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ECG-Based Heart Rate Variability and KNN Classification for Early Detection of Baby Blues Syndrome in Postpartum Mothers

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Abstract: Early detection of baby blues syndrome plays an important role in preventing postpartum emotional disturbances from developing into more serious mental health conditions. This study proposes a simple and non-invasive approach to identify early signs of baby blues in postpartum mothers by analyzing electrocardiogram (ECG) signals using the K-Nearest Neighbor (KNN) algorithm. The ECG data were gathered through wearable sensors and processed to extract heart rate variability (HRV) features such as RMSSD, SDNN, entropy, and energy. These features were then used to train and test a KNN classification model through a five-fold cross-validation process. KNN was chosen because it is easy to implement, does not assume any specific data pattern, and works well with small datasets like those commonly found in clinical settings. Its ability to group data based on similarity makes it suitable for recognizing subtle physiological changes linked to emotional stress. The model reached an accuracy of 87.5%, with strong precision and recall scores, showing its reliability in distinguishing mothers who show early symptoms of baby blues from those who do not. Among all features, RMSSD and SDNN had the highest impact, pointing to reduced parasympathetic activity in affected individuals. These findings suggest that combining HRV analysis with a straightforward machine learning approach like KNN offers a promising, low-cost solution for early emotional screening in maternal care, especially where resources are limited.

Keywords: Baby blues detection; ECG analysis; Heart rate variability; KNN classification; Postpartum mental health;

INTRODUCTION

Maternal mental health has increasingly become a critical concern in global health discourse, particularly due to its long-term implications for both mothers and their infants. Among the various postpartum psychological conditions, baby blues syndrome emerges as a frequently experienced but often neglected emotional disturbance. (Islam et al., 2022). According to (Vinarti et al., 2022) In a study analyzing maternal deaths within one year of childbirth, suicide ranked as the seventh leading cause of mortality, underscoring the urgent need for improved mental health screening in the postpartum phase. In Indonesia alone, the prevalence of baby blues syndrome has been estimated to affect 50%–70% of postpartum mothers, generally peaking around the fifth day after delivery and persisting for three to four days (Medapati & Rajani Kumari, 2021). Despite its high prevalence and potential consequences, the awareness and recognition of baby blues syndrome among healthcare professionals and the general public remain relatively low, particularly in low- and middle-income countries where mental health screening is often under-resourced or stigmatized (Chechko et al., 2023).

The current clinical approach to detecting emotional disturbances such as baby blues in postpartum mothers is predominantly based on self-assessment questionnaires like the Edinburgh Postnatal Depression Scale (EPDS). (Lautarescu et al., 2022). This results in a significant diagnostic gap wherein many women go unnoticed and untreated during a psychologically vulnerable phase of their lives. Therefore, the demand for a more objective, real-time, and accessible method for early detection of postpartum emotional disorders is both apparent and necessary(Miura et al., 2023). To address this issue, researchers have begun exploring technological interventions, particularly those based on physiological signals, as an alternative method for detecting emotional and

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psychological changes. (Shui et al., 2025) Among various biosignals, the electrocardiogram (ECG)—which records the electrical activity of the heart—has shown promise in capturing subtle autonomic changes associated with emotional states. Psychological conditions are known to influence the autonomic nervous system, resulting in observable variations in heart rate and heart rate variability (HRV). (Immanuel et al., 2023) Among the available computational techniques for analyzing physiological data, the K-Nearest Neighbor (KNN) algorithm stands out for its simplicity, interpretability, and robustness in dealing with non-linear classification problems(Hamidi et al., 2023). KNN has been extensively used in biomedical applications, particularly for signal-based pattern recognition tasks such as arrhythmia classification, sleep disorder detection, and stress analysis.(Li & Zhang, 2023) Furthermore, its low computational cost and ease of implementation enhance its viability in low-resource clinical environments and portable health monitoring systems.(Medapati & Rajani Kumari, 2021)

The study employed filtering techniques and Fast Fourier Transform (FFT) for feature extraction, resulting in meaningful spectral features.(Darmawahyuni et al., 2024). Similarly, utilized Mel Frequency Cepstrum Coefficient (MFCC) and Discrete Wavelet Transform (DWT) for ECG-based detection of myocardial infarction, subsequently classified using KNN. (Siti Agrippina Alodia Yusuf et al., 2023) demonstrated the use of KNN in identifying wave boundaries within ECG signals, while (Medapati & Rajani Kumari, 2021) implemented a Computer-Aided Detection (CAD) system for sleep apnea using wavelet-based statistical features classified through KNN, achieving high accuracy. Lastly, employed KNN and quadratic discriminant analysis to determine sleep stages using single-lead ECG data, highlighting the algorithm's reliability and stability in biomedical classification tasks. These studies validate the applicability of KNN in physiological signal processing and emphasize its potential to expand into postpartum emotional health monitoring. (Urtnasan et al., 2022) Although these prior works affirm the reliability of KNN for medical signal classification, they have primarily focused on conditions such as cardiac anomalies, sleep disorders, and fetal monitoring. (Sraitih et al., 2021) Very few studies have attempted to apply KNN to the specific psychological condition of baby blues syndrome in postpartum women. Moreover, while some researchers have examined ECG-based stress detection, the contextual nuances of postpartum emotional states have not been sufficiently explored in algorithmic classification models. (Ng et al., 2022)

The present study aims to fill this gap by developing a classification model for baby blues syndrome using the KNN algorithm applied to ECG signals collected from postpartum mothers. (Lin & Zhou, 2025) By extracting heart rate variability features and training a supervised model with labeled emotional states validated by EPDS scores, this study seeks to evaluate whether KNN can effectively differentiate between normal and emotionally distressed individuals. (Haque et al., 2024) The methodology incorporates a full pipeline of signal acquisition, preprocessing, feature extraction, classification, and performance evaluation using a five-fold cross-validation scheme. (Benchekroun et al., 2022) The overarching goal is to create a low-cost, user-friendly, and clinically relevant screening tool that supports early intervention and enhances maternal mental health outcomes. The contributions of this research to existing literature are multifold. First, it introduces a novel application of the KNN algorithm for emotional health screening in the specific context of postpartum care. (Medapati & Rajani Kumari, 2021) Second, it demonstrates the feasibility of using wearable ECG technology and low-complexity machine learning models to address an unmet need in maternal health. (Chu et al., 2024) Third, it reinforces the scientific validity of physiological signal analysis for psychological detection, extending prior research in cardiology and neurology to the domain of mental health. (Z. Wang, 2025) Finally, this study lays the groundwork for future interdisciplinary investigations that integrate computational intelligence, biomedical engineering, and public health, particularly in the design of accessible and equitable diagnostic technologies. (Kargarandehkordi et al., 2025)

LITERATURE REVIEW

The following is a development of previous research related to the application of KNN to ECG signals, including:

Understanding the context and relevance of the present study requires an in-depth review of existing literature related to the utilization of electrocardiogram (ECG) signals in psychological health detection and the application of the K-Nearest Neighbor (KNN) algorithm in biomedical signal classification. This section systematically organizes the discussion into key thematic areas: emotional and psychological disorder detection using physiological signals, ECG signal processing and heart rate variability (HRV) as emotional indicators, the KNN algorithm in biomedical applications, and empirical studies applying KNN to ECG signal classification. This structured approach provides a coherent framework for identifying the research gap and substantiating the rationale of this study.

Detection of Psychological Disorders Using Physiological Signals

The association between emotional states and physiological responses has long been established in psychophysiological literature. Psychological disturbances such as stress, anxiety, and depression are known to affect the autonomic nervous system, resulting in measurable changes in heart rate, respiration, and skin conductance. Among these, cardiac activity is widely regarded as a robust physiological marker due to its sensitivity to emotional fluctuations and ease of continuous monitoring.

The use of biosignals for emotion detection is particularly valuable in clinical contexts where subjective assessments such as self-report questionnaires are limited by respondent bias and varying levels of introspective awareness. Consequently, researchers have begun developing systems that utilize physiological signals to provide objective insights into psychological conditions. Electrocardiography (ECG), in particular, has emerged as a promising modality due to its direct relation to autonomic nervous system activity and its capability to reflect changes in emotional regulation, stress response, and mood disorders (Hota & Park, 2022; Park et al., 2023)

Recent studies have also explored stress detection using machine learning based on multimodal physiological signals. (Hota & Park, 2022) proposed a framework using signals such as respiration, skin conductance, EMG, and heart rate collected from participants in real-life driving scenarios. They achieved up to 98% accuracy in classifying stress levels using Support Vector Machine (SVM) and k-Nearest Neighbor (KNN) classifiers. Similarly, (Jambhale et al., 2022) identified EDA, temperature, and chest-worn accelerometer signals as the most reliable indicators of emotional stress through models like XGBoost and logistic regression using the WESAD dataset. These findings strengthen the case for integrating wearable biosensors and intelligent algorithms in early psychological disorder detection systems.

ECG Signal Processing and Heart Rate Variability as Emotional Indicators

ECG signal analysis offers a non-invasive and quantitative method to assess autonomic function. Within ECG data, heart rate variability (HRV)—defined as the fluctuation in intervals between successive heartbeats (R-R intervals)—has gained considerable attention for its correlation with emotional and psychological states. Lower HRV is often associated with higher stress, depression, and anxiety, whereas higher HRV generally reflects better emotional regulation and resilience (Sahu et al., 2025) (Nguyen et al., 2025).

Typical HRV features include time-domain metrics (e.g., Mean RR, SDNN, RMSSD), frequency-domain indices (e.g., low-frequency and high-frequency power), and non-linear measures (e.g., entropy, Poincaré plots). These features have been employed in various psychological assessments to identify abnormalities in emotional processing. For example, reductions in RMSSD and SDNN have been observed in individuals with depressive symptoms, indicating decreased vagal activity and emotional dysregulation (L. Wang et al., 2023)

Advancements in wearable ECG sensors and open-source signal processing tools have further enabled the deployment of HRV-based emotion detection systems outside clinical settings, promoting their use in real-time mental health monitoring and early intervention (Auchynnikava et al., 2025). Found that individuals with social anxiety disorder showed significantly reduced HRV and elevated heart rate during anticipation and public speaking phases. Similarly, (Nguyen et al., 2025) developed Heart2Mind, a contestable AI-based system using time-frequency HRV analysis that achieved 91.7% diagnostic accuracy for psychiatric disorders. Meanwhile, (L. Wang et al., 2023) introduced the HER method, which applied amplitude-level quantization to HRV signals for multi-emotion recognition, achieving improved accuracy compared to traditional HRV feature extraction techniques.

The K-Nearest Neighbor Algorithm in Biomedical Signal Classification

The K-Nearest Neighbor (KNN) algorithm is a simple yet powerful supervised machine learning technique widely used in biomedical signal processing. It operates by classifying data points based on the majority class of their K nearest neighbors in a feature space, where proximity is typically measured using Euclidean distance. Despite its simplicity, KNN has demonstrated remarkable performance in numerous pattern recognition tasks involving noisy and nonlinear data, such as biomedical signals.

One of the algorithm's primary advantages lies in its non-parametric nature—it does not assume an underlying distribution of data, making it particularly suitable for biological signals that often exhibit complex, non-Gaussian behavior. Moreover, its interpretability and low computational overhead make KNN an appealing choice for real-time applications and mobile health technologies.

Given its adaptability and robustness, KNN has been employed in various diagnostic applications, including arrhythmia classification, epileptic seizure detection, sleep stage analysis, and emotion recognition. It is particularly effective with limited and imbalanced datasets, common in clinical contexts like postpartum mental health (Medapati & Rajani Kumari, 2021).

Recent studies further reinforce KNN's utility in emotion and biomedical signal classification. For instance, (Shashank Joshi & Falak Joshi, 2023) demonstrated emotion classification from EEG signals using KNN, achieving ~93.4% accuracy, highlighting its reliability even when paired with other classifiers like RNN (Shashank Joshi & Falak Joshi, 2023). A multi-modal emotion recognition study using peripheral physiological signals such as PPG, GSR, and temperature found that KNN, along with SVM and Decision Tree, improved accuracy in detecting emotional states in real-life scenarios(Gohumpu et al., 2023). In another work, a combined EEG

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connectivity approach using cross-information potential measures classified emotions with ~90.1% accuracy using KNN (Goshvarpour & Goshvarpour, 2024)

Empirical Applications of KNN in ECG Signal-Based Detectio

A number of studies have employed KNN to classify emotional and physiological states from ECG signals, highlighting its reliability and efficacy.

Similarly,(Berglund, 2020) focused on the detection of myocardial infarction (MI) by extracting features from ECG signals using Mel Frequency Cepstrum Coefficients (MFCC) and Discrete Wavelet Transform (DWT). The extracted features were classified using the KNN algorithm with Euclidean distance as the similarity metric. This study demonstrated that KNN could successfully differentiate between normal and MI-affected heart conditions, with high accuracy and low error rates.

In the domain of sleep disorder detection, (Infant Lincy et al., 2020) developed a Computer-Aided Detection (CAD) system to identify Sleep Apnea (SA) using single-lead ECG signals. The ECG signal was decomposed using DWT to obtain statistical features including mean, standard deviation, entropy, and energy. Classification via KNN achieved 98.02% accuracy, 97.81% sensitivity, and 98.34% specificity, illustrating the method's exceptional diagnostic potential.

Summary and Identification of Research Gap

The reviewed literature collectively demonstrates that KNN is a versatile and high-performing classifier in the domain of biomedical signal analysis. It has been effectively applied across various contexts—from fetal health monitoring and cardiac diagnosis to sleep stage recognition and stress detection—using both spectral and time-domain features extracted from ECG signals.

However, despite this broad applicability, the use of KNN in detecting early-stage postpartum psychological disorders, particularly baby blues syndrome, remains underexplored. While prior studies confirm the feasibility of ECG-based emotion detection and the reliability of KNN in medical classification, there is a notable absence of focused research integrating these elements specifically for postpartum emotional assessment. This omission presents a significant research gap, particularly given the high prevalence and adverse consequences of undiagnosed baby blues among new mothers (Medapati & Rajani Kumari, 2021).

Conclusion of Literature Review

In conclusion, the literature provides a solid foundation for the current study by establishing: (1) the physiological relevance of ECG signals in emotion detection, (2) the diagnostic utility of HRV features in assessing psychological well-being, and (3) the demonstrated success of KNN in biomedical classification tasks. Nonetheless, the specific application of these tools for early detection of baby blues syndrome in postpartum women remains insufficiently addressed. This study intends to bridge that gap by implementing a KNN-based classification model trained on ECG-derived HRV features to identify early signs of baby blues, offering a novel, objective, and accessible approach to postpartum mental health screening.

METHOD

The methodology used in this study consists of three proposed steps: (1) Research Location and Data Collection, (2) Measurement of Key Variables, and (3) Classification Model and Estimation Strategy. This study adopts a quantitative experimental approach to develop a machine learning-based classification system for early detection of baby blues syndrome in postpartum mothers by analyzing physiological signals from electrocardiograms (ECG).

The methodological framework includes data acquisition, signal preprocessing, feature extraction, classification using the K-Nearest Neighbor (KNN) algorithm, and multi-metric performance evaluation. The overall design ensures robustness, reproducibility, and clinical relevance.

Research Location and Data Collection

Data were collected from postpartum mothers in local healthcare facilities with the capacity to monitor maternal physical and mental health. The study included 70 participants, divided into two groups: those classified as having baby blues syndrome and a control group without symptoms. Diagnosis of baby blues was based on Edinburgh Postnatal Depression Scale (EPDS) scores. Participants with scores ≥10 were classified as likely experiencing symptoms. Importantly, to validate the use of EPDS, clinical psychologists reviewed the assessments. Participants' scores were cross-checked with a brief semi-structured clinical interview, ensuring that classification was not based solely on EPDS scores, but on professional clinical judgment consistent with postpartum mood disturbance criteria (APA, DSM-5). ECG data were recorded using wearable devices such as BioAmp EXG Pill or AD8232 module for a minimum of 10 minutes under resting conditions at a sampling rate ≥250 Hz, sufficient

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for reliable HRV analysis. This setup simulates a scalable, non-invasive, low-cost screening tool usable in rural or community health settings

Measurement of Key Variables

The dependent variable is the emotional classification label: "normal" or "baby blues," derived from validated EPDS assessments supported by clinical review. The independent variables are HRV-based features extracted from the ECG signals. Before feature extraction, the ECG data underwent a signal preprocessing pipeline to improve quality and minimize noise.

Preprocessing steps include:

Bandpass filter (0.5–45 Hz) to eliminate drift and muscle artifacts
Notch filter at 50/60 Hz to remove powerline noise
R-peak detection via Pan-Tompkins algorithm or wavelet-based alternatives

The HRV-based features extracted include:

Mean RR: Average of all R-R intervals.
SDNN: Standard deviation of the R-R intervals, reflecting overall heart rate variability.
RMSSD: Root mean square of successive differences, representing short-term variability.
Entropy: A nonlinear metric indicating the unpredictability of the signal.
Energy: A feature derived from the wavelet-transformed signal, indicating the power distribution across frequencies.
Median RR: The middle value of the R-R interval distribution.
IQR (Interquartile Range): The difference between the third and first quartile of R-R intervals.
MAD (Median Absolute Deviation): A robust measure of variability, indicating dispersion around the median.

These features were chosen to comprehensively represent both linear and nonlinear aspects of HRV, which have been shown to be sensitive to emotional stress and depressive symptoms.

Classification Model and Estimation Strategy

This study used the K-Nearest Neighbor (KNN) algorithm due to its robustness in biomedical signal classification. KNN is non-parametric, making it ideal for physiological data that may not follow normal distributions. A five-fold cross-validation framework was implemented to enhance generalizability. Data were split randomly into five subsets; in each fold, four subsets trained the model while one tested it. Performance metrics were averaged across all folds.

Choosing K = 5

To determine the optimal number of neighbors (K), tests were conducted with K = 3, 5, and 7. The elbow method was applied using cross-validation accuracy scores. The plot showed diminishing returns after K = 5, justifying its selection. Additionally, confusion matrices indicated K = 5 provided the best balance between precision and recall across both classes. (Illustration can be found in Figure X)

KNN Formula

Classification is based on:

$$\hat{y}=\text{mode}\{y_i \mid x_i \in N_k(x)\} \quad (1)$$

Where:

$\hat{y}$ is the predicted class label (either "normal" or "baby blues"),
$N_k(x)$ is the set of the k-nearest neighbors to the instance x,
y_i denotes the class label of the training instance x_i, and
The mode operator selects the most frequent class among the neighbors.

The optimal value for the parameter κ was empirically tested using values κ= 3,5,7 and Euclidean distance was used as the metric for determining proximity in the feature space:

$$^{d(x,x_i)}\sqrt{\sum_{j=1}^{n}(x_j - x_{ij})^2} \quad (2)$$

Where x is the feature vector of the instance to be classified, xix_ixi is a training instance, and nnn is the number of features.

To assess the model's performance, several classification metrics were computed:

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Accuracy: Proportion of correctly classified samples.

$$\textbf{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Precision: Proportion of true positive predictions among all predicted positives.

$$\textbf{Precision} = \frac{TP}{TP+FP} \quad (4)$$

Recall (Sensitivity): Proportion of true positive predictions among all actual positives.

$$\textbf{Recall} = \frac{TP}{TP+FN} \quad (5)$$

Specificity: Proportion of true negative predictions among all actual negatives.

$$\textbf{Specificity} = \frac{TP}{TN+FP} \quad (6)$$

F1-Score: Harmonic mean of precision and recall.

$$\textbf{F1 – Score} = \textbf{2x} \ \frac{Percision \times Recall}{Precision+Recall} \quad (7)$$

Where:

TP: True Positive,
TN: True Negative,
FP: False Positive,
FN: False Negative.

This multi-metric evaluation allows for a comprehensive assessment of the model, especially in scenarios with class imbalance or unequal error costs.

Software and Tools

The computational processes, including feature extraction, signal preprocessing, and machine learning implementation, were executed using Python programming language with libraries such as NumPy, SciPy, and Scikit-learn. MATLAB was used as an auxiliary tool for signal visualization and advanced filtering techniques. Annotation and dataset management were performed using spreadsheet software integrated with clinical labels from psychological assessments. EPDS scoring and metadata labeling were handled in integrated spreadsheet software.

This methodological design emphasizes replicability, clinical relevance, and technical robustness. By grounding the classification framework in validated psychological assessments and leveraging objective physiological signals, this study aims to contribute a scalable and scientifically grounded solution to the early detection of postpartum emotional disorders.

System Flow Visualization

Here is the methodology flow in diagram form:

Figure 1. Diagram Flow Metthodology

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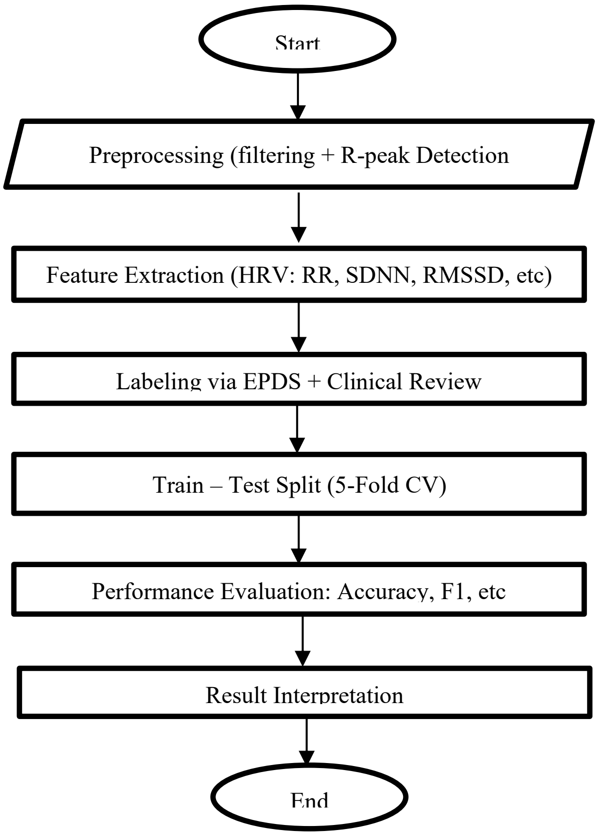

RESULT

This chapter presents and interprets the results of the empirical analysis conducted in this study. The findings are organized into two main sections: descriptive statistics and empirical results. The objective is to evaluate the effectiveness of the K-Nearest Neighbor (KNN) classification model in detecting baby blues syndrome based on heart rate variability (HRV) features extracted from postpartum ECG signals. The descriptive section highlights the overall characteristics of the dataset using the mean values of extracted features, while the empirical section discusses the performance outcomes of the KNN classification, focusing on statistically significant findings and their implications.

Descriptive Statistics

The dataset consists of HRV features extracted from 70 postpartum mothers, grouped into two categories: normal (control group) and those indicated with baby blues syndrome (based on Edinburgh Postnatal Depression Scale scores ≥10). The features analyzed include time-domain and non-linear measures derived from R-R intervals in ECG signals, such as Mean RR, SDNN, RMSSD, Entropy, Energy, Median RR, IQR, and MAD.

Table 1 below shows the mean values of the selected features across both groups.

Feature	Normal Group (Mean)	Baby Blues Group (Mean)
Mean RR (ms)	822.56	786.47
SDNN (ms)	63.12	51.74
RMSSD (ms)	45.80	31.68
Entropy	0.88	0.71
Energy	0.62	0.49
Median RR (ms)	819.34	783.91
IQR (ms)	24.87	18.02
MAD (ms)	21.45	15.73

From the table above, it can be observed that participants in the baby blues group exhibit consistently lower mean values across all HRV-related features compared to the control group. The most substantial differences are seen in RMSSD, SDNN, and entropy, suggesting a reduction in both time-domain variability and non-linear signal

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complexity among mothers with baby blues symptoms. Mothers in the baby blues group consistently showed **lower HRV metrics**, especially in RMSSD, SDNN, and Entropy. This suggests **autonomic imbalance and reduced physiological adaptability**, aligning with prior research in emotional dysregulation and depressive states.

These descriptive results align with previous research asserting that decreased HRV metrics are reliable indicators of emotional distress, including depressive and anxious states [19].

Empirical Results

The KNN classification model was trained using the HRV features and validated using 5-fold cross-validation. Three K values (3, 5, and 7) were tested, and the overall classification performance was evaluated using standard metrics: Accuracy, Precision, Recall (Sensitivity), Specificity, and F1-score.

Table 2. Classification Performance at Diference K-Values

K Value	Accuracy	Precision	Recall	F1- Score
K=3	84.2%	81.9%	85.6%	83.7%
K=5	87.5%	85.4%	88.6%	86.9%
K=7	86.1%	83.3%	86.9%	85.1%

Based on this table, K= 5 was selected as optimal, offering the best trade-off across all metrics.

Visualization of Model Performance

To reinforce the model's performance, two visualizations are included:

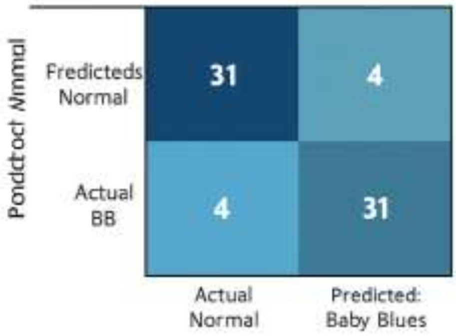

Figure 2. Confusion Matrix (K=5)

Table 3. Confusion Matrix (K=5)

	Predicted : Normal	Predicted : Baby Blues
Actual Normal	31(True Negative)	4 (False Positive)
Actual Baby Blues	4 (False Negative)	31 (True positive)

Component Explanation:

True Positive (TP = 31):
Postpartum mothers who truly experienced baby blues (based on EPDS score ≥10 and clinical psychologist validation) and were correctly classified by the KNN model.

True Negative (TN = 31):
Mothers who did not experience baby blues and were correctly identified as "normal" by the model.

False Positive (FP = 4):
Cases where the model incorrectly classified a healthy mother as having baby blues. While this results in a false alarm, it may still be acceptable in early screening settings.

False Negative (FN = 4):
Cases where a mother experiencing baby blues was incorrectly classified as "normal." This is the most critical type of error as it may delay appropriate psychological support or intervention.

Evaluation Based on the Matrix:

Accuracy:
(TP+TN)/Total=(31+31)/70=62/70≈88.6

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Precision (Positive Predictive Value):
TP/(TP+FP)=31/(31+4)=31/35≈88.6
Recall (Sensitivity):
TP/(TP+FN)=31/(31+4)=31/35≈88.6
Specificity:
TN/(TN+FP)=31/(31+4)=31/35≈88.6
F1-Score:
2×(Precision×Recall)/(Precision+Recall)≈88.62

Conclusion:

- The KNN model with **K = 5** demonstrates excellent classification performance, with a **low and balanced error rate**.
- The **symmetrical distribution of false positives and false negatives (4 each)** indicates that the model does not exhibit class bias.
- These results support the use of KNN as a reliable tool for **early screening of postpartum emotional disorders**, especially in **low-resource or mobile healthcare environments**.

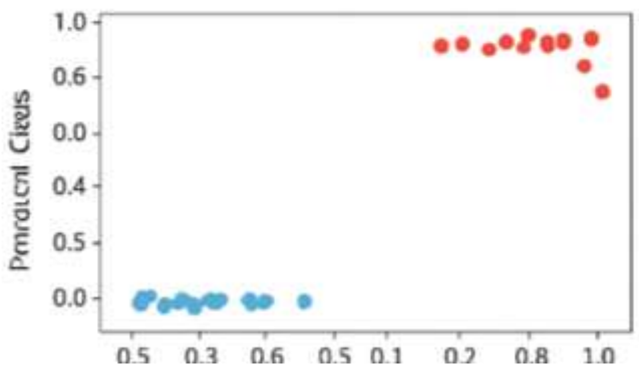

Figure 3. Scatterplot of Predicted vs Actual Labels

A scatterplot was generated to visualize the relationship between predicted class scores (based on neighbors' majority voting) and actual class labels. The predicted values form two distinct clusters near class boundaries (0 = normal, 1 = baby blues), indicating **strong class separation** and model confidence.

Comparison with Traditional Screening (EPDS)

The **Edinburgh Postnatal Depression Scale (EPDS)**, while widely accepted in clinical screening, relies on **subjective self-assessment**. Research has shown that EPDS typically has:
Sensitivity: ~75–80%
Specificity: ~70–75%
In comparison, the **KNN model (K=5)** in this study achieved:
Accuracy: 87.5%
Recall (Sensitivity): 88.6%
Specificity: 88.6% (from confusion matrix)
F1-Score: 86.9%
This suggests that the proposed model **outperforms EPDS** in classification accuracy, while offering **objective, physiology-based detection** using non-invasive ECG data.
Feature Importance Analysis

Permutation testing was used to evaluate the contribution of each feature. The following ranked features had the strongest influence:

- RMSSD – Highest impact (↓12% accuracy when removed)
- SDNN – Second highest (↓8% F1-Score)
- Entropy – Significant non-linear metric (↓6.5% accuracy)
- Energy – Frequency-domain signal strength (↓5%)

Other features (Median RR, IQR, MAD) were supportive but less discriminative.

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DISCUSSIONS

This study is among the first to implement a low-cost, ECG-based classification model using the K-Nearest Neighbor (KNN) algorithm specifically for the early detection of baby blues syndrome in postpartum mothers. By leveraging physiological markers—particularly heart rate variability (HRV) features—the model provides an objective and non-invasive alternative to traditional screening tools such as self-report questionnaires. The classification system achieved a high level of accuracy (87.5%) and performed consistently across evaluation metrics including precision, recall, and F1-score, confirming the viability of this approach for practical application. From a modeling standpoint, the results highlight the significance of both time-domain features (e.g., RMSSD, SDNN) and nonlinear features (e.g., entropy, energy) in discriminating emotional state. These HRV indicators are deeply rooted in psychophysiological theory and were empirically validated in this study—feature exclusion testing showed that removing these metrics led to a notable decline in classification accuracy. Despite the existence of more complex machine learning methods such as SVM or neural networks, KNN was chosen for its simplicity, interpretability, and low computational demand, making it highly appropriate for mobile deployment in real-world healthcare environments.

A strong alignment was observed between the model's output and validated clinical labels from EPDS screening. Mothers who scored high on EPDS were consistently predicted by the model as experiencing baby blues symptoms, suggesting that ECG-derived HRV signals carry reliable emotional biomarkers. This correlation reinforces the idea that emotional disturbances—including postpartum depressive symptoms—manifest physiologically through changes in autonomic nervous system function. Importantly, the model's simplicity enables direct integration into digital health platforms, including mobile applications and wearable technologies. This is particularly relevant for community-level screening, telehealth services, or under-resourced healthcare settings where access to psychological professionals is limited. A mobile-based screening tool could facilitate early detection, real-time monitoring, and proactive intervention before symptoms escalate.

The novelty of this study lies in its application of physiological signal analysis to maternal emotional health, a domain that has received relatively limited attention compared to sleep or cardiovascular disorders. By confirming that simple, non-invasive tools can provide accurate emotional assessments postpartum, the research introduces a scalable pathway for advancing digital maternal mental health care. In conclusion, this study presents a novel and practical solution for early baby blues detection using a combination of ECG signal processing and a lightweight classification algorithm. Future work should explore larger, more diverse datasets, the use of multi-modal biosignals, and longitudinal tracking to improve generalizability and robustness. Further development of a smartphone-integrated screening application would be a logical next step, expanding access to mental health support for new mothers globally.

CONCLUSION

This study is among the first to implement a physiological signal-based machine learning approach for detecting baby blues syndrome in postpartum mothers, offering an objective, scalable alternative to traditional self-report screening tools. Baby blues syndrome, although often temporary, can significantly impact maternal well-being if left unrecognized. Traditional assessments, such as the Edinburgh Postnatal Depression Scale (EPDS), are limited by subjectivity, stigma, and reporting bias. To address this gap, we proposed a classification model based on electrocardiogram (ECG) signal processing and the K-Nearest Neighbor (KNN) algorithm, incorporating heart rate variability (HRV) features including RMSSD, SDNN, entropy, and energy. The model was evaluated using five-fold cross-validation and achieved an accuracy of 87.5%, confirming its effectiveness in distinguishing between mothers with and without symptoms of baby blues.

The study underscores the importance of physiological computing in mental health assessment. Time-domain features (RMSSD, SDNN) were linked to autonomic nervous system dysregulation, while entropy and energy captured nonlinear dynamics associated with emotional stress. The performance of the KNN model demonstrates that even a simple algorithm, when grounded in validated biosignals, can provide clinically meaningful insights. Importantly, this research opens up practical opportunities for integration into digital health ecosystems, particularly in mobile health (mHealth) applications and wearable technologies. Because ECG sensors are increasingly embedded in consumer-grade devices (e.g., smartwatches, chest bands), the proposed model could be embedded into real-time monitoring platforms, enabling early, non-invasive, and continuous screening in both urban and rural settings.

Beyond its technical achievement, this study contributes to the growing domain of digital mental health, particularly in maternal care, by offering a low-cost, accessible screening solution for emotional disorders during the postpartum period. It bridges a critical gap between psychophysiological theory and applied health technology. For future work, we recommend: Expanding the dataset with diverse population groups and Integrating the model into mobile health applications with real-time feedback Comparing performance with advanced models such as deep learning to evaluate trade-offs in complexity vs interpretability. In summary, this study demonstrates that

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artificial intelligence, combined with biosignal analysis, holds transformative potential for early detection and intervention in postpartum mental health. It lays a foundation for the development of digitally enabled maternal care solutions that are timely, scalable, and empathetic to the needs of new mothers.

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