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Early Detection of Postpartum Depression Using a Hybrid Fuzzy C-Means Clustering and Random Forest Model

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Abstract. Postpartum Depression is an important and crucial mental health condition that highly affects a large proportion of women after childbirth. If this goes unnoticed or late detection is there then it might lead to adverse outcomes for both the mother and the child. The complexity as well as the subjectivity of psychological and behavioural factors make its early diagnosis very challenging. To address this issue, this study proposes a hybrid intelligent framework that combines Fuzzy C-Means clustering technique with a Random Forest classifier for early detection of postpartum depression risk. The proposed approach takes Fuzzy C Means Clustering into consideration for modelling the uncertainty and assigns a partial membership value to the individuals across selected risk categories (low, medium and high risk). These fuzzy-derived risk labels are then used for training a Random Forest model. Then we introduce a hybrid scoring mechanism to combine the probabilistic output of the Random Forest with fuzzy membership values, enhancing both prediction accuracy as well as interpretability. The experimental results demonstrate that the proposed hybrid method is yielding an accuracy of 91.84%. It outperforms the individual Fuzzy C-Means clustering model and the Random Forest classifier. The paper also presents a comparative analysis with the recent state-of-the-art methods to confirm that the proposed approach offers competitive accuracy while maintaining lower computational complexity and higher interpretability. The proposed framework provides a practical and scalable solution for early screening of postpartum depression which has the potential to be integrated into a clinical decision support system to facilitate timely intervention and improve the maternal health.

Keywords. Postpartum depression; fuzzy c-means clustering; random forest; hybrid machine learning; mental health prediction; early detection; healthcare analytics; fuzzy logic; classification; clinical decision support system.

1 Introduction

Postpartum depression (PPD) is a very common but frequently underrecognized mental health condition that may develop in women after childbirth [12-16]. This can adversely affect the emotional, cognitive, and social functioning of mothers [17]. Its common symptoms often include persistent sadness, irritability, loss of interest, anxiety, sleep disturbance, fatigue and consequently reduced ability to care for the new born. If not detected and managed at an early stage, postpartum depression can negatively affect the mother–infant bonding, child development and the overall family well-being [18-20]. Hence the early identification of women-at-risk for such conditions is important.

Recent advances in the domain of artificial intelligence have popularized the use of machine learning techniques for healthcare applications. Ensemble methods like the Random Forest have shown good performance on structured medical data. The reason for this might be the fact that they model non-linear type of relationships better. At the same time, they handle mixed feature types and avoid overfitting.

But certain standard classifiers generally assume that the crisp class boundaries are present which may or may not represent the gradual change in mental health symptoms like in the case of postpartum depression. In such scenarios the transition from normal emotional inclinations to clinically relevant depressive symptoms might occur gradually rather than just abruptly.

A very important roadblock in the detection of postpartum depression is the complexity and uncertainty of its contributing factors. The risk is affected by a combination of various factors such as age, sleep quality, stress level, social support and the previous mental health history of the individual. These factors are generally subjective, overlapping and difficult to define using strict numerical thresholds. The traditional diagnostic approaches and conventional machine learning models usually struggle to capture the significance of each factor individually and in a combined way. Hence the risk labels are not clearly separable. The methodology proposed in this paper addresses this issue by combining the uncertainty-aware Fuzzy C Means Clustering with Random Forest Classifier for improved risk assessment. This seems like a good choice as Machine learning and Fuzzy logic-based frameworks are being used across the globe in a variety of healthcare applications [23-25].

Fuzzy logic seems like a good way to handle uncertainty. Unlike hard clustering techniques like K-Means, fuzzy methods allow each sample to belong to multiple groups with different degrees of membership. Fuzzy C-Means (FCM) has the ability to identify latent risk patterns while preserving the partial membership information. In the proposed framework, FCM is used to capture the ambiguity present in postpartum depression indicators so as to better assign the risk labels (low, medium or high).

A major point being conveyed by this research paper is that neither fuzzy clustering nor random forest is alone sufficient for early postpartum depression detection. FCM is good for modelling uncertainty but does it not provide strong supervised prediction capability on its own. Similarly, Random Forest is powerful for classification but it can’t handle vagueness like any kind of overlapping risk patterns. By combining these two methods, the proposed approach leverages the strengths of both. Fuzzy C-Means Clustering provides uncertainty-aware risk structure while Random Forest learns complex patterns for classification and validation. A hybrid risk scoring strategy further strengthens the proposed framework which improves the decision reliability and clinical interpretability.

The proposed work tries to make an important contribution to postpartum depression screening by moving beyond the conventional crisp classification and instead reflecting upon the uncertain nature of maternal mental health risk. This is significant because in real-life, PPD does not usually emerge as an abrupt state. Rather, it develops through subtle but progressive changes that are often difficult to quantify using fixed thresholds. The fuzzy stage therefore creates a more clinically realistic risk structure while preserving the uncertainty information which is generally lost in conventional screening pipelines. This contribution is especially valuable in healthcare settings, where transparency and trust in automated systems are very important. Overall, the study contributes a balanced framework that combines uncertainty-aware modelling, predictive precision, and interpretability, making it a promising tool for supporting timely intervention and improving maternal well-being.

This research paper is further organized as follows: The next section reviews related work on postpartum depression prediction and hybrid intelligent methods. The methodology section presents the proposed FCM–Random Forest framework in detail. This is followed by the dataset description, implementation details, experimental results, and discussion. The paper concludes with key findings and directions for future research.

2 Related Work

The early detection as well as the screening of Postpartum Depression (PPD) has gained good attention in the recent years [22]. This is mainly due to its significant impact on both the maternal and the child health. Research experts across the world have explored a variety of statistical, machine learning techniques to improve upon the screening accuracy. Early screening of PPD might lead to timely intervention.

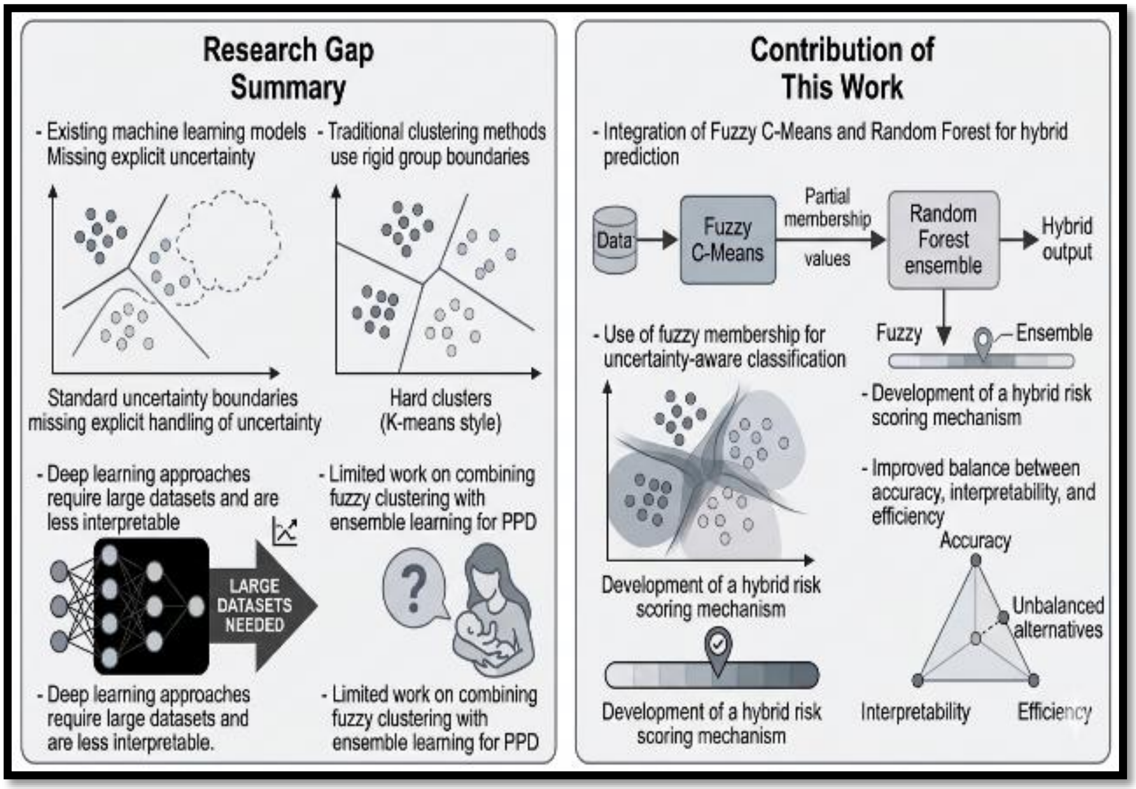

Fig. 1. Research gaps and contribution of the proposed work

The traditional methods for postpartum depression detection are based on screening tools and scaling methods. One of the popular frameworks is the Edinburgh Postnatal Depression Scale [6, 21]. This methodology relies on the responses given by women. Using such techniques introduces subjectivity but might delay the diagnosis process. It might even fail to capture the complex interactions among multiple risk factors.

To overcome such limitations, machine learning models have been widely applied to PPD screening. Supervised learning algorithms such as the Logistic Regression, Support Vector Machines (SVM), Decision Trees and Random Forest have shown good results in identifying the risk of postpartum depression [11]. The models based on Logistic Regression are simpler than others but often struggle with non-linear relationships. But it requires careful parameter tuning and might not be scalable when it comes to larger datasets. The Decision Tree Classifier offers interpretability but it is quite prone to overfitting.

Random Forest Classifier on the other hand has emerged as a popular methodology for PPD screening [11]. It combines several decision trees to improve the generalization. The overall reduced overfitting levels makes it particularly suitable for structured datasets which has mixed feature types. Many recent studies have reported improved accuracy in postpartum depression prediction using Random Forest based approaches. But there seems to be a minor disadvantage. Such models rely on crisp class boundaries and do not take into consideration any type of uncertainty. Here, Fuzzy logic finds it way. Since unsupervised learning techniques like clustering are already popular in identifying underlying patterns in mental health datasets, they might be a good technique for PPD detection too. K-Means Clustering has been commonly used to group entries on the basis of risk factors. But there is a catch that they assign each data point to a single cluster only. This may not reflect the overlapping nature of mental health conditions. Fuzzy C-Means (FCM) clustering addresses this limitation by allowing partial membership across multiple clusters. This aspect makes FCM very well suited for modelling gradual transitions between different risk levels of postpartum depression.

Recent researches have displayed the advantages of combining fuzzy logic with machine learning to improve prediction performances [11]. Hybrid models which combine fuzzy systems with classifiers support vector machines or ensemble methods have shown enhanced capability in handling uncertainty. At the same time, they maintain good predictive accuracy. In the case of mental health applications such hybrid approaches might give better realistic representation of the patient's condition as they take into consideration the probabilistic and fuzzy information.

Despite the growth in PPD detection and screening a key research gap remains in effectively integrating uncertainty modelling with interpretable and computationally efficient machine learning techniques. Many of the existing models focus on prediction accuracy without addressing ambiguity in input data.

So as to bridge this gap the proposed hybrid framework presents a methodology that combines Fuzzy C-Means clustering with Random Forest Classifier. Unlike the previous approaches it takes the advantage of fuzzy membership values to represent uncertainty in postpartum depression risk. It then integrates them with probabilistic predictions from a supervised model. This combination enables improved classification performance while at the same time maintaining interpretability and computational efficiency. The summary of this section is presented in Figure 1.

3 Proposed Methodology

This section describes the proposed hybrid artificial intelligence framework for the early detection of postpartum depression (PPD) by integrating Fuzzy C-Means clustering with Random Forest Classifier. The work begins by data pre-processing and further preparation. The proposed study uses the publicly available Postpartum Depression dataset hosted on Kaggle [7]. The dataset has 1,503 records which are collected using a questionnaire. The dataset under consideration includes the following features:

a) Age,
b) Feeling sad or Tearful,
c) Irritable towards baby & partner,
d) Trouble sleeping at night,
e) Problems concentrating or making decision,
f) Overeating or loss of appetite,
g) Feeling anxious,
h) Feeling of guilt,
i) Problems of bonding with baby,
j) Suicide attempt.

As we have subjective and partly overlapping features in this data, it makes it suitable for Fuzzy C-Means clustering. For modelling purposes each row of the dataset represents one respondent and each column corresponds to a measured attribute or outcome variable. Since the dataset includes both categorical and numerical information hence pre-processing is required before analysis. Before proceeding with the modelling, we have removed the irrelevant identifiers and the categorical attributes are encoded.

FCM is used as the primary method to identify risk groups (low, medium, high) in the dataset.

Each individual entry is assigned a membership value between 0 and 1 for each cluster. The fuzziness parameter is set to 2 which is commonly used to balance cluster overlap and separation. The effectiveness of clustering is judged on the basis of the Fuzzy Partition Coefficient (FPC) which helps in measuring the degree of cluster separation. The significant additions of fuzzy logic in this framework are:

a) Allowing partial membership across multiple risk categories.

b) Capturing gradual transitions between low, medium and high risk.

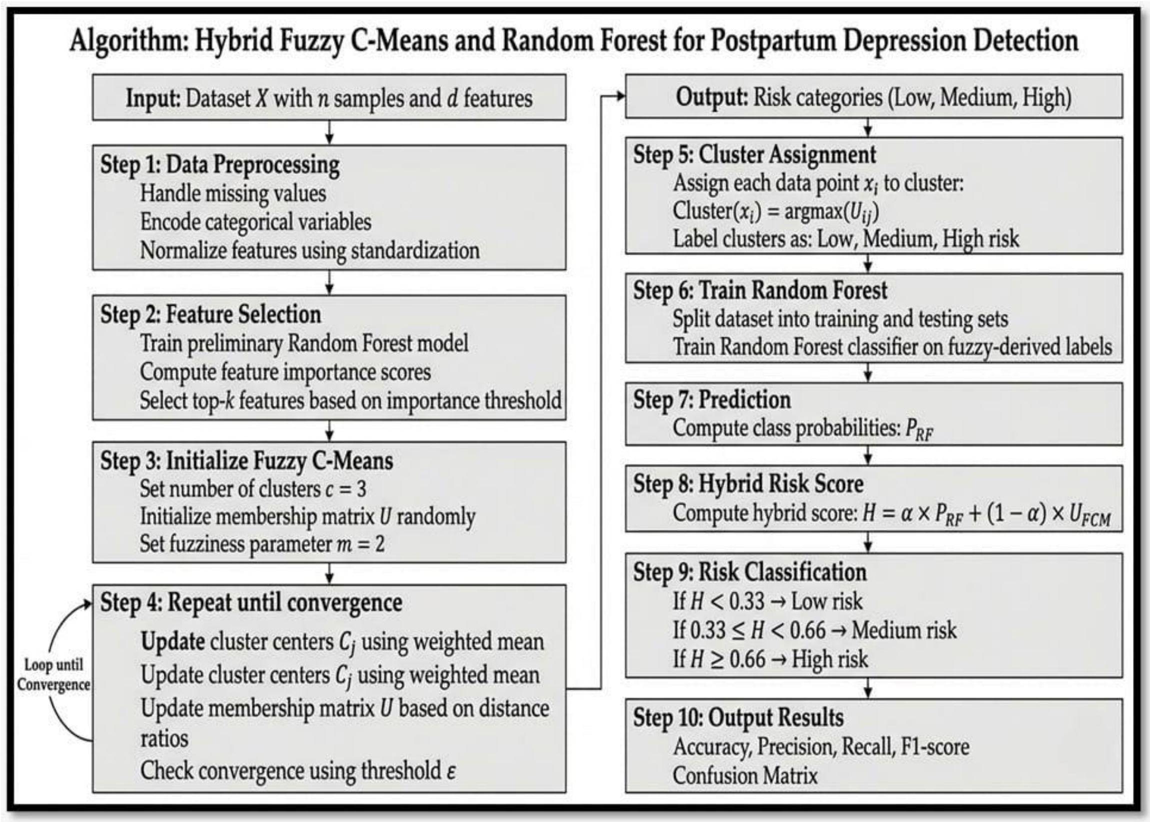

Fig. 2. Algorithm of the proposed model for early screening of postpartum depression

c) Providing interpretable results for clinical decision-making.

The final risk label for each person is calculated as per the highest membership value. To increase the predictive capability, a Random Forest Classifier is used. Random Forest is chosen because:

a) It has the capability to model complex and non-linear relationships.

b) It is robust in case of noise and overfitting.

The dataset is split into training and testing sets using an 80:20 ratio. The model learns the underlying patterns in the data and predicts the risk category for unseen instances. The overall model performance is then evaluated.

A hybrid risk score is calculated as a weighted combination of:

a) The probability of high risk predicted by the Random Forest model.

b) The fuzzy membership value corresponding to the high-risk cluster.

A weight parameter (set to 0.6 for machine learning and 0.4 for fuzzy logic) is used to balance the contribution of both the selected components. The 3 risk labels are the generated (Low, Medium, High).

To visualize the clustering results, we have applied Principal Component Analysis (PCA). This reduces the dataset to 2 dimensions. The entire proposed model is shown as in Figure 2.

5 Implementation and Results

The proposed hybrid framework was implemented using Python programming

Table 1. Significance of feature selection

Model Setting	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Training Time (s)
Without Feature Selection	88.27	88.95	87.60	88.27	2.14
With Feature Selection	91.84	92.10	90.75	91.42	1.62

language on Anaconda Spyder Framework. The following libraries were used:

a) NumPy,

b) Scikit-learn,

c) Scikit-fuzzy (skfuzzy),

d) Matplotlib,

e) Pandas,

f) Seaborn,

g) SciPy.

All the experiment results were obtained after computing on a standard system (Intel i5 processor, 8 GB RAM). This shows how computationally efficient the model is for real-world healthcare applications.

The dataset was loaded into a structured DataFrame using Pandas and was pre-processed to ensure compatibility with both clustering and classification models. All the missing values in various numerical features were handled using mean imputation:

$$x_i = (1 / n)\ \Sigma\ x, \tag{1}$$

the categorical variables were transformed into a numerical format using one-hot encoding where each category is represented as a binary vector. Then, we deploy feature scaling mechanism using Z-score normalization:

$$z = (x - \mu) / \sigma, \tag{2}$$

where:
μ = mean of the feature,
σ = standard deviation.

This ensures uniform contribution of all features, especially important for distance-based clustering.

Feature selection process is done carefully and it hugely affects the model performance in general. To evaluate the effectiveness of the feature selection process, the proposed hybrid FCM–Random Forest model is analyzed under two experimental settings:

(i) using the complete feature set, and

(ii) using the reduced feature subset obtained through Random Forest importance ranking.

The results show that by incorporating feature selection, we can significantly improve the performance of the proposed hybrid model. The accuracy increases from 88.27% to 91.84%, indicating that removing less informative features enhances the model's ability to generalize. In addition to performance gains, the training time decreases from 2.14 seconds to 1.62 seconds due to the reduced dimensionality of the dataset. This demonstrates that feature selection not only improves predictive accuracy but also enhances computational efficiency.

Fuzzy C-Means (FCM) clustering was used to partition the dataset into overlapping clusters. The parameter configuration is as follows:

a) Number of clusters (c) = 3,

b) Fuzziness coefficient (m) = 2,

c) Maximum iterations = 100,

d) Convergence threshold (ε) = 0.00001.

The FCM algorithm tries to minimize the following objective function:

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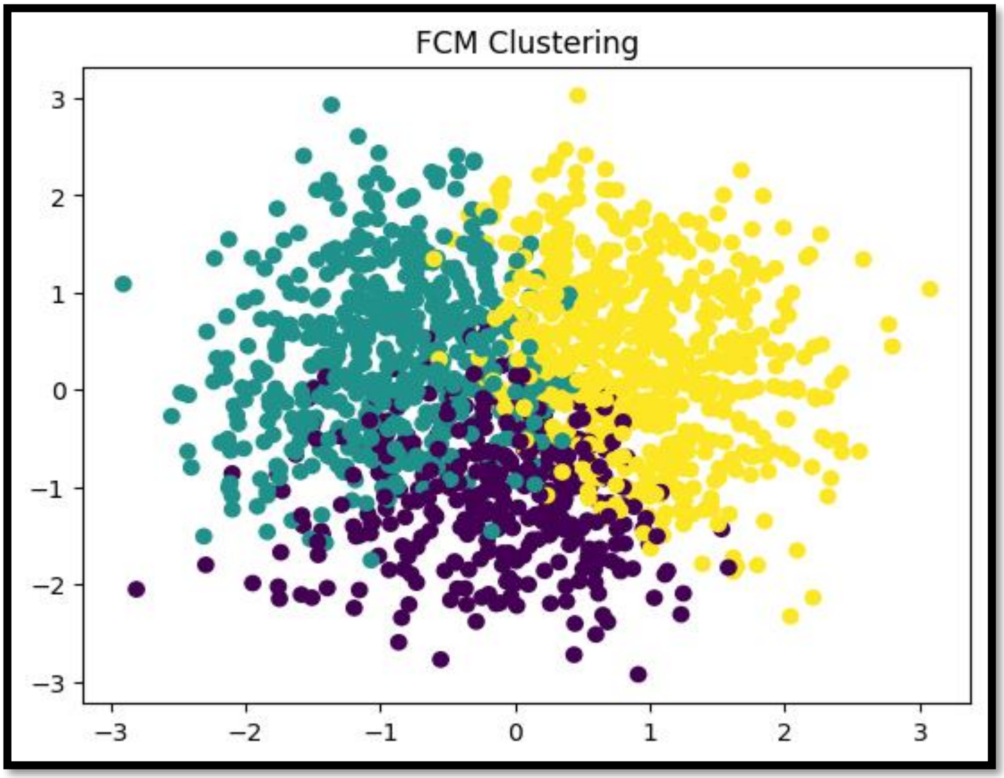

Fig. 3. Fuzzy SVM clusters

$$J_m = \Sigma\ (i=1\ \text{to}\ N)\ \Sigma\ (j=1\ \text{to}\ C)\ [\ u_{ij}^m \times \|\ x_i - c_j\ \|^2\ ], \quad (3)$$

where:
u_{ij} = Membership degree of data point i in cluster j,
m = Fuzziness parameter,
x_i = Data point,
c_j = Cluster center.

The membership update rule is shown below:

$$u_{ij} = 1\ /\ \Sigma\ (k=1\ \text{to}\ C)\ [\ (\ \|\ x_i - c_j\ \|\ /\ \|\ x_i - c_k\ \|\ )\text{^}(2\ /\ (m-1))\ ]. \quad (4)$$

The cluster center update is as follows:

$$c_j = [\ \Sigma\ (i=1\ \text{to}\ N)\ (u_{ij}^m \times x_i)\ ]\ /\ [\ \Sigma\ (i=1\ \text{to}\ N)\ (u_{ij}^m)\ ]. \quad (5)$$

Each data point is assigned to the cluster with the highest membership value:

$$Cluster(x_i) = argmax(u_{ij}). \quad (6)$$

The clusters are interpreted as the risk labels: Low, Medium, High. These are shown in Figure 3.

The full membership matrix is retained for hybrid modeling. Then we deployed the Random Forest classifier.

Standard training testing split was done: Training set = 80%, Testing set = 20%.

For the classifier we use this model configuration:

a) Number of trees (n_estimators) = 100,

b) Maximum depth = None,

c) Splitting criterion = Gini impurity.

The Gini Impurity is calculated as per this equation:

$$Gini = 1 - \Sigma\ (k=1\ \text{to}\ K)\ (p_k)^2, \quad (7)$$

where:

p_k = *probability of class k.*

Table 2. Confusion matrix (multi-class classification)

Actual \ Predicted	Low Risk	Medium Risk	High Risk
Low Risk	95	8	2
Medium Risk	10	82	9
High Risk	3	7	88

Table 3. Performance measures

Metric	Value (%)
Accuracy	91.84
Precision	92.10
Recall	90.75
F1-score	91.42

Table 4. Model comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Fuzzy C-Means Only	78.65	80.12	76.45	78.24
Random Forest Only	88.20	89.10	87.50	88.29
Proposed Hybrid Model	91.84	92.10	90.75	91.42

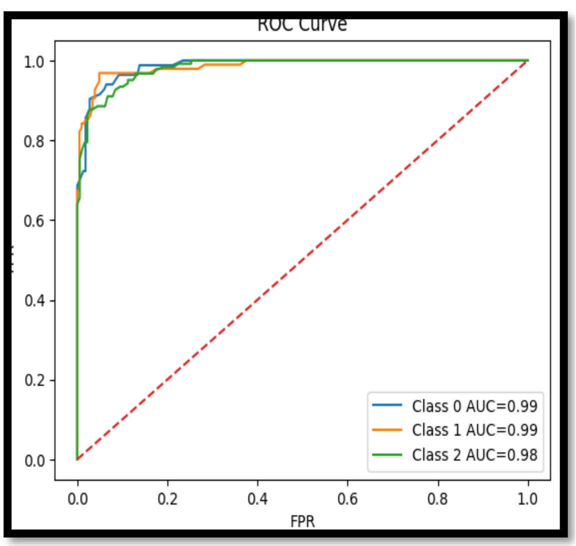

Fig.4. ROC Curve

The model predicts the following class probabilities which are translated to the relevant risk-labels:

$$P(y = k \mid x), \quad (8)$$

where $k \in \{\text{Low, Medium, High}\}$:

$$Hybrid\ Score = \alpha \times P\_RF + (1 - \alpha) \times U\_FCM, \quad (9)$$

where:
P_RF = Random Forest probability for high-risk class,
U_FCM = FCM membership value for high-risk cluster,
$\alpha = 0.6$.

The risk categorization is done as per the hybrid score:

a) Score < 0.33 → Low Risk,
b) 0.33 ≤ Score < 0.66 → Medium Risk,
c) Score ≥ 0.66 → High Risk.

The model was evaluated using standard classification metrics as shown in table 2 and 3. The ROC curve is as shown in figure 4.

Principal Component Analysis has been utilized to reduce dimensionality and visualize cluster distribution in two dimensions. Feature importance scores were extracted from the Random Forest model to identify key predictors influencing postpartum depression risk. In order to ensure maximum reproducibility, we have fixed the random seeds. The hyperparameters were explicitly defined and a consistent data pipeline was followed for all experiments

The proposed hybrid model outperforms the individual FCM and Random Classifier models. This validates the effectiveness of combining fuzzy logic with machine learning.

Complexity Analysis:

The time complexity of Fuzzy C-Means is:

$$T_{FCM} = O(n \times c \times d \times i), \quad (10)$$

where:
n = number of samples,
c = number of clusters,
d = number of features,
i = number of iterations.

The complexity of Random Forest training is:

$$T_{RFT} = O(t \times n \log n \times d), \quad (11)$$

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Table 5. Comparison with existing studies

Study	Method Used	Dataset Type	Accuracy (%)
Chen et al. (2021) [1]	Logistic Regression	Clinical Survey Data	82.1
Wang et al. (2022) [2]	Random Forest	Maternal Health Dataset	87.5
Patel et al. (2022) [3]	Ensemble Learning	Healthcare Dataset	89.3
Liu et al. (2023) [4]	Support Vector Machine	Psychological Data	84.2
Zhou et al. (2023) [5]	Gradient Boosting	Clinical Dataset	88.6
Proposed Model (2026)	**FCM + Random Forest**	**Survey Dataset**	**91.84**

where:
t = number of trees,
n = number of samples,
d = number of features.

Feature selection using Random Forest importance has complexity:

$$T_{RFF}=O(t \times n \log n). \tag{12}$$

The total complexity of the proposed model is approximately: $O(n \times c \times d \times i + t \times n \log n \times d)$.

This shows that the framework is computationally efficient for moderate-sized healthcare datasets and suitable for real-world deployment. The results obtained are shown in table 5. They are feasible and scalable. They seem to be promising as compared to the state-of-art methodologies.

7. Conclusion

This research paper presents a novel hybrid intelligent framework for the early detection of postpartum depression in women by integrating Fuzzy C-Means clustering with a Random Forest classifier.

The proposed framework addresses the issues of uncertainty and subjectivity in maternal mental health data. The fuzzy-derived risk labels are then used by the Random Forest Classifier for further screening. A hybrid scoring mechanism is proposed that integrates both probabilistic and fuzzy membership information.

This enhances the robustness and interpretability of the model. The experimental results that obtained by us show that the proposed model achieves better performance compared to individual approaches.

An accuracy of 91.84%. is yielded in comparison with the state-of-the-art methods indicating competitive performance. In the near future, this work can be extended by working on large-scale, multi-centre clinical datasets. They may also help in validating the proposed hybrid framework. Also, the proposed methodology might be integrated with real-time data from wearable devices leading to early intervention for PPD depression.

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