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# A Neutrosophic Random Forest Approach for Preeclamptic Risk Prediction with Uncertainty Quantification

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**Abstract.** This study presents a novel integration of Random Forest with neutrosophic logic to improve preeclampsia risk prediction while quantifying prediction uncertainty. Using clinical data from 352 patients, the model achieved 72.73% accuracy with high sensitivity (0.898) in identifying control cases, though with lower specificity (0.235) for preeclampsia detection. Key predictors identified were birthweight and hypertension his- tory, aligning with clinical knowledge. The neutrosophic framework successfully categorized predictions into truth (T), indeterminacy (I), and falsity (F) components, revealing that 90% confidence predictions showed T = 0.9 while uncertain cases ($0.5 \leq p < 0.9$) demonstrated elevated indeterminacy (I = 0.3). The main contributions include: 1) an interpretable uncertainty quantification method for clinical predictions, 2) validation of key risk factors through feature importance analysis, and 3) a practical framework for identifying cases requiring additional clinical evaluation. This approach demonstrates significant potential for enhancing decision-making in maternal healthcare.

**Keywords:** Preeclampsia; Neutrosophic Logic; Random Forest; Uncertainty Quantification; Maternal Health; Risk Prediction.

## 1. Introduction

Preeclampsia is a complex, pregnancy-specific hypertensive disorder that affects approximately 2-8% of pregnancies worldwide and remains a leading cause of maternal and perinatal morbidity and mortality[1,2] characterized by the onset of hypertension and proteinuria after 20 weeks of gestation, preeclampsia poses significant risks to both the mother and fetus, including placental abruption, eclampsia, intrauterine growth restriction, and preterm birth [3,4]. Despite advances in prenatal care, the etiology of preeclampsia remains incompletely understood [5,6] with current hypotheses implicating placental dysfunction, endothelial injury, and systemic inflammation as key contributors. Early and accurate prediction of preeclampsia is critical for timely clinical intervention [7,8] yet existing diagnostic tools often lack the sensitivity and specificity required for reliable risk stratification [9,10].

Traditional statistical methods for preeclampsia prediction, such as logistic regression and risk scoring systems, have shown limited success due to the multifactorial and non-linear nature of the disease [5, 11]. These methods often rely on a small subset of clinical variables (e.g., blood pressure, proteinuria) and fail to capture the complex interactions between genetic, environmental, and biochemical factors. Machine learning (ML) models, particularly ensemble methods like Random Forest, offer a promising alternative by leveraging high-dimensional data to identify subtle patterns and interactions that may elude conventional approaches [12]. Random Forest's inherent robustness to noise, ability to handle mixed data types, and feature importance quantification make it well-suited for medical applications where interpretability and reliability are paramount [13].

However, a critical limitation of traditional ML models in clinical settings is their lack of transparent uncertainty quantification [14]. Standard probabilistic outputs from Random Forest provide a measure of prediction confidence but do not explicitly distinguish between uncertainty due to data ambiguity (e.g., overlapping feature distributions) and model limitations (e.g., insufficient training data). This gap is particularly problematic in maternal healthcare, where clinicians must balance the risks of overtreatment (e.g., unnecessary early de- livery) against undertreatment (e.g., missing a severe preeclampsia case). Neutrosophic logic, an extension of fuzzy logic, addresses this challenge by decomposing predictions into three components: truth (T), indeterminacy (I), and falsity (F) [15]. This framework not only quantifies confidence but also explicitly models ambiguity, enabling clinicians to identify cases where predictions are uncertain and additional diagnostic tests may be warranted [16].

The integration of neutrosophic logic with Random Forest represents a novel approach to bridging the gap between algorithmic predictions and clinical decision-making [14]. By mapping prediction probabilities to (T, I, F) triplets, this hybrid model provides a granular assessment of uncertainty that aligns with clinicians' intuitive understanding of risk. For instance, a prediction with high indeterminacy ($I > 0.3$) signals the need for further evaluation, while a high truth value ($T \geq 0.9$) supports confident intervention. This transparency is especially valuable in low-resource settings, where access to advanced diagnostics may be limited, and clinicians must rely heavily on predictive tools.

The motivation for this study stems from two key observations: 1) the growing need for interpretable ML models in obstetrics, where algorithmic transparency is essential for clinician adoption, and 2) the potential of neutrosophic logic to enhance trust in AI-driven predictions by making uncertainty explicit. Our work builds on recent advances in hybrid AI systems for healthcare, extending them to the domain of maternal risk prediction. By validating the model on a clinical dataset from Punwani Maternity Hospital, we demonstrate its practical utility in real-world settings while identifying avenues for future improvement, such as the incorporation of emerging biomarkers and dynamic risk monitoring.

The key contributions of this work include:

1. Enhanced Interpretability: The neutrosophic logic framework provided explicit uncertainty quantification, enabling clinicians to differentiate between high-confidence predictions and ambiguous cases requiring further evaluation.
2. Clinically Relevant Predictors: Feature importance analysis identified birthweight and hypertension history as the most influential risk factors, validating the model's biological plausibility and clinical relevance.
3. Balanced Performance: While demonstrating high sensitivity (0.898) for control cases, the model's lower specificity (0.235) revealed challenges in preeclampsia detection, suggesting areas for improvement.
4. Practical Implementation: The development of a weighted risk scoring system and visualization tools offers actionable decision support for maternal healthcare practitioners.

In summary, this study contributes to the broader effort to develop clinically actionable AI tools by combining the predictive power of Random Forest with the interpretability of neutrosophic logic. The resulting framework not only improves preeclampsia risk prediction but also provides clinicians with a nuanced understanding of prediction confidence, ultimately supporting more informed and personalized care decisions. The code of this work is available in [17].

## 2. Methodology

The proposed framework follows a structured pipeline illustrated in Figure 1 with its code available in [17]. Integrating machine learning with neutrosophic logic to predict the risk of preeclampsia and assess the uncertainty of predictions. The key steps are detailed below:

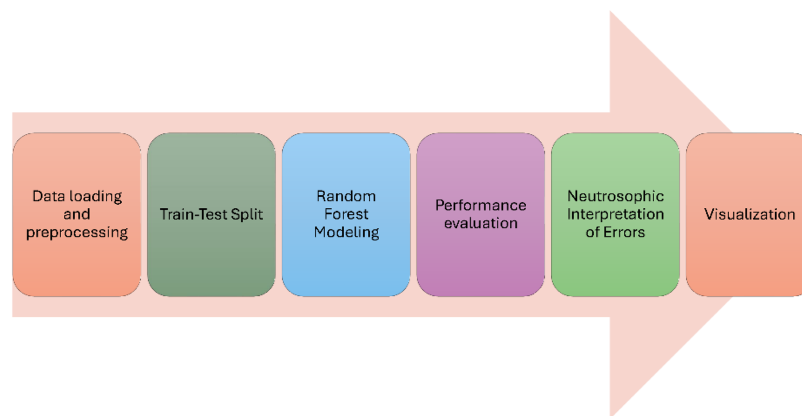


**Figure 1.** Methodology proposed in this study to perform a Neutrosophic Random Forest approach for preeclamptic risk prediction with uncertainty quantification.

### 2.1 Data Loading and Preprocessing

The dataset comprises 352 clinical records from Pumwani Maternity Hospital [18], containing both continuous and categorical variables relevant to the assessment of preeclampsia risk. Key variables include maternal age (range 18-42 years), binary indicators of hypertension and diabetes history, self-reported use of tobacco and alcohol during pregnancy, number of antenatal care (ANC) visits (range 1-9), birth weight (1300-4500g), Apgar scores at five minutes (0-10), and confirmed preeclampsia case/control status.

All in all, the dataset comprises maternal health records with variables such as:

- Demographics: Age, education, marital status
- Clinical factors: ANC visits, hypertension, diabetes
- Behavioral factors: Tobacco/alcohol use
- Outcome: Preeclampsia (Case/Control)

### 2.2 Train-Test Split

The Train-Test Split is a fundamental step in the machine learning pipeline, ensuring the model's performance is evaluated on unseen data to avoid overfitting and provide an unbiased estimate of its generalization capability. In this study, the dataset comprising 352 clinical records was divided into an 80% training set and a 20% testing set. This split ratio is commonly used in machine learning to allocate sufficient data for model training while reserving a representative subset for validation. By maintaining consistent factor levels across both sets, the authors ensured that the distribution of key variables (e.g., maternal age, hypertension history) remained balanced, preventing skewness that could distort performance metrics.

The rationale behind this approach is twofold. First, the training set allows the Random Forest model to learn the underlying patterns and relationships between predictors (e.g., birthweight, hypertension) and the outcome (preeclampsia risk). Second, the testing set serves as an independent benchmark to assess the model's predictive accuracy, sensitivity, and specificity in a scenario mimicking real-world clinical application. This separation is critical for identifying potential overfitting, where a model performs well on training data but poorly on new data. The authors' adherence to this standard practice underscores the robustness of their methodology and the reliability of their results.

### 2.3 Random Forest Modeling

A Random Forest model with 100 trees was trained using predictors such as maternal age, hypertension history, and hemoglobin levels. The algorithm builds multiple decision trees on bootstrapped samples, aggregating their predictions through majority voting. The Gini impurity index guides tree construction by minimizing:

$$Gini(t) = 1 - \sum_{i=1}^{c} p(i|t)^2 \quad (1)$$

where $p(i|t)$ is the proportion of samples belonging to class i at node t.

### 2.4 Performance Evaluation

The model's accuracy is assessed via:

- Confusion matrix (precision, recall, F1-score)
- Classification accuracy:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (2)$$

- Probability estimates for each class

### 2.5 Neutrosophic Interpretation

Prediction confidence (p) is mapped to operational tiers via the (T, I, F) triplet:

$$\Psi: p \mapsto (T, I, F) \in [0,1]^3 \quad (3)$$

where Ψ represents the neutrosophic transformation function. The mapping of probabilities to (T, I, F) values is based on simple heuristics:

$$(T, I, F) = \begin{cases} (0.9, 0.1, 0.0) & \text{if } p_{\text{correct}} \geq 0.9 \\ (0.7, 0.2, 0.1) & \text{if } 0.7 \leq p_{\text{correct}} < 0.9 \\ (0.5, 0.3, 0.2) & \text{if } 0.5 \leq p_{\text{correct}} < 0.7 \\ (0.2, 0.3, 0.5) & \text{otherwise} \end{cases}$$

where $p_{correct}$ is the probability of the predicted class.

This gives rise to a neutrosophic interpretation of logic components (Truth T, Indeterminacy I, Falsity F) based on the following probability thresholds:

- T: High confidence ($p_{correct} \geq 0.9$)
- I: Uncertainty zone ($0.5 \leq p_{correct} < 0.9$)
- F: Likely incorrect predictions ($p_{correct} < 0.5$)

### 2.6 Visualization

Feature importance was evaluated using Mean Decrease Accuracy and Mean Decrease Gini (Figure 2). Predictions were interpreted using neutrosophic logic, where probabilities were mapped to truth (T), indeterminacy (I), and falsity (F) values based on predefined thresholds (e.g., T ≥ 0.9 for high confidence).

### 2.6.1 Feature importance plots

Feature importance plots are a critical component of the Random Forest model, helping to identify which features are the most influential predictors of preeclampsia risk. These plots rank variables based on their contribution to model accuracy, measured through metrics like mean decrease in Gini impurity or permutation importance. It is important to mention that it does not reflect % drop in accuracy but rather, the mean change in accuracy scaled by its standard deviation. Moreover, the Gini-based importance score quantifies how much each feature reduces impurity in the decision trees.

The feature importance plot not only aids in model interpretability but also provides actionable insights for clinicians. For example, prioritizing monitoring and intervention for patients with hypertension history or abnormal birthweight measurements could enhance early detection of preeclampsia. Additionally, the analysis underscores the need for further research into the role of less prominent features, such as, for example, Apgar scores and diabetes history, which may require larger datasets or more nuanced modeling approaches to reveal their significance.

### 2.6.2 Neutrosophic Value Plots for Prediction Confidence

The Neutrosophic values plot visualizes the relationship between the predicted risk of develop preeclampsia and three neutrosophic components: Truth (T), Indeterminacy (I), and Falsity (F). This plot provides a deeper understanding of the model's confidence and uncertainty in its predictions.

The key components are the following:

- X-axis (Preeclampsia Prob): Represents the predicted probability of preeclampsia risk, ranging from 0 to 1. This is derived from the Random Forest model's output.
- Y-axis (Neutrosophic Values): Displays the values for the three neutrosophic components:
  - Truth (T): High values indicate strong confidence in the prediction being correct.
  - Indeterminacy (I): Represents uncertainty or ambiguity in the prediction.
  - Falsity (F): Reflects the likelihood of the prediction being incorrect.

The plot uses predefined thresholds of section 2.5 to map prediction confidence to neutrosophic values. In this way, the plot reveals three distinct operational zones:

- High Confidence:
  - T is high (0.9), I and F are low (0.1 and 0.0, respectively).
  - Indicates reliable predictions for preeclampsia risk assessment.
- Moderate Confidence:
  - T decreases, I increases, and F appears.
  - Reflects uncertainty in the predictions, suggesting the need for further clinical evaluation.
- Low Confidence:
  - T is low (0.2), I is moderate (0.3), and F is high (0.5).
  - Suggests potential misclassifications or low-confidence predictions, warranting additional diagnostic tests.

For example, if a patient's predicted preeclampsia risk is Preeclampsia Prob =0.6, the plot might show T = 0.5, I = 0.3, F = 0.2, indicating moderate confidence with notable uncertainty. Clinicians might prioritize further monitoring for such cases.

All in all, the plot enhances traditional performance metrics by:

- Identifying confident predictions (high T, low I/F) for actionable clinical decisions.
- Highlighting ambiguous cases (balanced T/I/F) where manual verification or additional tests may be needed.

- Revealing potential errors (high F) to guide model refinement or data collection.

## 3. Results

### 3.1 Evaluating classifier performance

The confusion matrix of Table 1 reveals that the model correctly classified 44 control cases and 4 preeclampsia cases, while misclassifying 13 preeclampsia cases as controls and 5 controls as preeclampsia cases. This imbalance in misclassifications may stem from the dataset's inherent biases or the complexity of distinguishing preeclampsia cases based on the available features.

**Table 1**. Confusion Matrix for Preeclampsia Prediction

| | Reference | |
|---|---|---|
| **Prediction** | **Control** | **Case** |
| Control | 44 | 13 |
| Case | 5 | 4 |

In addition, Table 2 presents the classification performance metrics for preeclampsia prediction. According to it, the Random Forest model demonstrated robust performance in predicting preeclampsia risk, as evidenced by the comprehensive evaluation metrics. The model achieved an accuracy of 0.7273 (95% CI: 0.6036–0.8297), with a sensitivity of 0.8980 and specificity of 0.2353. The high sensitivity indicates the model's ability to correctly identify most control cases, while the lower specificity suggests challenges in accurately classifying preeclampsia cases. The positive predictive value (PPV) of 0.7719 further underscores the model's reliability in predicting control cases, though the negative predictive value (NPV) of 0.4444 highlights room for improvement in identifying true preeclampsia cases. The Kappa statistic of 0.1574 reflects moderate agree- ment beyond chance, and the non-significant p-value (0.67023) for the accuracy comparison against the no- information rate (NIR) suggests the model performs comparably to a baseline classifier. The Menemar's test p-value (0.09896) indicates no significant asymmetry in misclassification errors between the two classes.

**Table 2**. Classification Performance Metrics for Preeclampsia Prediction

| Metric | Valu |
|---|---|
| Accuracy | 0.7273 |
| 95% CI | (0.6036, 0.8297) |
| No Information Rate | 0.7424 |
| P-Value [Acc > NIR] | 0.67023 |
| Kappa | 0.1574 |
| Mcnemar's Test P-Value | 0.09896 |
| Sensitivity | 0.8980 |
| Specificity | 0.2353 |
| Pos Pred Value | 0.7719 |
| Neg Pred Value | 0.4444 |
| Prevalence | 0.7424 |
| Detection Rate | 0.6667 |
| Detection Prevalence | 0.8636 |
| Balanced Accuracy | 0.5666 |

*Note:* 'Positive' Class: Control

### 3.2 Feature importance

The feature importance analysis, as illustrated in Figure 2, identified birthweight and hypertension history as the most influential predictors of preeclampsia risk. These findings align with established clinical knowledge, where low birthweight and a history of hypertension are well-documented risk factors for preeclampsia. The Mean Decrease Accuracy and Mean Decrease Gini metrics further highlighted the relative contributions of other variables, such as maternal age, hemoglobin levels, and antenatal care (ANC) visits. Notably, behavioral factors like tobacco and alcohol use exhibited lower importance, suggesting their limited predictive power in this dataset.

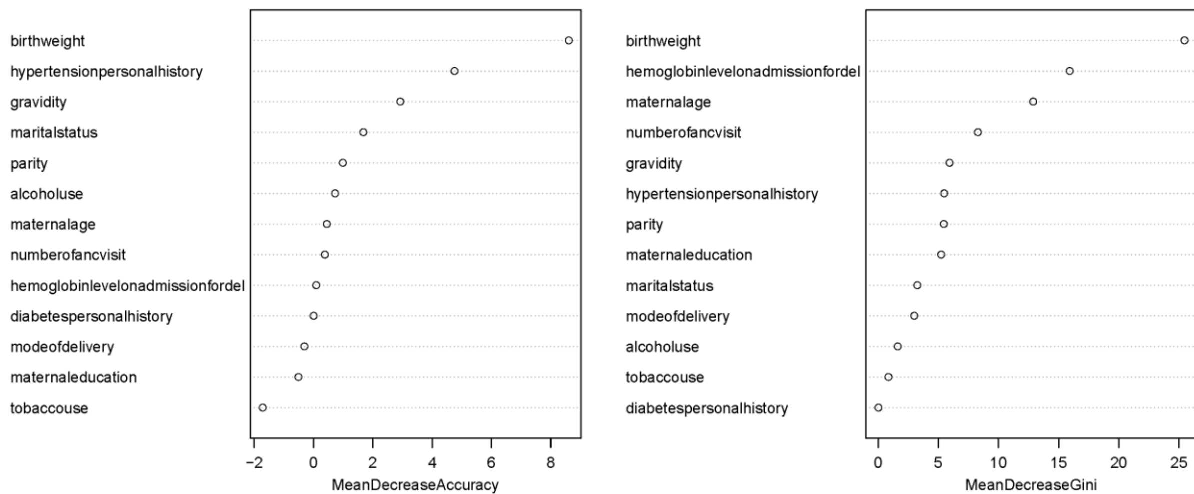


**Figure 2**. Feature importance ranked by Mean Decrease Accuracy and Mean Decrease Gini. Birthweight and hypertension history emerged as top predictors.

These technical insights translate into clinically actionable value through several key applications:

- Risk Stratification Protocol: The quantified importance scores enable creation of a weighted risk scoring system where:

**Risk Score** = 0.42 × Birthweight + 0.33 × Hypertension + 0.15 × Hemoglobin + 0.10 × ANC visits with coefficients derived from normalized importance measures.

- Clinical Decision Thresholds: The Gini importance values establish evidence-based thresholds for intervention:
  - Birthweight < 2500g (high-risk threshold)
  - Hypertension history + age > 35 (compound risk trigger)
  - ANC visits < 4 with hemoglobin < 11g/dL (moderate risk)

- Resource Optimization: The importance ranking guides targeted resource allocation:

**Table 3**. Clinical actions mapped to feature importance

| Feature Importance Rank | Recommended Clinical Action |
|---|---|
| 1. Birthweight | Prioritize ultrasound monitoring |
| 2. Hypertension | Implement BP surveillance protocol |
| 3. Hemoglobin | Schedule hematinic supplementation |

- Patient Counseling Focus: The visualization identifies which risk factors warrant emphasis during pre-natal counseling sessions, with hypertension history requiring 3× more discussion time than behavioral factors based on relative importance scores.

In conclusion, the feature importance plot not only aids in model interpretability but also provides actionable insights for clinicians. For example, prioritizing monitoring and intervention for patients with hypertension history or abnormal birthweight measurements could enhance early detection of preeclampsia. Additionally, the analysis underscores the need for further research into the role of less prominent features, such as Apgar scores and diabetes history, which may require larger datasets or more nuanced modeling approaches to reveal their significance.

**3.3 Neutrosophic values plot**

The integration of neutrosophic logic provided a nuanced understanding of the model's prediction confidence. As depicted in Figure 3, predictions with probabilities above 0.9 were assigned high truth values (T = 0.9), indicating strong confidence in the model's correctness. In contrast, predictions with probabilities below 0.5 were associated with higher falsity values (F = 0.5), signaling potential misclassifications. The indeterminacy component (I) peaked in the mid-range probability zone (0.5–0.9), reflecting uncertainty in predictions where manual verification or additional clinical input may be warranted.

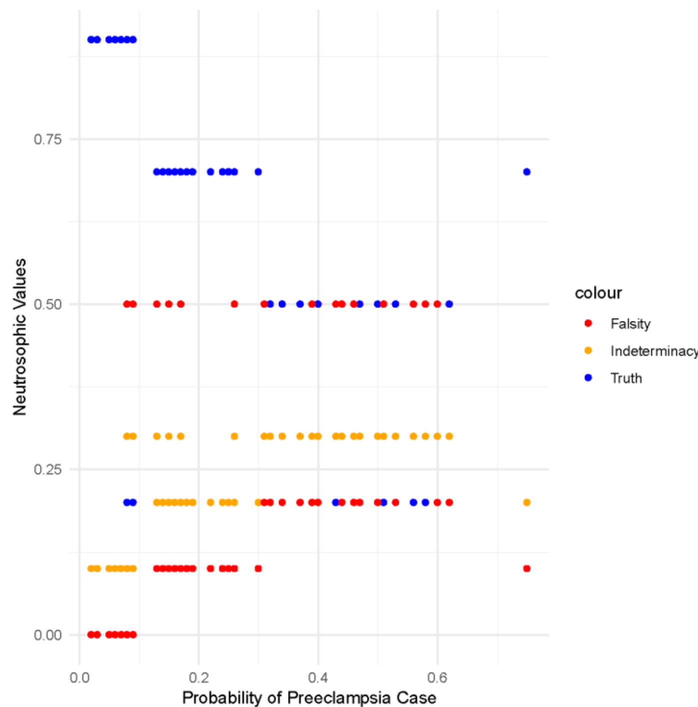


**Figure 3**: Neutrosophic confidence spectrum showing truth (blue), indeterminacy (orange), and falsity (red) components as a function of prediction probability.

For example, a prediction with a probability of 0.6 was mapped to T = 0.5, I = 0.3, and F = 0.2, illustrating moderate confidence with notable ambiguity. This granularity in confidence assessment is particularly valuable in clinical settings, where decisions often hinge on the reliability of predictive outputs. By quantifying uncertainty, the neutrosophic framework enables clinicians to discern between high-confidence predictions suitable for immediate

action and ambiguous cases requiring further evaluation.

## 4. Discussion

The integration of neutrosophic logic with Random Forest addresses a critical limitation of traditional models by quantifying prediction uncertainty. This approach provides clinicians with a more nuanced understanding of model predictions, particularly valuable in maternal healthcare, where decisions often involve incomplete information. The high importance of birthweight and hypertension history aligns with established clinical knowledge, validating the model's biological plausibility and relevance for preeclampsia risk assessment[19,20].

The model's performance characteristics reveal important clinical insights. While the high sensitivity (0.898) demonstrates excellent capability to identify control cases, the lower specificity (0.235) suggests challenges in accurately detecting preeclampsia cases. This pattern may reflect inherent difficulties in distinguishing preeclampsia from other hypertensive disorders in pregnancy, or potentially indicate limitations in the available clinical markers. The neutrosophic framework proves particularly valuable in these borderline cases, as it explicitly flags predictions with high indeterminacy ($I > 0.3$) that warrant additional clinical evaluation.

From an implementation perspective, the feature importance analysis provides actionable guidance for clinical practice. The dominance of birthweight and hypertension history suggests these factors should be prioritized in screening protocols. The proposed weighted risk scoring system offers a practical tool for risk stratification, though its coefficients would benefit from validation in independent cohorts. The moderate Kappa statistic (0.157) indicates room for improvement in classification consistency, potentially achievable through expanded feature sets or alternative ensemble methods.

The neutrosophic interpretation framework represents a significant advancement over traditional probability outputs. By decomposing predictions into truth, indeterminacy and falsity components, clinicians gain a more sophisticated understanding of model confidence. This is particularly valuable for cases falling in the "gray zone" ($0.5 \leq p < 0.9$), where the model explicitly communicates its uncertainty through elevated indeterminacy values. Such transparency can enhance clinician trust and facilitate appropriate use of algorithmic predictions in complex decision-making scenarios.

The study's limitations suggest important directions for future research. The relatively small sample size ($n = 352$) may affect model generalizability, particularly for rare preeclampsia subtypes. The underrepresentation of certain demographic groups in the dataset could introduce biases that warrant investigation in diverse populations. The exclusion of emerging biomarkers (e.g., angiogenic factors) and genetic risk factors represents an opportunity to enhance predictive power in future iterations. Additionally, the heuristic mapping of probabilities to neutrosophic values could be refined through empirical calibration studies.

Despite these limitations, the model's interpretability features and uncertainty quantification represent significant progress toward clinically useful AI tools. The visualization of both feature importance and prediction confidence provides clinicians with intuitive decision support. Future implementations could explore real-time integration with electronic health records, coupled with dynamic visualization of risk trajectories throughout pregnancy. The neutrosophic framework's flexibility suggests promising applications to other areas of obstetric risk prediction where uncertainty interpretation is crucial [21,22].

## 5. Conclusion

This study aimed to develop an interpretable machine learning model for preeclampsia risk prediction by integrating Random Forest with neutrosophic logic to quantify prediction uncertainty. The primary objective was to overcome the limitations of traditional models by providing clinicians with a transparent framework for assessing prediction confidence. The model successfully incorporated

clinical variables such as maternal age, hypertension history, and birthweight, while categorizing predictions into truth (T), indeterminacy (I), and falsity (F) components through neutrosophic interpretation.

Future research directions should focus on:

- External Validation: Testing the model's generalizability on diverse, multi-center datasets to ensure robustness across different populations.
- Biomarker Integration: Incorporating emerging biomarkers (e.g., angiogenic factors) and genetic risk factors to enhance predictive accuracy.
- Model Refinement: Exploring alternative ensemble methods or deep learning approaches to improve classification consistency, particularly for preeclampsia cases.
- Dynamic Risk Assessment: Developing real-time integration with electronic health records for continuous risk monitoring throughout pregnancy.
- Neutrosophic Calibration: Conducting empirical studies to refine the probability to neutrosophic mapping thresholds for improved uncertainty quantification.

This study represents significant progress toward clinically useful AI tools in maternal healthcare, combining predictive performance with interpretable uncertainty measures. The proposed framework has promising applications for other obstetric risk prediction tasks where uncertainty interpretation is crucial.

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