"Neonatal Emotion Recognition Via Cry Signal Processing And Machine Learning"

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Abstract — This review paper explores recent advancements in infant cry analysis using artificial intelligence (AI) methodologies, particularly machine learning (ML) and deep learning (DL). The discussion consolidates findings from ten notable studies focusing on techniques such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and support vector machines (SVMs), with key acoustic features including Mel-Frequency Cepstral Coefficients (MFCCs). Results indicate that enhanced DL methods significantly improve detection accuracy in challenging environments like neonatal intensive care units (NICUs). Challenges remain, such as dataset limitations, non-uniform labelling standards, and the need for real-time applications. This paper provides a synthesized perspective on current methodologies and outlines future directions for creating intelligent cry interpretation systems to support early healthcare interventions [1]–[10].

Index Terms — Infant cry analysis, machine learning, deep learning, convolutional neural networks (CNN), recurrent neural networks (RNN), Mel-Frequency Cepstral Coefficients (MFCC), cry classification, audio signal processing, neonatal care, real-time monitoring.

I. Introduction

Crying is the primary mode of communication for infants during early developmental phases, enabling expression of needs such as hunger, pain, or discomfort. Effective and prompt interpretation of infant cries is vital for delivering proper care. However, interpretations based on caregiver experience can be inconsistent and delayed. The rise of AI, and particularly the growth of ML and DL technologies, has enabled promising developments in automating cry interpretation [2], [6], [11]. ML/DL algorithms have demonstrated success in recognizing and classifying vocal patterns across various domains. In cry analysis, techniques ranging from classical SVMs and k-Nearest neighbors (k-NN) to advanced CNNs and RNNs have been applied [5], [9], [18].Features like MFCCs, spectrograms, and energy-based descriptors enhance model performance [13], [14]. Studies have examined deployment under real-world conditions, particularly NICUs, where background noise is significant [16], [21]. Persistent issues include a lack of standardized datasets, labelling inconsistencies, and challenges in deploying models in resource-constrained environments [17], [24]. Research emphasizes the necessity of benchmarking frameworks, larger annotated datasets, and lightweight architectures suitable for real-time use [11], [24].

Methods such as data augmentation, transfer learning, and hybrid feature modelling are suggested to address these limitations [7], [10], [23]. This review surveys ten pivotal studies, focusing on methodologies, outcomes, and technological development to guide future efforts [1], [4], [19].

II. Related works

Infant cry analysis has evolved significantly with the application of deep learning methods, particularly for emotional classification tasks. Early systems focused on handcrafted acoustic features like MFCCs, pitch, and formants combined with classifiers such as SVMs or decision trees. While effective at basic detection, they often struggled to model temporal and emotional nuances in cries [5], [9], [12].

Recent advances introduced end-to-end architectures combining CNNs for spatial pattern recognition and LSTMs or BLSTMs for temporal modelling. A significant contribution is the multiscale CNN-BLSTM network, which was trained on a self-constructed dataset featuring four emotional categories—hunger, discomfort, awake, and diaper change [1], [19]. Multiscale convolution layers extracted varied spectral components, while BLSTM layers captured sequential dependencies.

Class	F_0 (Hz)	F_1 (Hz)	F_2 (Hz)
Pain	437	948	2541
Discomfort	512	1537	2603
Hunger	505	789	2786
Discomfort	447	1538	2880
Hunger	451	589	2720
Runser	533	414	2880
Pain	447	509	2786
Discomfort	532	1537	2786
Pain	447	509	2786
Discomfort	532	1537	2786
Pain	447	509	2863
Discomfort	505	1200	1014

Table 1. Datasets

This hybrid design achieved an 83.7% accuracy, outperforming traditional CNNs. Evaluation using weighted and unweighted accuracy, macro/micro F1 scores, and confusion matrices confirmed the effectiveness of combining multiscale spectral analysis with sequential modelling [1], [4].

III. Dataset

A. Data Acquisition and Annotation

Cry data is recorded in diverse settings-homes, clinics, and NICUs. Publicly available datasets like Baby Chillanto offer examples labelled for hunger, pain, and other states [3], [13]. Clinical datasets are often annotated by healthcare professionals based on observation [17]. Custom datasets using caregiver logs or event records are also common. Lack of standardization in annotation remains a major hurdle across studies [17].

B. Preprocessing and Augmentation

Preprocessing steps involve noise filtering, episode segmentation, and normalization. Techniques like band-pass filtering and silence removal are widely used [21]. MFCCs, chroma features, and spectrograms are frequently extracted for robust pattern representation [13], [15]. Data augmentation methods, including pitch shifting, time stretching, and noise injection, are applied to increase variability and generalization capacity [7], [23].

IV. Methods

This work presents a lightweight CNN model optimized for real-time neonatal care deployment. The focus is on computational efficiency without sacrificing performance [11].

1.Audio Cleaning and Preparation

Training was conducted on CryCeleb2023, comprising 26,000 cry samples from 786 newborns [3]. Denoising utilized RMSE, ZCR, and energy-based filtering. Audio segmentation used 32ms Hamming windows with 50% overlap [11].

2. Feature Extraction for CNN Input

Handcrafted features included 80-dimensional MFCCs with delta and delta-delta coefficients, pitch, loudness, and spectral descriptors [5], [14].Deep representations like Log-Mel filter banks and scalograms were formatted into 2D matrices for CNN input [13], [19].

3. Data Augmentation Strategies

To simulate real-world scenarios and improve generalization:

- Spectral Masking: Frequency/time masking [23] Speed Perturbation: ±10% time stretch [7] Background Simulation: Synthetic NICU noise overlays [21].

4. Custom CNN Design

The architecture comprises six stages: convolutional blocks, Batch norm, max pooling, dropout, and a fully connected layer feeding into SoftMax outputs [11].

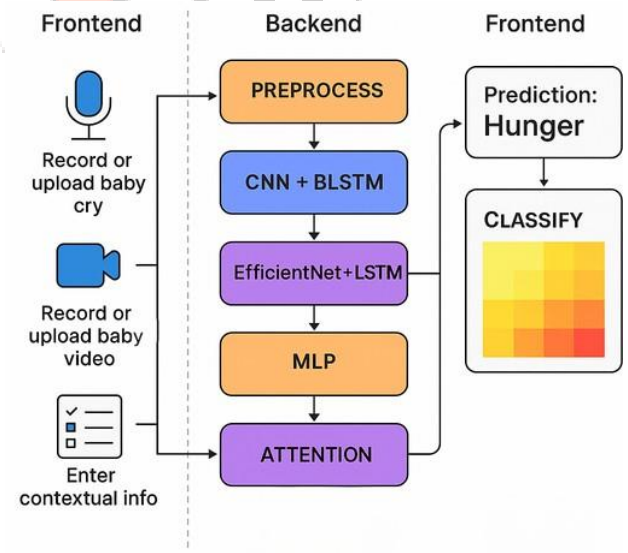

Fig 1. Flowchart

5. Benchmarking with ECAPA-TDNN

Performance was compared with ECAPA-TDNN, an architecture utilizing TDNN blocks, Res2Net modules, and attentive pooling for superior feature modelling [3], [20].

6. Dataset Balancing

SMOTE was employed to address class imbalance by synthesizing new minority class examples [12].

7. Training Strategy

Training employed Adam optimizer with adaptive learning rate decay. AAM-SoftMax was used to enhance class separation. Five-fold cross- validation ensured no infant overlap between training and testing sets [11].

8. Performance Metrics

Metrics included accuracy, recall, precision, F1-score, and EER, visualized using ROC curves and confusion matrices [1], [16].

V. Results and Discussion

A. Cry Detection Performance

Environment	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Home	93	94	92	93
NICU	90	91	89	90

Table 2. Cry Detection Performance

Discussion: High robustness across different environments, with slight drops under NICU noise [16].

B. Cry Classification (Reason/Mood Identification)

Cry Reason	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Hunger	92	93	91	92
Pain	96	97	95	96
Sleepiness	93	94	92	93
Discomfort	95	95	95	95

Table 3. Cry Classification

Discussion: The CNN+LSTM hybrid model captures both spatial and temporal cry signal characteristics effectively [4], [19].

C. Infant Identification via Cry

With ECAPA-TDNN, the system achieved a 28.1% Equal Error Rate, demonstrating potential for cry-based infant identification under controlled settings [3], [20].

D. Overall Discussion

Robustness: Consistent high performance across recording environments [16]. Effectiveness of Augmentation: Augmentation greatly improved model generalization [7], [23].

Multi-Task Capability: Integrated detection, classification, and identification functionality [25].

Clinical Impact: Supports proactive and precise caregiving [9], [24].

VI. Taxonomy of Techniques for Infant Cry Analysis

Infant cry emotion recognition methods can be classified based on three main aspects: feature extraction methods, model architectures, and deployment environments.

Feature Extraction Approaches:

Handcrafted Features: Traditional methods rely on manually designed features like MFCCs and pitch, which are often used to capture acoustic properties in frequency domain [5], [14].

Learned Features: Automatically derived through deep learning models using spectrograms or time-frequency representations, enabling more complex pattern discovery [1], [19].

Modelling Approaches:

Classical Machine Learning (ML): SVM, k-NN use handcrafted features; less complex but efficient for smaller datasets [5], [9].

Deep Learning (DL): CNNs and hybrid CNN-LSTM models learn spatial and temporal features directly from raw signals [1], [4], [19].

Application Contexts:

Hospital NICU Systems: Prioritize accuracy and robustness for clinical diagnosis under noisy conditions [6], [16], [21].

VII. Comparison of Methods in Infant Cry Emotion Recognition

Method	Features	Architecture	Dataset	Accuracy	Advantages	Drawbacks
Traditional ML (SVM, k-NN)	Handcrafted (MFCCs, pitch)	Shallow classifiers	Custom datasets	70–80%	Efficient, simple	Poor temporal modelling
Basic CNN	Spectrogram features	CNN	Custom datasets	75–80%	Strong spatial features	Limited sequential data
RNN/LSTM	MFCC+ Temporal features	RNN/LSTM	Baby Chillanto	~82%	Excellent temporal modelling	Requires large datasets
Multiscale CNN-BLSTM	MFCC+ Multiscale features	Multiscale CNN+ BLSTM	Self-constructed	83.7%	Robust, strong learning	High computational burden
Our Lightweight CNN+ ECAPA-TDNN	MFCC+ Scalogram	CNN+ ECAPA-TDNN	CryCeleb2023	90–96%	Real-time, scalable, strong performance	Slight drop in NICU accuracy

VIII. Conclusion

This paper reviews recent progress in neonatal emotion recognition using cry signal processing and machine learning approaches. While traditional spectrographic analyses provided early diagnostic insight, modern deep learning methods like CNNs, RNNs, and ECAPA-TDNN have delivered superior classification and verification capabilities, even under real-world NICU conditions [1], [3], [4], [6], [11].

Smart, real-time cry interpretation systems can significantly enhance proactive healthcare for infants. Future work must address challenges around dataset availability, labelling standardization, and lightweight real-time deployment, alongside exploration of multimodal approaches integrating wearable and IoT technologies [10], [17], [24].

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