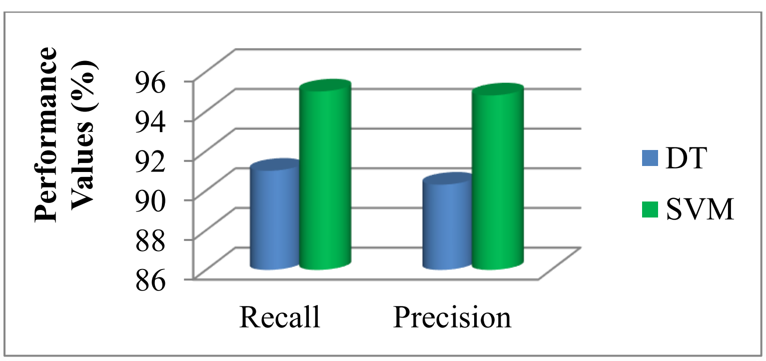


**Figure 3:** Recall and Precision Comparison

The SVM Algorithm has achieved better recall and precision than the DT model for predicting the risk level of pregnant women. Figure 3 shows the Accuracy and F1-score Comparison.

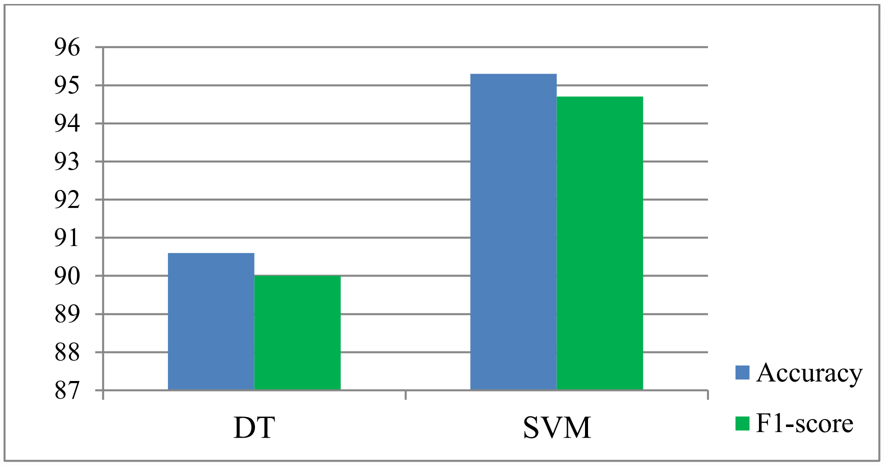


**Figure 4:** Accuracy and F1-score Comparison

Compared to the DT model, the presented SVM has achieved better Accuracy and F1-score. Hence, the presented system has demonstrated significant performance in predicting the risk level for pregnant women.

## V. Conclusion

This analysis presents a Smart Pregnant Women Health Care System for Risk Level Prediction Using Machine Learning. Firstly, the patient's details, such as age, weight, lab reports, BP levels, Blood sugar levels, Heart rate, and Temperature, are collected. Appropriate features are selected and unnecessary features are removed. The data is applied to SVM after being divided into training and testing sets. This system predicts the three levels of risks of pregnant woman, such as low level, midlevel and high level, based on their lab reports, BP level, blood sugar level, Weight, and age. In this analysis, SVM is used to predict the risk levels and health conditions of pregnant women. Accuracy, Precision, Recall, and F1-score are used to evaluate the performance of the presented approach. Compared to earlier models, the presented model has obtained better performance. In addition, when a patient's risk level exceeds a threshold, this system notifies registered family members and medical professionals.

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