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Prediction of Current Maternal Health Risk Levels Get Pregnant Using the Decision Tree Algorithm

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Abstract

This study aimed to develop and evaluate an interpretable Decision Tree model for classifying maternal health risk levels during pregnancy into low-, mid-, and high-risk categories. A quantitative computational classification design was employed using 1,025 maternal health records obtained from the UCI Machine Learning Repository. Six numerical predictors were analyzed: maternal age, systolic blood pressure, diastolic blood pressure, blood sugar, body temperature, and average heart rate. Data preparation involved validation, cleaning, integration, transformation, and reduction or discretization, followed by Decision Tree modeling in RapidMiner. Predictive performance was assessed using a confusion matrix, overall accuracy, class-specific precision, and recall. The model achieved an overall accuracy of 71.92%. High-risk classification produced 88.53% recall and 84.28% precision, while low-risk classification achieved 92.31% recall and 65.79% precision. Intermediate-risk classification demonstrated weaker performance, with 33.83% recall and 71.65% precision, including 146 actual mid-risk observations incorrectly classified as low risk. The findings demonstrate that interpretable classification rules do not necessarily ensure balanced predictive reliability across maternal risk categories. The Decision Tree provides a transparent computational framework for maternal risk assessment, although improved intermediate-risk discrimination and independent validation are required before clinical application.

Keywords: Decision Tree, Machine Learning, Maternal Health, Risk Classification, Risk Prediction.

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INTRODUCTION

Maternal health risk assessment has become a significant challenge in contemporary healthcare systems as the increasing availability of clinical data creates opportunities to improve pregnancy surveillance, risk stratification, and clinical decision support through computational methods. Maternal complications may develop through interactions among physiological conditions, pre-existing health vulnerabilities, and changes occurring throughout pregnancy, making timely recognition of unfavorable clinical patterns essential for appropriate monitoring and intervention. Research on artificial intelligence in maternal healthcare has consequently expanded from conventional statistical risk estimation toward machine learning applications capable of identifying complex relationships among routinely collected clinical measurements (Bertini et al., 2022; Islam et al., 2022). Studies concerning pregnancy complications have examined predictive applications for gestational diabetes mellitus, hypertensive disorders, preeclampsia, preterm birth, postpartum hemorrhage, and broader maternal health risk classifications, reflecting the diversification of computational approaches to obstetric assessment (Mennickent et al., 2023; Hennessy et al., 2024). The application of predictive algorithms is particularly relevant in healthcare environments where clinical resources, specialist availability, and technological infrastructure may constrain the implementation of comprehensive maternal monitoring systems (Khan et al., 2022). Recent developments in Internet of Things-enabled medical cyber-physical systems have further expanded the potential for integrating physiological measurements with automated risk prediction, although the availability of additional data does not independently establish the clinical reliability of predictive classifications (Hossain et al., 2026). Artificial intelligence applications must also address algorithmic

bias, clinical translation, and the consequences of inaccurate risk categorization before their outputs can be considered suitable for healthcare decision-making (Bashir et al., 2026). The potential for predictive technologies to influence maternal anxiety, access to care, and discriminatory treatment reinforces the need to examine classification performance beyond a single aggregate accuracy measure (Ji & Wang, 2026). Maternal healthcare research in Indonesia provides a relevant healthcare background, although studies addressing postpartum conditions should be distinguished from investigations concerned specifically with computational pregnancy-risk prediction (Widiastuti & Jati, 2020). Within intelligent engineering and healthcare computing, the scientific problem extends beyond determining whether maternal risk can be predicted computationally to examining whether interpretable models can distinguish clinically meaningful risk categories with sufficient consistency to inform subsequent assessment.

The contemporary literature on machine learning for maternal health prediction can be organized into three interconnected research directions: pregnancy-specific complication prediction, general maternal risk classification, and the development of interpretable or computationally optimized predictive architectures. The first direction primarily examines defined obstetric outcomes using heterogeneous clinical characteristics, including gestational diabetes prediction from maternal attributes, population-based records, and specialized biological measurements (Chan et al., 2023; Kang et al., 2023; Watanabe et al., 2023; Kaya et al., 2024). Related investigations have extended machine learning applications to preeclampsia and hypertensive disorders, where predictive modeling is constructed around identifiable pregnancy complications rather than a general classification of maternal health status (Liu et al., 2022; Schor et al., 2024; Özcan & Peker, 2025). Preterm birth research demonstrates a comparable methodological orientation, combining conventional predictive methods and machine learning with maternal clinical histories, electronic health records, and additional population-specific characteristics (Sharifi-Heris et al., 2022; Sun et al., 2022; Zhang et al., 2023; Belaghi, 2024; Park et al., 2024). Investigations of postpartum hemorrhage represent another complication-specific application, including decision tree, random forest, and other machine learning approaches applied to obstetric outcomes (Sinambela et al., 2023; Shah et al., 2023). The second research direction addresses broader maternal risk categorization rather than predicting a single complication, using models intended to identify differences among pregnancy-related risk conditions (Al Mashrafi et al., 2024; Pavagada & Vemuri, 2025; Pi et al., 2025). Within this direction, decision tree-based methods have received attention because their classification structures can be expressed through attribute-based rules, while comparative investigations examine their predictive characteristics relative to alternative machine learning configurations (Byna, 2019; Setiawan et al., 2024). The third direction emphasizes methodological refinement through hybrid architectures, ensemble learning, semi-supervised methods, and systematic algorithm selection, reflecting attempts to address predictive complexity and improve model suitability for maternal healthcare datasets (Macrohon et al., 2022; Togunwa et al., 2023; Khadidos et al., 2024; Mousavi Nogholi et al., 2026). Research on interpretable prediction of birth weight also illustrates the broader relevance of identifying influential predictors rather than treating predictive algorithms exclusively as instruments for generating outcome labels (Liu et al., 2022). Collectively, these research directions demonstrate a mature interest in computational pregnancy assessment but differ substantially in their prediction targets, data characteristics, modeling strategies, and evaluation priorities, limiting the extent to which reported performance across distinct obstetric tasks can be interpreted as directly comparable evidence.

Despite the expansion of machine learning applications in maternal healthcare, the available literature leaves several analytical questions insufficiently resolved for the specific task of interpretable multiclass maternal health risk classification. A central distinction concerns the difference between predicting a defined obstetric complication and assigning a maternal observation to low-, intermediate-, or high-risk categories, since these tasks involve different target definitions and potentially different patterns of classification error. Research on gestational diabetes, preeclampsia, preterm birth, and postpartum hemorrhage establishes the applicability of computational prediction to particular clinical outcomes, but its findings cannot automatically establish equivalent discriminatory performance across three general maternal risk categories (Kang et al., 2023; Hennessy et al., 2024; Belaghi, 2024; Shah et al., 2023). Studies directly examining maternal risk prediction provide a more relevant methodological foundation, particularly those investigating decision tree models, alternative

classification algorithms, ensemble methods, and model optimization (Al Mashrafi et al., 2024; Setiawan et al., 2024; Khadidos et al., 2024; Mousavi Nogholi et al., 2026). Nevertheless, aggregate predictive performance and comparative algorithmic effectiveness do not independently explain how consistently a particular model identifies each risk category or how misclassification is distributed between adjacent categories. This distinction is especially consequential for intermediate-risk observations, which require separate examination rather than being evaluated exclusively through a combined performance statistic. The broader literature on pregnancy-outcome prediction has recognized substantial variation in data sources, modeling approaches, and evaluation practices, indicating that predictive findings must be interpreted in relation to the characteristics of the underlying research design (Bertini et al., 2022; Islam et al., 2022). Similar concerns arise when computational frameworks developed from specialized biomarkers, longitudinal health records, or complex model architectures are considered alongside models constructed from a limited set of routine physiological attributes (Chan et al., 2023; Park et al., 2024; Hossain et al., 2026). Although semi-supervised, hybrid, and ensemble techniques offer alternative approaches to maternal risk modeling, their methodological complexity does not eliminate the need to establish the classification behavior of an interpretable reference model (Macrohon et al., 2022; Togunwa et al., 2023). The research gap addressed in the present investigation is consequently defined as the need for a focused examination of how a Decision Tree classifies three maternal health risk levels using six routinely available physiological and demographic attributes, with particular attention to category-specific discrimination and the distribution of misclassification. This gap concerns the interpretability and evaluation of a specific multiclass prediction task rather than an unsupported claim that Decision Tree algorithms or maternal risk prediction have not previously been investigated.

The unresolved relationship between model interpretability, aggregate predictive accuracy, and category-specific classification performance has direct implications for both intelligent healthcare engineering and maternal risk assessment. A classification model that achieves an acceptable aggregate performance statistic may still produce uneven recognition across risk groups, making its apparent effectiveness dependent on the distribution of correctly and incorrectly identified observations. For maternal healthcare applications, this distinction deserves attention because assigning an observation to a lower or higher risk category may influence how the prediction is interpreted, even when the computational output has not been validated as a clinical decision rule. Research on machine learning implementation in resource-constrained maternal healthcare emphasizes the relevance of practical model characteristics, including data accessibility and the feasibility of incorporating computational predictions into healthcare processes (Khan et al., 2022). The increased availability of electronically collected physiological measurements makes this issue more immediate, since predictive systems can operate on data derived from monitoring infrastructures without necessarily providing evidence of equal reliability across all maternal risk categories (Hossain et al., 2026). From a methodological standpoint, failure to distinguish overall accuracy from class-specific precision and recall can conceal weaknesses affecting particular subsets of observations and can restrict meaningful comparisons among prediction models. Developments in ensemble learning and optimized model selection demonstrate continuing efforts to improve maternal risk prediction, but the interpretability of model outputs remains an independent consideration when computational results are intended to support professional assessment (Khadidos et al., 2024; Mousavi Nogholi et al., 2026). Research examining artificial intelligence for adverse pregnancy outcomes also identifies clinical translation and algorithmic bias as issues that require attention beyond computational model development (Bashir et al., 2026). Similarly, concerns about anxiety and discrimination associated with algorithmic high-risk pregnancy prediction indicate that risk labels should not be interpreted independently of classification limitations and the intended healthcare application (Ji & Wang, 2026). An interpretable Decision Tree offers an analytically relevant basis for investigating these concerns because its decision structure can be examined alongside the resulting classification performance. Evaluating prediction errors separately for high-, intermediate-, and low-risk cases can clarify which portions of the classification task are adequately represented by the model and which require further methodological refinement. The practical significance of this investigation is therefore not the immediate substitution of automated predictions for professional judgment, but the provision of transparent computational evidence that can inform subsequent model development, technical evaluation, and decisions concerning additional validation.

The present study is positioned within the field of interpretable machine learning for maternal healthcare, with its contribution defined by the focused evaluation of a single Decision Tree model for three-category maternal health risk prediction using routinely measurable clinical attributes. Unlike studies emphasizing particular pregnancy complications, including gestational diabetes, hypertensive disorders, and preterm birth, the present investigation addresses a general maternal risk label comprising low-, mid-, and high-risk categories (Watanabe et al., 2023; Liu et al., 2022; Zhang et al., 2023). Its methodological position also differs from research centered on hybrid neural architectures, ensemble frameworks, or optimized algorithm selection because it prioritizes the examination of an interpretable tree structure rather than the development of an increasingly complex predictive architecture (Togunwa et al., 2023; Khadidos et al., 2024; Mousavi Nogholi et al., 2026). The analytical foundation consists of 1,025 maternal health records obtained from the UCI Repository, with age, systolic blood pressure, diastolic blood pressure, blood sugar, body temperature, and average heart rate serving as predictors. These attributes are used to construct a multiclass Decision Tree in RapidMiner, while model evaluation is organized around a confusion matrix, overall accuracy, class precision, and class recall. Previous investigations of Decision Tree-based maternal prediction provide an established methodological reference, making it necessary to distinguish the present contribution from the earlier introduction or application of tree-based classification techniques (Byna, 2019; Setiawan et al., 2024). The proposed contribution lies specifically in integrating an interpretable rule-based classification structure with a differentiated evaluation of the model's capacity to recognize each maternal risk category and characterize errors between categories. This approach also connects the interest in explainable predictive relationships, illustrated by research on interpretable machine learning in maternal and neonatal outcomes, with the practical requirements of multiclass maternal risk assessment (Liu et al., 2022). Its novelty is therefore an evaluative and application-specific contribution rather than the invention of a new machine learning algorithm, the introduction of an unprecedented dataset, or an unverified claim of superior predictive performance. By examining class-level recognition within a defined computational workflow, the study seeks to clarify the strengths and limitations of Decision Tree-based maternal risk classification without attributing clinical effectiveness to findings derived solely from the available dataset.

This study aims to develop and evaluate an interpretable Decision Tree classification model for predicting maternal health risk levels during pregnancy using a dataset of 1,025 maternal health records containing six clinical and demographic predictors. Specifically, the investigation seeks to establish a computational classification workflow using RapidMiner, construct a Decision Tree capable of assigning maternal observations to low-, mid-, and high-risk categories, and evaluate the resulting predictions through a confusion matrix, overall accuracy, class precision, and class recall. The analysis is designed to determine how consistently the model identifies each risk category, examine the distribution of classification errors, and identify differences in predictive performance among the three maternal health risk levels. Particular analytical attention is directed toward the model's ability to distinguish intermediate-risk observations from the remaining categories, while preserving the evaluation of high- and low-risk classifications as separate components of predictive performance. The study further aims to examine the interpretability of the generated classification structure by considering how the selected clinical attributes contribute to decision rules within the resulting tree. Its scientific contribution consists of providing a category-sensitive assessment of an interpretable machine learning model, thereby extending the evaluation of maternal risk prediction beyond aggregate classification accuracy. The methodological contribution concerns the systematic integration of Decision Tree modeling, explicit classification rules, and class-specific performance indicators within a reproducible computational framework, subject to the data preparation and validation procedures documented in the study. From an applied perspective, the investigation provides an evidence-based assessment of the model's potential and limitations as a computational component for maternal health risk screening and decision-support development. The findings are intended to inform subsequent improvements in model configuration, risk-category discrimination, and validation procedures rather than establish immediate clinical readiness. The study ultimately contributes to intelligent healthcare computing by clarifying how the predictive behavior and interpretability of a conventional Decision Tree can be evaluated for a multiclass maternal health assessment problem using a defined set of routinely available attributes.

RESEARCH METHODS

This study employed a quantitative computational classification design to predict maternal health risk levels during pregnancy using a Decision Tree algorithm. The research was conducted through secondary data analysis using the Maternal Health Risk dataset obtained from the University of California, Irvine (UCI) Machine Learning Repository. The dataset consisted of 1,025 maternal health records, with each record representing an observation characterized by six numerical predictors and one categorical outcome variable. The predictor variables comprised maternal age, systolic blood pressure, diastolic blood pressure, blood sugar, body temperature, and average heart rate, while the target variable, Maternal Health Risk Level, consisted of three categories: low risk, mid risk, and high risk. These attributes provided the input structure for examining how combinations of maternal physiological and demographic characteristics could be computationally classified into distinct risk levels. Data preparation involved validation, cleaning, integration and transformation, followed by reduction or discretization to establish a dataset suitable for classification. The cleaning procedure addressed missing or empty attribute values and inconsistent observations, while integration and transformation organized the available data into a format compatible with the modeling process. Reduction and discretization were incorporated into the preparation workflow to simplify the representation of the dataset and support computational processing. The analysis was restricted to the available secondary records and their documented attributes, without collecting new clinical observations, conducting patient examinations, or administering interventions. The original methodological documentation did not specify the dataset selection procedure, the temporal coverage of the observations, or the detailed rules applied during preprocessing; these elements were consequently not assigned unverified methodological specifications.

The computational experiment was implemented in RapidMiner using a workflow consisting of data retrieval, role assignment, and Decision Tree modeling. Following data preparation, the six numerical attributes were designated as predictor variables, and Maternal Health Risk Level was assigned as the classification target. The Decision Tree operator was applied to construct a hierarchical classification model in which internal nodes represented attribute-based decision conditions, branches represented the outcomes of those conditions, and terminal nodes represented predicted maternal risk categories. The generated model was examined through its decision structure and corresponding classification rules to identify how the available clinical attributes contributed to the assignment of individual observations to low-, mid-, or high-risk categories. Predictive performance was evaluated using a multiclass confusion matrix comparing predicted risk classifications against the recorded target labels. Overall classification accuracy was used to quantify the proportion of correctly classified observations, while class-specific precision and recall were examined separately for each maternal risk category. Precision represented the proportion of observations assigned to a particular predicted category that belonged to that category, whereas recall represented the proportion of observations in an actual risk category that were correctly identified. The distribution of correctly classified and misclassified observations was examined to assess differences in discrimination among high-, mid-, and low-risk cases, including errors involving the intermediate-risk category. Model evaluation was limited to the classification measures and procedures documented in the computational experiment; the original record did not establish a specific training–testing partition, cross-validation scheme, Decision Tree hyperparameter configuration, or independent external validation procedure. The confusion matrix and corresponding performance measures therefore provided evidence of classification behavior within the reported evaluation, without establishing prospective clinical validity or generalizability to an independent maternal population.

RESULTS AND DISCUSSION

Dataset Characteristics and Decision Tree Modeling for Maternal Health Risk Classification

The computational analysis was conducted using 1,025 maternal health records obtained from the UCI Machine Learning Repository, with each observation represented by six numerical predictors and one categorical risk label. The dataset provided a structured foundation for examining the relationship between maternal physiological measurements and three predefined classifications: low risk, mid risk, and high risk. Unlike predictive investigations focused on individual pregnancy complications, the present classification framework addresses a broader categorization of maternal

health conditions using routinely measurable attributes. This distinction is relevant to the development of computational maternal risk assessment, where the definition of the prediction target determines the interpretation and applicability of model outputs (Al Mashrafi et al., 2024; Pavagada & Vemuri, 2025).

The selected predictors comprised maternal age, systolic blood pressure, diastolic blood pressure, blood sugar, body temperature, and average heart rate, representing a combination of demographic and physiological information. Their inclusion enabled the Decision Tree to construct classification rules based on recorded numerical characteristics without requiring additional biological markers or specialized diagnostic measurements. Previous investigations have employed more extensive clinical information, including longitudinal records, laboratory indicators, and other pregnancy-specific measurements, to predict gestational diabetes and related complications (Kang et al., 2023; Watanabe et al., 2023; Chan et al., 2023). The comparatively restricted attribute structure of the present dataset supports a focused examination of rule-based classification, although the absence of additional clinical information limits the range of maternal health characteristics represented by the resulting model.

The input attributes were organized as numerical variables, while Maternal Health Risk functioned as the categorical target with three mutually exclusive labels. This arrangement required a multiclass classification procedure rather than a binary prediction of whether a single pregnancy complication would occur. Research examining machine learning applications in maternal and fetal health indicates that prediction targets and input characteristics vary considerably across studies, making the precise specification of dataset attributes essential for interpreting computational performance (Mennickent et al., 2023; Islam et al., 2022). The original attribute structure is presented in Table 1, which identifies the variables available for constructing the Decision Tree and distinguishes the classification target from its numerical predictors.

Table 1. Maternal Health Risk Dataset Attributes

Attribute	Value
Age	Numeric
Systolic BP	Numeric
Diastolic BP	Numeric
Blood Sugar	Numeric
Body Temperature	Numeric
Average Heart Rate	Numeric
Maternal Health Risk	Low, Mid, and High

Table 1 demonstrates that maternal health risk classification was based on six numerical inputs rather than a multidimensional clinical assessment incorporating medical history, pregnancy complications, or treatment information. Blood pressure and blood sugar provide potentially relevant physiological information, but their predictive meaning depends on the relationships captured by the fitted classification model rather than on the presence of individual attributes alone. Earlier research on hypertensive disorders and gestational diabetes has examined the predictive contribution of clinical measurements within models developed for specific obstetric outcomes (Liu et al., 2022; Schor et al., 2024; Kaya et al., 2024). Since the dataset documentation does not establish the measurement units, gestational ages, or diagnostic criteria underlying all recorded values, individual attributes should not be interpreted as independently validated clinical thresholds.

The dataset was prepared through validation, cleaning, integration and transformation, and reduction or discretization before its introduction into the classification procedure. These operations established the computational workflow used to organize available observations and attributes for Decision Tree processing, although the original documentation did not report the number of records affected by each operation. Data preparation is a consequential component of maternal health prediction because differences in data structure, completeness, and attribute representation may influence the construction and evaluation of machine learning models (Bertini et al., 2022; Sharifi-Heris et al., 2022). The absence of detailed preprocessing counts restricts independent assessment of

how individual preparation operations affected the final analytical dataset, particularly when evaluating the reproducibility of the classification process.

The prepared data were processed in RapidMiner through a modeling sequence comprising data retrieval, role assignment, and application of the Decision Tree operator. Figure 1 presents the original computational workflow, showing the relationship between the retrieved maternal health dataset, the definition of the classification target, and the construction of the tree-based prediction model. This procedure corresponds to a supervised learning framework in which the algorithm uses labeled observations to establish attribute-based classification rules for predefined maternal risk categories. Decision Tree-based maternal prediction has been examined in earlier computational investigations, while comparative studies have demonstrated the relevance of evaluating tree-structured algorithms as distinct predictive approaches rather than assuming equivalent behavior across machine learning models (Byna, 2019; Setiawan et al., 2024).

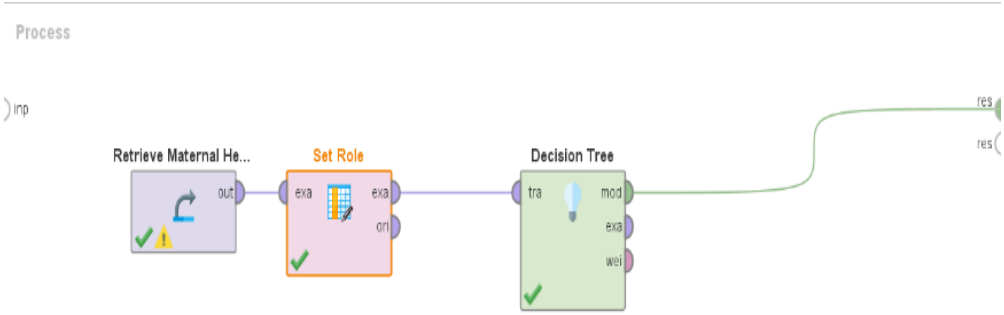


Figure 1. Decision Tree Modeling Process

The workflow illustrated in Figure 1 provides evidence of the computational sequence used to generate the maternal risk classification model, but it does not independently document the application of a particular training–testing partition or cross-validation procedure. Its principal methodological significance lies in the explicit assignment of the target variable before the Decision Tree operator processes the available predictor attributes. Research on predictive modeling for maternal health emphasizes the value of distinguishing model construction from the separate procedures required to demonstrate predictive generalizability and clinical applicability (Khan et al., 2022; Bashir et al., 2026). Accordingly, the modeling sequence should be interpreted as evidence of the implemented classification architecture rather than as confirmation of external predictive validation.

The resulting Decision Tree organized classification decisions through successive numerical conditions derived from the available maternal health attributes, as displayed in Figure 2. The documented rules included combinations of blood sugar, systolic blood pressure, maternal age, body temperature, and heart rate, allowing different observation profiles to follow distinct classification branches. This rule-based representation provides a degree of interpretability because predicted risk labels can be related to explicit attribute conditions, a characteristic relevant to research on interpretable machine learning for maternal and neonatal outcomes (Liu et al., 2022). The resulting thresholds nevertheless represent conditions learned by the computational model and should not be interpreted as independent diagnostic criteria or evidence of causal relationships between individual predictors and maternal health outcomes.



Figure 2. Decision Tree Model

The decision structure presented in Figure 2 illustrates how multiple physiological attributes were combined to produce differentiated maternal health risk predictions, although the displayed branches do not establish that each attribute contributed equally to the classification process. The original manuscript reports rules involving blood sugar thresholds and additional conditions associated with blood pressure, age, heart rate, and body temperature, indicating that the resulting predictions depended on successive attribute-based decisions rather than a single uniformly applied condition. Research employing ensemble learning and optimized model-selection strategies has emphasized computational performance as an important consideration in maternal risk prediction, while the present model permits direct examination of its explicit classification structure (Khadidos et al., 2024; Mousavi Nogholi et al., 2026). The scientific contribution of this modeling stage lies in establishing a transparent computational representation of multiclass maternal risk assessment, with the reliability of individual risk assignments requiring separate evaluation through the confusion matrix and class-specific performance indicators presented in the subsequent analysis.

Classification Performance and Class-Specific Predictive Reliability of the Decision Tree Model

The predictive performance of the Decision Tree model was evaluated using a multiclass confusion matrix that compared predicted maternal health risk categories with their recorded classifications. The computational evaluation reported an overall classification accuracy of 71.92%, indicating that the model correctly assigned approximately seven out of ten evaluated observations to their corresponding risk categories. This performance measure provides an initial assessment of the

model's ability to discriminate among high-, low-, and mid-risk maternal conditions, but it does not establish whether classification effectiveness was distributed consistently across the three categories. Previous investigations have demonstrated the applicability of machine learning algorithms to maternal risk prediction, while also indicating that predictive performance requires interpretation according to the characteristics of the classification problem and evaluation framework (Al Mashrafi et al., 2024; Pavagada & Vemuri, 2025).

The confusion matrix provides a more differentiated representation of predictive behavior by distinguishing correctly classified observations from cases assigned to alternative risk categories. Among the 218 observations labeled as high risk, 193 were correctly identified, whereas 10 were classified as low risk and 15 as mid risk. For the 325 low-risk observations, the model correctly classified 300 cases, with the remaining observations distributed between high-risk and mid-risk predictions. The intermediate-risk category exhibited a substantially different pattern, with only 91 of 269 observations correctly identified, indicating that aggregate accuracy alone was insufficient to characterize the model's classification reliability, consistent with methodological concerns identified in systematic evaluations of machine learning for pregnancy outcomes (Islam et al., 2022; Bertini et al., 2022).

The detailed confusion matrix is presented in Table 2, preserving the original classification counts and performance indicators reported in the computational experiment. The matrix distinguishes actual maternal risk classifications across columns and predicted classifications across rows, allowing the direction of each misclassification to be examined directly. Its structure also permits the calculation of class-specific precision and recall, which provide complementary information concerning the reliability of predicted labels and the proportion of actual cases recovered by the model. This distinction is relevant to maternal health risk prediction because the clinical interpretation of a classification error depends partly on which category is incorrectly assigned, rather than solely on the number of correct predictions (Khan et al., 2022; Bashir et al., 2026).

Table 2. Confusion Matrix

Predicted class	True high risk	True low risk	True mid risk	Class precision
Pred. high risk	193	4	32	84.28%
Pred. low risk	10	300	146	65.79%
Pred. mid risk	15	21	91	71.65%
Class recall	88.53%	92.31%	33.83%	

Table 2 identifies a pronounced difference between the recognition of high- and low-risk observations and the recognition of intermediate-risk observations. The high-risk category achieved a recall of 88.53% and precision of 84.28%, indicating that the model recovered a substantial proportion of actual high-risk cases while maintaining relatively consistent predictions within that category. The low-risk category achieved higher recall at 92.31%, but its precision was substantially lower at 65.79%, demonstrating that successful recovery of actual low-risk observations did not correspond to equally reliable low-risk predictions. This distinction supports the need to evaluate precision and recall separately, particularly in maternal health classification tasks where predictive models may demonstrate different strengths across risk categories (Setiawan et al., 2024; Khadidos et al., 2024).

The most pronounced classification weakness occurred in the mid-risk category, where recall reached only 33.83% despite a reported precision of 71.65%. Of the 269 observations actually labeled as mid risk, 146 were classified as low risk and 32 were assigned to the high-risk category, leaving 91 correctly identified observations. The predominance of mid-risk observations assigned to the low-risk category demonstrates that a substantial proportion of intermediate-risk cases were not recovered by the fitted classification model, although the available data do not establish the underlying physiological or statistical causes of these errors. Studies exploring hybrid neural architectures, ensemble learning, and algorithm optimization indicate that maternal health classification remains an active methodological problem, with alternative computational strategies providing relevant directions for investigating weaknesses in predictive discrimination (Togunwa et al., 2023; Mousavi Nogholi et al., 2026).

The distribution of misclassification errors further demonstrates that incorrect predictions were not evenly distributed among the possible risk-category transitions. The model assigned 146 actual mid-risk observations to the low-risk category, compared with 32 mid-risk observations assigned to high risk and 21 actual low-risk observations assigned to mid risk. These directional differences indicate that the low-risk prediction category incorporated a considerable number of observations whose recorded labels represented an intermediate maternal risk level, explaining its lower precision despite its high recall. Research on machine learning for pregnancy complications has similarly emphasized the importance of evaluating predictive outputs according to their intended clinical tasks, although findings from complication-specific models cannot be directly equated with the present three-category classification framework (Mennickent et al., 2023; Özcan & Peker, 2025).

The observed contrast between class-specific performance indicators provides an important basis for interpreting the analytical value of the Decision Tree model. The model demonstrated stronger recognition of observations at the high- and low-risk ends of the classification structure than of those assigned to the intermediate category, suggesting that the available decision rules did not distinguish all three recorded classes with comparable effectiveness. However, the confusion matrix alone cannot determine whether this difference resulted from overlapping attribute distributions, the composition of the dataset, class representation, preprocessing decisions, or the configuration of the classification algorithm. Investigations using semi-supervised learning and optimized prediction architectures have examined alternative methods for modeling complex maternal health classifications, but identifying the source of the present classification errors would require additional analyses not documented in the original experiment (Macrohon et al., 2022; Pi et al., 2025).

The reported accuracy of 71.92% should also be interpreted in relation to the limits of the documented model evaluation procedure. Although the confusion matrix describes the observed classification outcomes, the original methodological record does not specify a training–testing partition, cross-validation configuration, or independent external validation dataset. Consequently, the reported performance provides evidence of classification behavior within the recorded computational evaluation but does not establish how consistently the model would perform on independent maternal populations or under different healthcare data conditions. Research on machine learning applications for pregnancy prediction has identified dataset heterogeneity and methodological variation as continuing considerations for evaluating predictive models, reinforcing the distinction between reported computational performance and independently validated predictive capability (Sharifi-Heris et al., 2022; Hennessy et al., 2024).

From an intelligent healthcare engineering standpoint, the principal significance of these findings lies in the difference between producing interpretable predictions and demonstrating balanced predictive reliability across maternal risk categories. The Decision Tree generated a classification structure capable of identifying a substantial proportion of high- and low-risk observations, but its limited recall for mid-risk cases restricts the interpretation of aggregate accuracy as evidence of uniform classification effectiveness. The unequal distribution of classification errors warrants attention because algorithmic risk categories may influence subsequent decisions if predictive outputs are incorporated into maternal health decision-support systems without appropriate validation and professional oversight. Recent research addressing artificial intelligence translation, fairness, and risk communication in pregnancy care reinforces the need to assess predictive limitations before introducing automated classification outputs into clinical practice (Bashir et al., 2026; Ji & Wang, 2026).

Interpretability, Classification Limitations, and Implications for Maternal Health Decision Support

The interpretability of the Decision Tree model represents an important analytical characteristic of the maternal health risk classification framework, particularly because its predictions can be traced through explicit conditions involving recorded clinical attributes. The generated classification structure incorporated blood sugar, systolic blood pressure, maternal age, body temperature, and heart rate into successive decision rules, providing an observable relationship between predictor values and assigned risk categories. This characteristic distinguishes rule-based classification from computational approaches in which predictive decisions may be less directly accessible to clinical interpretation,

although interpretability alone does not establish clinical correctness. Research on interpretable machine learning in maternal and neonatal health has emphasized the relevance of identifying influential predictive characteristics, while investigations of maternal risk classification continue to examine the relationship between computational complexity and predictive performance (Liu et al., 2022; Setiawan et al., 2024).

The decision rules documented in the original experiment included blood sugar conditions combined with systolic blood pressure and maternal age, indicating that classification outcomes were not necessarily determined by a single physiological measurement. One reported branch assigned a low-risk classification when blood sugar was less than or equal to 9.500 and systolic blood pressure was less than or equal to 132.500, while other reported branches incorporated different blood sugar conditions and additional attributes to distinguish maternal risk categories. These numerical thresholds represent algorithm-generated partitioning conditions and cannot independently establish diagnostic boundaries, particularly because the original dataset documentation did not specify the measurement units or clinical validation of the resulting rules. Research on gestational diabetes and hypertensive pregnancy complications demonstrates the relevance of physiological measurements to computational prediction, but the clinical interpretation of their relationships remains dependent on the outcome definition, underlying population, and analytical design (Kaya et al., 2024; Schor et al., 2024; Hennessy et al., 2024).

The relationship between model interpretability and predictive reliability becomes more apparent when the classification structure is examined alongside the confusion matrix. Although the Decision Tree produced identifiable attribute-based rules, the recorded evaluation showed a marked difference between recognition of high-risk, low-risk, and intermediate-risk observations, demonstrating that transparent rules do not necessarily produce balanced multiclass discrimination. The model's 33.83% recall for intermediate-risk observations is particularly relevant because a substantial number of cases carrying that label were assigned to the low-risk category, despite the model's comparatively stronger recognition of the two remaining categories. The principal findings and their implications for computational maternal health assessment are synthesized in Table 3, following the emphasis on model evaluation and clinical translation identified in contemporary maternal artificial intelligence research (Al Mashrafi et al., 2024; Bashir et al., 2026).

Table 3. Analytical Synthesis of Decision Tree Classification Findings and Implications

Analytical dimension	Documented finding	Scientific interpretation	Implication
Classification structure	Decision Tree using six numerical predictors	Risk categories determined through attribute-based rules	Supports examination of explicit classification conditions
Aggregate performance	Overall accuracy of 71.92%	Correct classification was not uniform across risk categories	Requires complementary class-specific assessment
High-risk classification	Recall 88.53%; precision 84.28%	Relatively strong recognition of recorded high-risk observations	Supports further evaluation of high-risk screening capability
Low-risk classification	Recall 92.31%; precision 65.79%	High recovery of actual low-risk cases accompanied by less reliable low-risk predictions	Requires examination of falsely assigned low-risk labels
Mid-risk classification	Recall 33.83%; precision 71.65%	Limited recovery of intermediate-risk observations	Indicates a priority for classification refinement
Dominant misclassification	146 actual mid-risk cases predicted as low risk	Classification errors concentrated in a specific direction	Warrants attention before potential decision-support applications
Validation	No specified external	Generalizability cannot be	Further validation is

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documentation	validation or training–testing configuration	established from the necessary available documentation	

Table 3 demonstrates that the model's principal methodological strength and predictive limitation concern different dimensions of its performance. Its interpretable structure permits examination of the conditions associated with maternal risk assignments, whereas the class-specific findings reveal that the resulting decisions differed considerably in reliability across the three categories. The concentration of intermediate-risk observations within the low-risk prediction category is especially consequential because the low-risk label exhibited high recall but substantially lower precision, indicating that its apparent ability to recover actual low-risk observations should not be confused with the reliability of every low-risk prediction. Investigations of maternal health classification using hybrid and ensemble architectures illustrate alternative modeling directions, although their reported effectiveness cannot be assumed to transfer directly to the present dataset or evaluation procedure (Togunwa et al., 2023; Khadidos et al., 2024).

An important analytical limitation concerns the absence of sufficient evidence to attribute intermediate-risk misclassification to particular physiological variables or Decision Tree configurations. The reported confusion matrix identifies the frequency and direction of classification errors, but it does not establish whether those errors arose from similarities among recorded attribute values, the relative representation of target categories, preprocessing operations, or specific model parameters. Although the available dataset contained 269 intermediate-risk observations, this numerical distribution alone cannot explain the considerably lower recall recorded for that category without further examination of its predictor characteristics and the corresponding decision boundaries. Research employing semi-supervised learning and algorithm optimization has demonstrated the methodological diversity of high-risk pregnancy prediction, making alternative classification strategies relevant subjects for future comparative investigation rather than established explanations for the observed errors (Macrohon et al., 2022; Mousavi Nogholi et al., 2026).

The computational results also require consideration of the relationship between dataset characteristics and the potential transferability of the model to clinical environments. The investigation used secondary maternal health records containing six numerical attributes, but the source documentation did not establish the temporal distribution, clinical setting, gestational characteristics, or detailed population composition of the observations. These omissions restrict assessment of whether the resulting classification rules would remain applicable to maternal populations with different physiological profiles, healthcare access conditions, or measurement practices. Research examining electronic health records, pregnancy cohorts, and emerging medical cyber-physical systems demonstrates that maternal prediction models may operate on substantially different data structures, making population characteristics and data provenance relevant considerations for subsequent validation (Sun et al., 2022; Watanabe et al., 2023; Hossain et al., 2026).

The potential application of Decision Tree predictions to maternal health decision support must be distinguished from the demonstration of effectiveness in actual clinical practice. The present study established computational classification outcomes using recorded maternal health data, but it did not examine prospective screening decisions, healthcare professional responses, patient outcomes, or the consequences of using predicted categories in treatment or referral processes. This distinction matters because a model capable of generating interpretable predictions may still require additional evaluation before its outputs can support decisions affecting maternal healthcare. Studies addressing machine learning implementation in resource-constrained healthcare settings and artificial intelligence applications in pregnancy care emphasize the need to consider operational feasibility, clinical relevance, and validation when translating computational predictions into practical systems (Khan et al., 2022; Mennickent et al., 2023).

A related concern involves the potential implications of classification errors for the communication and interpretation of maternal health risk. Incorrectly assigning an intermediate-risk observation to the low-risk category may create a misleading representation of the recorded classification if the predicted label is interpreted without reference to the model's limitations, although the present experiment did not measure any resulting clinical consequences. Conversely, the assignment of observations to higher-risk categories does not independently establish that those

observations would require additional clinical intervention, since the dataset labels and learned decision rules were not evaluated against prospective diagnostic outcomes. Research examining algorithmic bias, patient anxiety, and discriminatory implications of artificial intelligence-based pregnancy prediction provides a basis for treating automated risk labels as decision-support information requiring appropriate interpretation rather than definitive clinical judgments (Ji & Wang, 2026; Bashir et al., 2026).

The findings identify several methodological priorities for the continued investigation of interpretable multiclass maternal health prediction. The contrast between high aggregate recognition of selected risk categories and substantially weaker intermediate-risk recall indicates that subsequent computational evaluations should examine classification balance rather than rely exclusively on overall accuracy. Further model development would also benefit from clearly documented preprocessing procedures, explicit validation configurations, and independent assessment of the stability of classification rules, although these additional procedures were not part of the documented experiment. Existing research on optimized machine learning, ensemble frameworks, and interpretable prediction provides relevant methodological alternatives for future comparison, but the present evidence does not establish that any particular alternative would resolve the observed classification limitations (Pi et al., 2025; Pavagada & Vemuri, 2025; Liu et al., 2022).

The contribution of the Decision Tree experiment lies in providing an empirically documented illustration of the relationship between interpretable classification rules and uneven category-specific prediction performance in maternal health risk assessment. Using six routinely measurable attributes, the model generated classifications for three maternal risk levels and produced an overall accuracy of 71.92%, with class-specific evaluation revealing stronger recognition of high- and low-risk observations than intermediate-risk observations. These findings establish the analytical value of examining confusion-matrix distributions alongside explicit decision rules, while limiting conclusions to the recorded dataset and computational evaluation rather than extending them to unverified clinical effectiveness. The results are consistent with the continuing emphasis on interpretability, methodological transparency, and rigorous predictive evaluation in maternal healthcare machine learning research, particularly where classification outputs may eventually inform clinical decision-support development (Islam et al., 2022; Bertini et al., 2022; Özcan & Peker, 2025).

CONCLUSION

This study demonstrated the application of a Decision Tree algorithm for classifying maternal health risk levels using 1,025 records from the UCI Machine Learning Repository and six numerical predictors: maternal age, systolic blood pressure, diastolic blood pressure, blood sugar, body temperature, and average heart rate. The computational model generated interpretable classification rules for low-, mid-, and high-risk categories and achieved an overall accuracy of 71.92%. Class-specific evaluation revealed substantial differences in predictive performance, with high-risk observations achieving 88.53% recall and 84.28% precision, while low-risk observations achieved 92.31% recall and 65.79% precision. The intermediate-risk category demonstrated the weakest recognition, with 33.83% recall and 71.65% precision, including 146 actual mid-risk observations incorrectly assigned to the low-risk category. These findings indicate that the Decision Tree was more effective in identifying high- and low-risk observations than intermediate-risk cases, while demonstrating that aggregate accuracy cannot independently represent the reliability of multiclass maternal health predictions. The principal scientific contribution lies in integrating interpretable decision rules with category-specific performance evaluation, providing a clearer understanding of the strengths and limitations of Decision Tree classification for maternal health risk assessment. The findings also establish the relevance of examining the direction and distribution of misclassification errors when evaluating computational models intended for healthcare decision support.

The practical implications of this study concern the potential use of interpretable machine learning as a preliminary computational component of maternal health risk assessment rather than as an independently validated clinical diagnostic instrument. Although the generated classification rules provide a transparent representation of relationships among recorded attributes and predicted risk categories, the limited recognition of intermediate-risk observations restricts the model's readiness for applications requiring consistent classification across all maternal risk levels. Interpretation is further constrained by the absence of documented training–testing partition details, cross-validation

procedures, and independent external validation, preventing conclusions regarding predictive generalizability beyond the reported computational evaluation. Subsequent investigations should prioritize more rigorous validation, transparent documentation of preprocessing and model configurations, and targeted refinement of intermediate-risk classification while preserving the interpretability of the resulting predictions. Comparative evaluation with alternative classification approaches may also clarify whether improvements in category-specific performance can be achieved without compromising the transparency of the model. The study establishes that Decision Tree-based maternal risk prediction offers an interpretable computational framework, but its prospective application in maternal healthcare requires further methodological development and independent validation.

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