

EXPLOITING MULTISPECTRAL FEATURES FOR NEONATAL CRY ANALYSIS

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ABSTRACT

Infant cries are the primary means of communication for newborns, conveying needs such as hunger, pain, sleepiness, or discomfort. Globally, it is estimated that caregivers misinterpret up to 40% of baby cries, which can lead to delayed responses and potential health risks. Traditionally, the identification of cry types relies on manual listening and observation, requiring caregivers or medical staff to interpret acoustic patterns, which is highly subjective and prone to error. The proposed system combines audio preprocessing, feature extraction using MFCCs, traditional machine learning models such as Support vector machine (SVM) classifier, K-nearest neighbours classifier (KNN), Decision tree classifier (DTC), Adaptive Boosting classifier (Adaboost), and Linear discriminant analysis (LDA), and a 1D Convolutional Neural Network (CNN) to provide a robust framework for categorizing infant cries. By integrating a user-friendly Tkinter-based graphical interface, the system allows seamless dataset uploading, preprocessing, model training, evaluation, and prediction on unseen audio data. Performance metrics including accuracy, precision, recall, F1-score, confusion matrices, and ROC curves ensure rigorous evaluation, while visualizations such as waveforms and training graphs enhance interpretability. This approach not only addresses the limitations of manual systems by providing objective and scalable classification but also enables real-time monitoring and early health intervention. The proposed automated system demonstrates the advantages of combining classical machine learning with deep learning, offering a reliable, efficient, and practical solution for caregivers and healthcare providers to interpret infant needs accurately, ultimately contributing to better infant care and timely medical response.

Keywords: Non-invasive Diagnosis, Real-Time Audio Classification, AI for Neonatal Care, Spectral–Temporal Feature Learning, Infant Cry Classification

1. INTRODUCTION

Babies cry as an innate reflex to express their needs, such as hunger, discomfort, and sleeplessness. Understanding these cries accurately and quickly is critical to babies' healthy development and happiness. Languages provide an ease for humans to communicate their sentiments with each other. However, it is difficult for infants to express their feelings or discomfort due to lack of linguistic skill development. High pitched sound of screaming or crying is the primary means for kids to signal any unease or needs. Although parents remain most attentive, still sometimes it is difficult for them to know the exact reason for baby's cry. In order to improve infant well-being as well as parent's responsiveness to address infant needs promptly, it is significantly important to understand and interpret the cry of the baby. Parents and caregivers traditionally rely on individual experiences and instincts to guess or understand the reason of baby cry, this may be inaccurate and inconsistent. Employing advanced machine learning techniques can help to offer a reliable solution, which can help to accurately detect the cry reason

Caring for newborns is a sensitive and demanding responsibility, especially during the first months of life when infants cannot communicate through words. Crying becomes their only expressive tool, conveying everything from basic needs to serious distress. While technologically advanced countries have already adopted intelligent cry-analysis systems, real-time audio monitoring, and automated classification tools in homes and hospitals, such advancements are still limited in India.



Figure 1. Baby cry symptoms analysis

Figure 1.1 illustrates a pain-intensity scale ranging from 0 to 10, helping caregivers interpret the meaning behind an infant's cry. At the lower end of the scale (0–3), babies typically show signs of no pain to mild discomfort, represented by calm or slightly uneasy facial expressions in shades of green. Mid-range values (4–6) indicate moderate pain, where the baby's facial expressions begin to shift toward noticeable discomfort, shown through yellow-toned icons with uncertain or worried faces. As the intensity increases to levels 7–9, the scale describes severe to very severe pain, visually represented with orange-colored baby icons showing distress and stronger emotional reactions. At level 10, marked by a deep red icon, the baby is shown crying loudly with the expression associated with the worst pain possible, indicating an urgent need for attention.

This visual scale serves as an intuitive tool for parents and caregivers to correlate crying patterns with possible pain levels, helping them understand what an infant might be trying to communicate when verbal expression is not possible. By associating facial expressions and color coding with numerical ratings, the figure simplifies the assessment of infant discomfort, making it easier to evaluate whether the baby is calm, mildly uneasy, moderately uncomfortable, severely distressed, or in extreme pain. Such standardized interpretation aids in quicker decision-making, helps reduce caregiver confusion, and improves responsiveness in real-life scenarios like feeding needs, illness-related pain, or discomfort due to environmental factors.

Globally, childbirth remains a significant demographic event, with an estimated 130–135 million babies born every year worldwide. Although global birth rates have been gradually declining, the absolute number of births remains high, especially in low- and middle-income countries. Alongside births, child survival has improved substantially over the past few decades due to better maternal care, immunization, nutrition, and medical access. Despite this progress, child mortality remains a serious concern. In 2023, around 4.8 million children under the age of five died worldwide, out of which nearly 2.3 million were newborns who died within the first 28 days of life. This shows that the

neonatal period is the most vulnerable stage of life and requires continuous care and timely detection of health issues

2. LITERATURE SURVEY

Hashemi, et al. [1] reviewing existing Datasets, preprocessing methodologies and audio feature extraction such as MFCC, RMS energy, etc., are discussed. For infant cry detection and classification, several algorithms, such as support vector machines (SVM), convolutional neural networks (CNN), k-nearest neighbors (KNN), Random Forest, etc., have been analyzed and utilized for such processes in general. Finally, the study explores various applications of infant cry analysis, highlighting its potential to improve infant care and facilitate early diagnosis. Shayegh, et al. [2] proposed mel-Frequency Cepstral Coefficients (MFCCs) and Filterbank (FBANK) features were extracted and transformed into fixed-dimensional embeddings using a lightweight X-vector model with mean-SD or attention-based pooling, followed by a binary classifier. Model parameters were optimized via grid search. Performance was evaluated using accuracy, precision, recall, F1-score, and ROC-AUC under stratified 10-fold cross-validation. MFCC + mean-SD achieved $93.59 \pm 0.48\%$ accuracy, while MFCC + attention reached $93.53 \pm 0.52\%$ accuracy with slightly higher precision, reducing false RDS alarms and improving clinical reliability. Shah, et al. [3] analyzed approaches include spectrotemporal analysis to detect atypical acoustic patterns, deep learning models like convolutional neural networks (CNNs) for automated feature learning, and explainable AI techniques that connect model outputs to clinically interpretable vocal features. We also explore multimodal approaches that combine vocal data with physiological and behavioral signals to improve diagnostic accuracy. The review addresses challenges in neonatal vocal analysis, including data scarcity, demographic variability, and the need for generalization across different recording environments.

Dey, et al. [4] explores feature extraction using Mel-Frequency Cepstral Coefficients (MFCCs), where the features are categorized into time and frequency domains. [Data preprocessing](#) techniques, such as noise removal, handling missing values, outliers, and label encoding, are applied to ensure clean data. To address class imbalance, the Random Oversampling (ROS) technique is employed. Hyperparameter optimization is performed using GridSearchCV for various machine-learning models. The performance of different ML and DL models is evaluated, with Logistic Regression (LR) achieving an accuracy of 99.16% and a 0.008% error rate. In comparison, ANN1 outperforms other DL models with an accuracy of 98.20% and a 0.018% error rate. Cao, et al. [5] analyzed an audio data analysis tool capable of accurately segmenting inhalation and exhalation phases in infant cries, followed by extraction of the duration, frequency, and intensity parameters of each segment. Here, 226 sound clips of infants' cries were collected and analyzed. The results revealed the significant differences in sound parameters between premature and term infants. Shinya, et al. [6] proposed convolutional neural network models showed high accuracy in classifying gestational groups (92.4%) and in estimating the relative and continuous differences in GA ($r = 0.73$; $p < 0.0001$), outperforming previous studies. Grad-CAM and spectrogram manipulations further revealed that GA variations in infant crying were prominently reflected in temporal structures, particularly at the onset and offset regions of vocalizations.

Bonafas, et al. [7] analyzed the cries of premature babies, born between gestational age 26 and 33 weeks, every week while they were hospitalized in a neonatal intensive care unit. Our results show that as premature babies approach their theoretical term, their cries become increasingly tonal, less marked by noisy components, and carrying individual cues. We then compared these cries with those recorded in 25 healthy full-term babies. Despite the evolution of premature baby cries over time, the acoustic structure of these cries remains different from that of full-term infants. Kadiroglu, et al. [8]

proposed the study included neonates ($N=66$) with a gestational age of ≥ 37 weeks and a postnatal age of < 24 h. Heel blood samples were collected from the neonates in the control group according to the procedures followed by the hospital. Unlike the control group, an automatic lancet was used instead of a manual lancet for the experimental group. The Newborn Information Form and the ALPS-Neo Neonatal Pain and Stress Assessment Scale (ALPS-Neo) were used for data collection. Maya-Enero, et al. [9] performed swaddling, administered 1 mL of oral sucrose, and let the newborn suck for 2 min. In the experimental group, we placed a gauze pad with two drops of colostrum, whereas in the control group, we used one drop of LEO 2 cm under the neonate's nose prior to and during the frenotomy. Results: We enrolled 142 patients (71 experimental cases and 71 controls). The experimental group showed lower crying times (28.0 vs. 40.2 s, $p = 0.03$). Both groups showed similar NIPS scores (1.4 vs. 1.5, $p = 0.28$).

Acharya, et al. [10] analyzed that neonates were allocated to two groups: the intervention group ($n=70$), which received 2 mL of 25% glucose, and the expressed breast milk group ($n=70$), which received 2 mL of expressed breast milk, which was administered two minutes before the heel prick procedure. Physiological parameters were assessed using a biophysiological assessment proforma at baseline and following the heel prick procedure. The biophysiological assessment proforma was validated with reliability coefficients of 0.80. Maiti, et al. [11] proposed the study utilized by Mel Frequency Cepstral Coefficients (MFCC) method to extract features from internet-sourced MP3 and WAV audio data. The technique successfully captured the unique qualities of each crying sound using various machine-learning models, including Random Forest and XGBoost. These models outperformed others with accuracy rates of 94.5% and 94.2%, respectively. These findings show how well these algorithms perform in correctly categorizing various newborn cries. Khalilzad, et al. [12] analyzed neighborhood component analysis (NCA) feature selection was employed with two goals: (i) Exploring how the elements of each feature set contributed to classification outcome; (ii) investigating to what extent the feature space could be compacted. The attained results showed success of both experiments introduced in this study, with 88.66% for the decision template fusion (DTF) technique and a consistent enhancement in comparison to all feature sets in terms of accuracy and 86.22% for the NCA feature selection method by drastically downsizing the feature space from 86 elements to only 6 elements.

Jahangir, et al. [13] proposed this limitation, in this research, different conventional and hybrid ML models were developed and analyzed in detail to find out the best model for detecting infant cries in a household setting. A stacked classifier is proposed using different state-of-the-art technologies, outperforming all other developed models. The proposed CNN-SCNet's (CNN-Stacked Classifier Network) precision, recall, and f1-score were found to be 98.72%, 98.05%, and 98.39%, respectively. Infant monitoring systems can use this classifier to detect infant cries in noisy household settings. Vaishnavi, et al. [14] analyzed cry signals are first preprocessed to remove distortion caused by short sample times. MFCC (Mel-frequency cepstral coefficient), Power Normalized Cepstral Coefficients (PNCC), BFCC (Bark-frequency cepstral coefficient), and LPCC (Linear Prediction cepstral coefficient) are used to identify abnormal weeping through their prosodic aspects. The Elephant Herding optimization (EHO) algorithm is utilized for choosing the best features from the extracted set to form a fused feature matrix. Giordano, et al. [15] aimed to evaluate the effectiveness of an AI system designed for automatic facial recognition by comparing its performance with the expert opinion of health care provider. The performance of AI software, FaceReader 9, was compared to experts' evaluations using a visual-analog scale, focusing on identifying specific facial action units associated with different pain levels. The study found significant differences in AI-generated metrics—arousal and valence across three stimulus types: non-noxious thermal, short-noxious, and

prolonged-noxious, with p-values below 0.001. A strong correlation ($r = 0.84$, $p \leq .001$) was observed between AI metrics and expert ratings.

3. PROPOSED METHODOLOGY

The proposed system for neonatal cry analysis aims to systematically analyze infant cry audio recordings to identify and differentiate cry types that indicate various neonatal needs. The system follows a structured pipeline starting from dataset preparation and exploratory analysis, progressing through feature extraction and multiple classification models. By combining traditional machine learning techniques with a deep learning approach, the system enables comprehensive evaluation of cry patterns and improves the reliability of neonatal cry interpretation. This multi-model framework supports accurate classification and comparative analysis, contributing to effective early-stage neonatal monitoring and caregiver assistance.

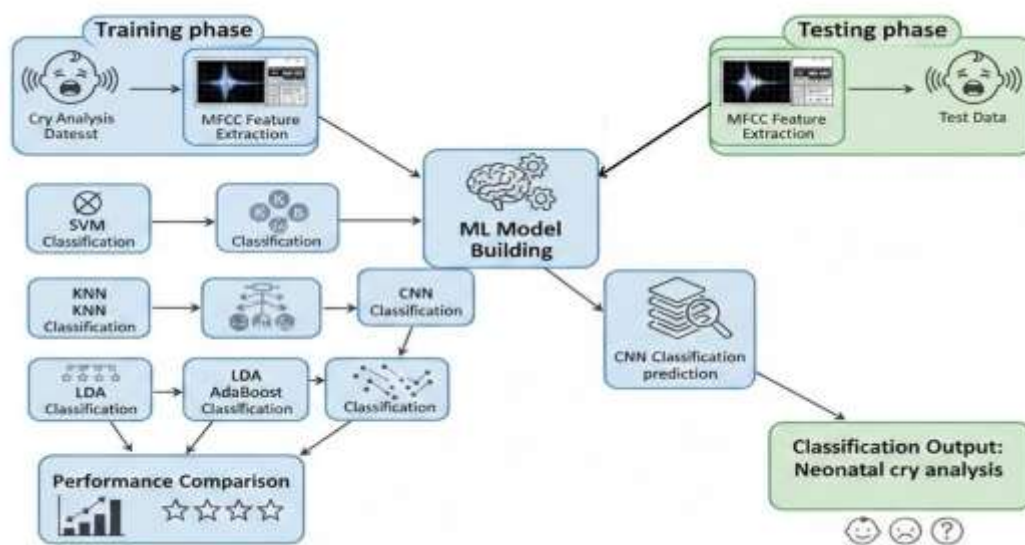


Figure 2. Proposed system architecture of neonatal cry analysis

The proposed methodology begins with the creation of a neonatal cry analysis dataset by collecting and labeling infant cry recordings under different conditions, followed by preprocessing steps such as standardization of sampling rate, duration alignment, and removal of noisy or corrupted samples to ensure data quality. Subsequently, Mel-Frequency Cepstral Coefficients (MFCCs) are extracted from each audio signal to capture critical spectral and perceptual features, transforming the raw cry sounds into meaningful numerical representations. Finally, these extracted features are split into training and testing sets, and multiple machine learning models are developed with initialized hyperparameters, enabling systematic training and comparative evaluation for accurate cry classification.

The methodology continues by applying multiple classification techniques to the extracted MFCC features, where SVM identifies optimal decision boundaries for accurate separation of cry classes, and KNN classifies samples based on similarity using distance metrics and majority voting. The DTC constructs interpretable hierarchical rules for classification, while AdaBoost enhances performance by combining weak learners and focusing on misclassified instances. LDA further improves efficiency by reducing dimensionality while maximizing class separability, and a CNN is employed to automatically learn complex spectral-temporal patterns from MFCC representations for robust classification. Subsequently, all models are systematically evaluated using metrics such as accuracy, precision, recall, and F1-score to identify the most effective approach. Finally, the best-performing

model is utilized to predict neonatal cry types from new audio inputs, demonstrating real-time applicability in intelligent infant monitoring and caregiver assistance systems.

Convolutional Neural Network

Convolutional Neural Networks (CNNs) are a class of deep learning models designed to automatically extract hierarchical features from structured data, such as images, signals, or sequential data. CNNs are particularly effective at capturing local patterns, spatial hierarchies, and correlations in input features. Instead of relying on handcrafted feature extraction, CNNs learn filters during training that highlight essential characteristics of the data. In the context of baby cry classification, CNNs process MFCC feature vectors derived from audio signals to identify patterns in the spectral-temporal domain that differentiate cry types such as Hunger, Pain, Sleepy, and Discomfort.

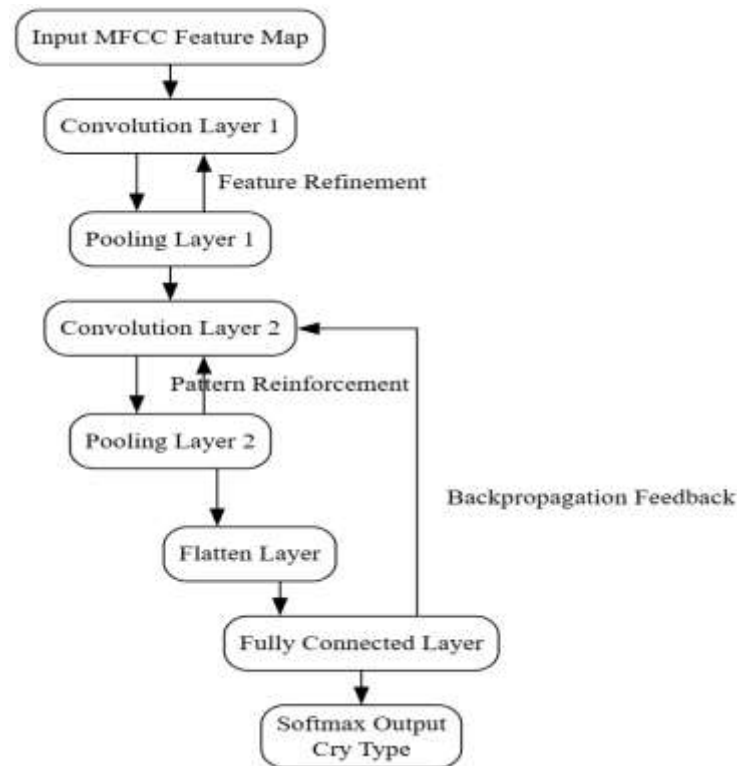


Figure 3. Internal working flow of Convolutional neural network.

CNNs combine convolutional layers, which detect local feature patterns, with pooling layers that reduce dimensionality and introduce translation invariance. Fully connected layers at the end of the network integrate the extracted features to perform classification. The model is trained using backpropagation with a categorical cross-entropy loss, allowing it to minimize prediction errors iteratively. This deep learning approach can capture subtle differences between cry categories that traditional machine learning models might miss, improving classification accuracy

4. RESULTS DESCRIPTION

Figure 4 shows the confusion matrix of the CNN classifier used in the neonatal cry analysis system, where the rows represent the true cry classes (tired, hungry, discomfort, burping, and belly pain) and the columns represent the predicted classes. The matrix clearly demonstrates strong performance of the CNN model, as most values are concentrated along the diagonal, indicating a high number of correct predictions. For instance, all 76 tired cries are correctly classified as tired, 63 hungry cries are

correctly identified with only minor confusion (5 misclassified as discomfort and 2 as burping), 60 discomfort cries are perfectly classified, 79 burping cries are correctly recognized, and 83 belly pain cries are accurately predicted with no misclassification. The near-zero off-diagonal values show minimal confusion between classes, highlighting the CNN’s ability to effectively learn complex and non-linear acoustic features from cry signals. This confusion matrix confirms that the CNN classifier significantly outperforms traditional machine learning models by achieving highly accurate and reliable neonatal cry classification, making it well-suited for real-time clinical and caregiver support applications.

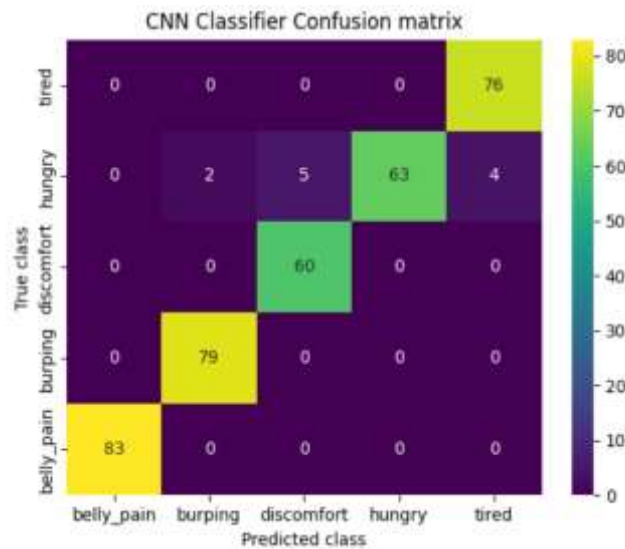


Figure 4. Confusion matrix obtained using proposed CNN model

The figure 5 shows presents the receiver operating characteristic (ROC) curves of the CNN classifier using a one-vs-rest approach for five classes—belly pain, burping, discomfort, hungry, and tired—showing strong discriminative performance across all categories. The ROC curves for belly pain, burping, discomfort, and tired rise almost vertically from a false positive rate of 0 to a true positive rate close to 1, achieving perfect classification with an area under the curve (AUC) of 1.00 for each of these four classes. The hungry class also demonstrates excellent performance, with its ROC curve remaining close to the top-left corner and yielding an AUC of 0.98, which is substantially higher than the diagonal random baseline. The dashed diagonal line represents random guessing, where the true positive rate increases linearly with the false positive rate from 0 to 1. The large separation between the CNN ROC curves and the random reference indicates that the CNN model provides highly reliable sensitivity–specificity trade-offs and significantly outperforms traditional classifiers for all five classes.

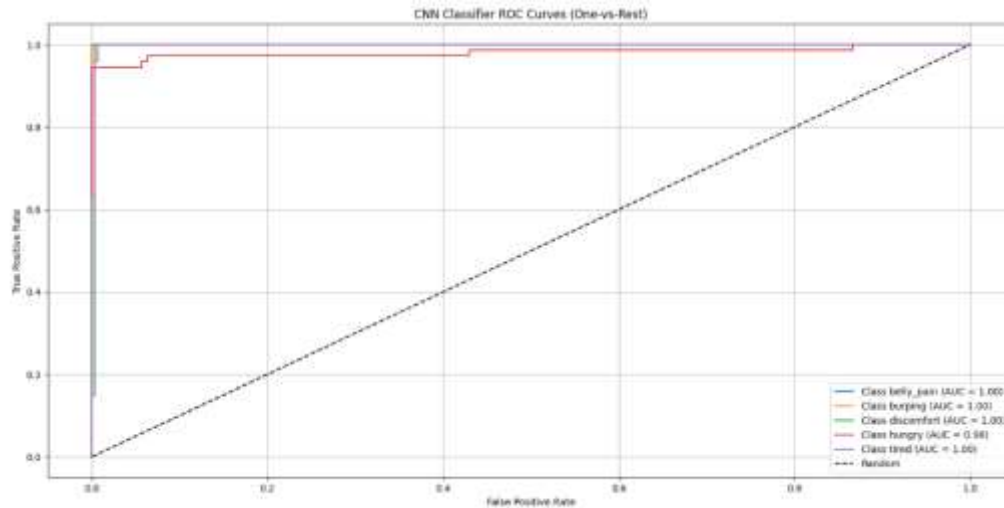


Figure 5. ROC curve obtained using proposed CNN model

The table 1 shows overall performance comparison that clearly highlights the strengths and limitations of each classification model used for neonatal cry analysis. Traditional machine learning models such as KNN and SVM show relatively low performance, with KNN achieving only 28.49% accuracy and an F1-score of 20.08%, indicating severe difficulty in distinguishing between acoustically similar cry classes. SVM performs slightly better with 46.50% accuracy and balanced precision and recall values, but it still struggles to generalize effectively across all classes due to overlapping feature distributions. These results suggest that distance-based and margin-based classifiers are not sufficiently robust for capturing the complex and non-linear characteristics present in neonatal cry signals.

Table 1 Overall Performance Comparison

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	46.50	51.65	46.11	47.03
KNN	28.49	20.51	26.26	20.08
Decision Tree (DTC)	61.56	60.75	60.25	57.60
AdaBoost	52.69	54.94	52.44	53.24
LDA	54.30	53.11	53.93	53.17
CNN	97.04	96.97	97.03	96.83

Among the conventional models, the DTC demonstrates the best performance, achieving 61.56% accuracy and an F1-score of 57.60%, showing its ability to model non-linear decision boundaries and capture class-specific patterns more effectively than SVM and KNN. AdaBoost and LDA offer moderate performance, with accuracies of 52.69% and 54.30% respectively, indicating some improvement through ensemble learning and dimensionality reduction, but they still suffer from misclassification in challenging classes such as hungry and tired. In contrast, the CNN significantly outperforms all other models, achieving 97.04% accuracy with precision, recall, and F1-score all around 97%. This exceptional performance demonstrates the CNN's ability to automatically learn deep, discriminative features from cry representations, effectively handling complex temporal and spectral variations. The comparison clearly confirms that deep learning-based approaches, particularly CNNs, are far more suitable for neonatal cry classification than traditional machine learning models.

The figure 6 illustrates a time-domain waveform of a neonatal cry signal analyzed as part of a neonatal cry analysis system, where the model has predicted the emotional or physiological state as tired. The horizontal axis represents time in seconds, while the vertical axis shows the amplitude of the cry signal, capturing variations in loudness and intensity over the recording duration. The waveform exhibits repeated bursts of sound energy separated by short pauses, a pattern commonly associated with fatigue-related crying, where the infant produces intermittent vocalizations rather than continuous, high-energy cries.

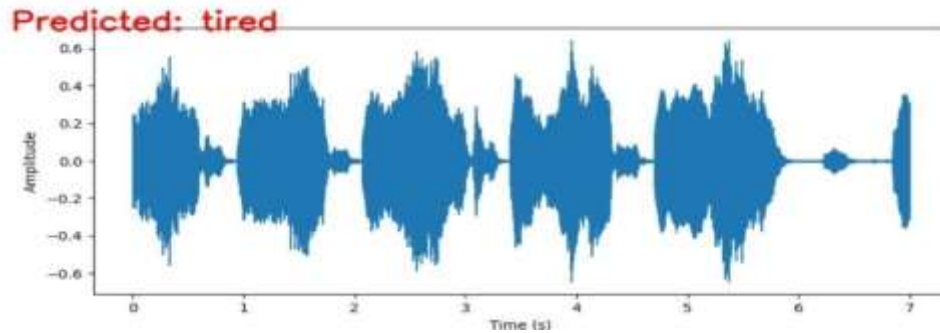


Figure 6. Prediction obtained as tired on sample test sound using proposed CNN

The figure 7 presents the time-domain waveform of a neonatal cry signal that has been classified as discomfort within a neonatal cry analysis framework. The x-axis represents time in seconds, while the y-axis shows the amplitude of the cry signal, indicating variations in vocal intensity. The waveform displays irregular and high-amplitude segments with frequent fluctuations and limited silent intervals, which are characteristic of discomfort-related cries.

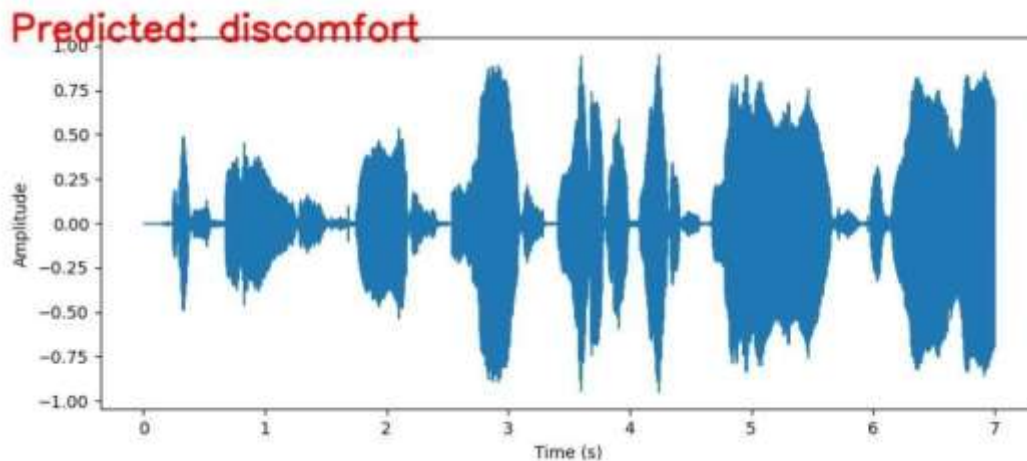


Figure 7. Prediction obtained as discomfort on sample test sound

The figure 8 illustrates the time-domain waveform of a neonatal cry that has been classified as belly pain in a neonatal cry analysis system. The horizontal axis indicates time in seconds, while the vertical axis represents the amplitude of the cry signal, showing the intensity of vocalization over time.

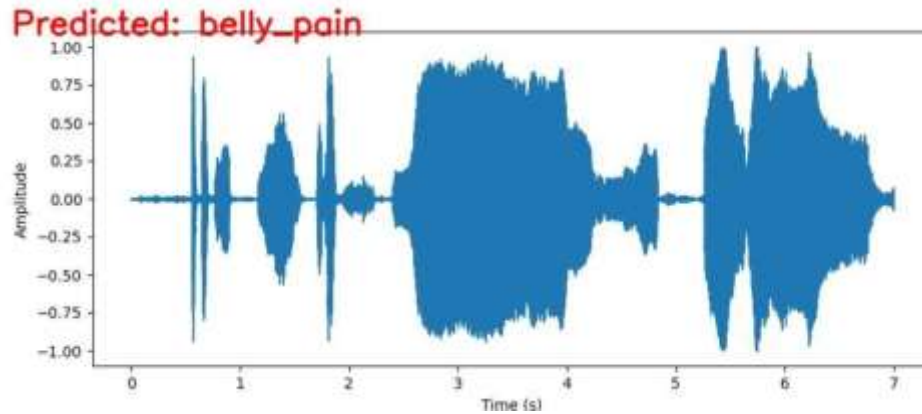


Figure 8. Prediction obtained as belly_pain on sample test sound

The figure 9 presents the time-domain waveform of a neonatal cry that has been classified as hungry by the cry analysis system. The x-axis indicates time in seconds while the y-axis shows the amplitude, representing the strength of the sound signal. The waveform displays repeated cry bursts with moderate amplitude and short pauses between them, forming a rhythmic and patterned structure that is commonly associated with hunger-related crying.

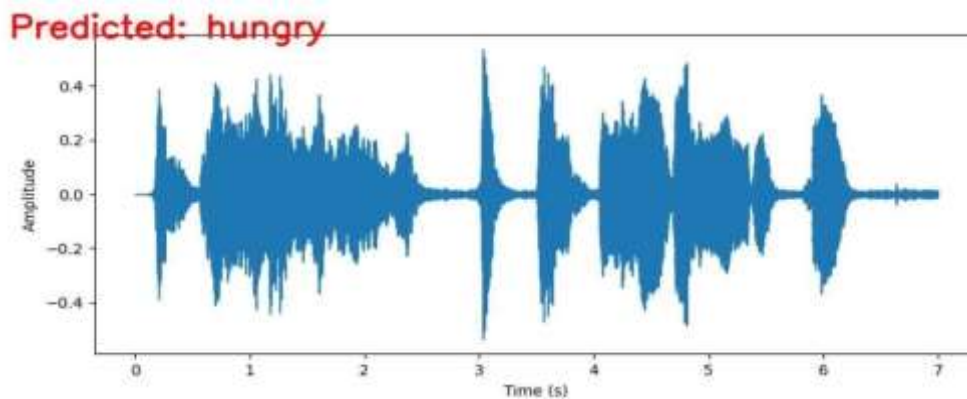


Figure 9. Predicted Infant Cry Signal Corresponding to Hungry State

5. CONCLUSION

The baby cry classification system effectively demonstrates the integration of audio signal processing, feature extraction, traditional machine learning, and deep learning techniques to identify different types of baby cries. By preprocessing raw audio data, extracting MFCC features, and training both classical ML models and a 1D CNN, the system achieves accurate classification of cry categories such as hunger, pain, sleepy, and discomfort. The use of a GUI ensures ease of use, allowing users to handle datasets, perform training, evaluate models, and predict new audio samples without technical expertise. Performance evaluation through metrics like accuracy, precision, recall, F1-score, confusion matrices, and ROC curves confirms the system's robustness, reliability, and effectiveness in distinguishing nuanced audio patterns in infant cries. The framework provides a comprehensive pipeline from audio acquisition to real-time predictions, highlighting the advantages of combining traditional and deep learning approaches in audio classification tasks.

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