AUTOMATED SYSTEM FOR CRY ANALYSIS AND PAIN ASSESSMENT IN NEONATES AND INFANTS

Sana Khan[1], Dr. Shubhangi Neware[2]

Article History: Received: 05.02.2023 **Revised:** 20.03.2023 **Accepted:** 05.05.2023

Abstract

Cry analysis and pain assessment in neonates and infants is a crucial aspect of paediatric healthcare. Pain in neonates and infants is often underdiagnosed and undertreated, which can lead to long-term negative consequences on their health and development. Traditional pain assessment methods, such as behavioural observation scales, have limitations in accuracy and reliability. Cry analysis has emerged as a promising non-invasive method for pain assessment in neonates and infants. Machine learning techniques have been applied to cry analysis for pain assessment, which has shown great potential in improving the accuracy and reliability of pain assessment. This research has significant implications for improving the quality of care provided to neonates and infants. A reliable and comprehensive automated system for pain assessment can help healthcare professionals make informed decisions about pain management strategies, leading to improved outcomes for these vulnerable populations.

Keywords: Cry analysis, Pain assessment, automated pain assessment, Neonatal pain assessment

[1]Student, Shri Ramdeobaba College of Engineering and Management, Nagpur
[2]Assistant Professor, Shri Ramdeobaba College of Engineering and Management, Nagpur

Email: [1]khansa4@rknec.edu, [2]newares@rknec.edu

DOI: 10.31838/ecb/2023.12.s3.498

1. Introduction

A promising method for automating pain evaluation in newborns is cry analysis. Through the analysis of neonatal and infant crying signals, this study seeks to provide a comprehensive and trustworthy automated approach for assessing pain in newborns and infants. Cries are the primary form of communication for neonates and infants. Cry is a natural reaction to several conditions, including pain, discomfort, and hunger. Scientific studies have shown that diverse situations, such as pain, hunger, and discomfort, result in different crying patterns [1,2]. Another significant problem is that newborns and infants are unable to express their pain either by talking or non-verbally (via gestures like pointing). This makes it challenging for new parents and care givers to determine why a child is crying. Correctly addressing the cause of an infant's crying is essential and a significant concern for new parents and guardians. Numerous scientific studies have demonstrated the link between early life pain exposure and a variety of short and long-term effects, including elevated heart rate, oxidative stress, and a number of long-term effects like IQ decline and neurodevelopmental impairment. The suggested approach will examine neonatal and neonatal demands such as pain, hunger, and discomfort to determine the cause of crying.

Due to its ability to detect multiple conditions in newborns, such as pain, discomfort, and hunger, cry analysis has been the focus of substantial research in recent years. Cry analysis consists of analysing the sound, frequency, and intensity of infant crying signals, and correlating them with physiological and behavioural changes. One significant benefit of cry analysis is its non-invasive nature, which makes it the ideal choice for neonatal and infant pain assessment.

Cry analysis involves the quantitative measurement of acoustic features of infant cries, such as pitch, duration, and intensity. These features can be used to differentiate between different types of cries, including those associated with pain. Machine learning algorithms can be trained on datasets of cry recordings to identify patterns that are associated with pain. These algorithms can then be used to classify new cry recordings as either indicative or non-indicative of pain.

Future carer robots will be more sophisticated as a result of advances in the development of smart technologies that can interpret infant cry. Another crucial job in infant cry research is disease prediction, in addition to comprehending new-borns' daily requirements. Since various disorders have an impact on an infant's vocal tract and respiratory system, unhealthy infants' cry signals have distinctive features that set them apart from fit infants' sounds of cry. Illustration of such illnesses include suffocation, neurological disorder, and deafness, among others. A quick, non-invasive procedure that can prevent baby deaths is the analysis of pathological cry signals to detect diseases, especially in places where there is a shortage of medical resources.

Literature Review

Machine learning algorithms have been used to analyze cry signals and classify them as indicative of pain or non-pain states. These algorithms can be trained on large datasets of cry signals that have been annotated by experts for pain or non-pain states. Features extracted from the cry signal can include spectral features, such as frequency content and harmonics, as well as temporal features, such as duration and amplitude modulation.

Cohen and Lavner employed the K-nearest neighbour algorithm, which categorises every frame as either a cry or not, and then classifies the example as a cry signal if there are more samples of frames are recognised as a cry. [3].

In 2016, Banica et al. classified Dunstan baby cry using the GMM-UBM technique.

A GMM model called the universal background model (UBM) is trained using a lot of generic cry signals without any labelling. The GMM-UBM with MFCC's classification accuracy was 70% on Dunstan baby cries [4] and 50.6% on the SPLANN database [5].

An SVM system was trained using the cry signals of 20 preterm babies who were having a heel lance, a common operation. For pain vs non-pain phases, 85% accuracy was attained [6].

Another research classified cry signals from 50 term new-borns receiving regular vaccinations using a convolutional neural network (CNN). For pain vs non-pain states, the CNN had a 92% accuracy rate [7].Another research classified cry signals from 32 preterm children undergoing common heel lance procedures using a deep belief network (DBN). For states of pain vs non-pain, the DBN's accuracy was 86% [8].

For assessing pain, Zamzmi et al. [9] utilised the technique described in [10]. 18 babies who were recorded at baseline and while undergoing common, unpleasant treatments (such heel lancing) make up the database for this study. The babies were 36 gestational weeks old. Medical experts gathered and categorised all footage. The Motion Images between subsequent video frames were calculated in order to categorise an infant's emotional state as being in pain or not. Then, the Motion Image's pixels were added up to determine how much motion there was in total for each frame. The calculated total motion feature underwent thresholding with an accuracy of 87.5%.

This research show that machine learning algorithms can be used to analyse cries and estimate pain in new-borns and babies, but there are still a number of issues that need to be resolved. The absence of standardisation in cry analysis techniques is a problem that can cause results to vary between investigations. Large annotated datasets are required for machine learning algorithm training and validation, which presents another difficulty.

2. Methodology

Data collection, pre-processing, feature extraction, feature selection, and classification are the five processes that typically make up automated new-born cry study as shown in figure 1. The performance of the final classification accuracy can be enhanced by the discovery of innovative approaches at any point in the process.

Fig. 1 Phases of cry research

Figure 2 shows the different audio features of crying signal. The essential job of infant cry analysis and processing is performed by feature extraction tasks in the temporal or frequency domain. It is easy and simple to compute time domain characteristics, such as zero-crossing rate, amplitude, and energy-based features, etc. Frequency domain features have a significant capacity to represent the properties inside newborn cry signals, however time domain features are not robust enough to capture the changes within infant cry signals and the features are vulnerable to background disturbances. In comparison to employing time domain characteristics, the frequently utilised MFCCs, LPCCs, and LFCCs have demonstrated superior performance.

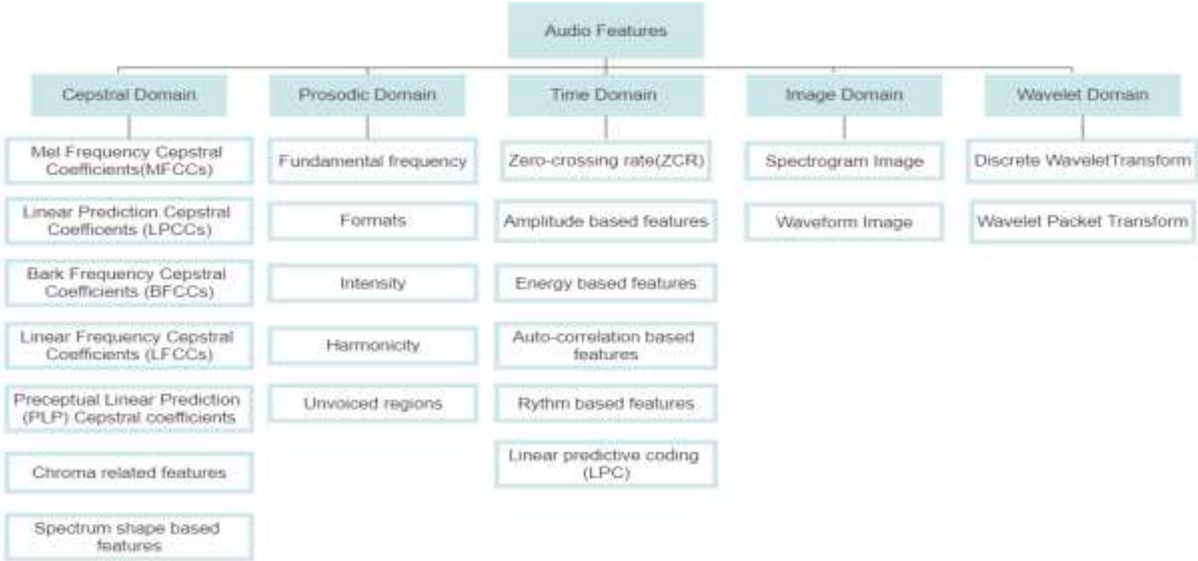


Fig. 2 Different Audio Features

The complete operation of the suggested research is depicted in Figure 3. There will be a loading of a data set with audio data in it. The data set is pre-processed to remove unwanted distortions from the audio, boost some essential characteristics, and prepare it for further analysis of the trained model. The feature extraction stage follows. By removing the features from pre-processed new-born audio and turning it into Mel Spectrograms, feature extraction improves the model's accuracy. The machine learning algorithms are taught to correctly forecast the cause of crying based on this stage.
Based on the training weights, this model is retained for use in future prediction tasks. A classification model is trained in the classification stage to identify different cry- and pain-states-related explanations from the audio sample. It will indicate the likelihood of an audio clip representing one or more of the classes the model was trained on. The system's training phase is based on the theory that it learns from pre-processed data and develops a classification logic based on the category of crying and pain it belongs to. This trained model is recorded and utilised in the section on predictions later. The stored model automatically determines the cause of the crying from the audio provided by the user during the prediction step.

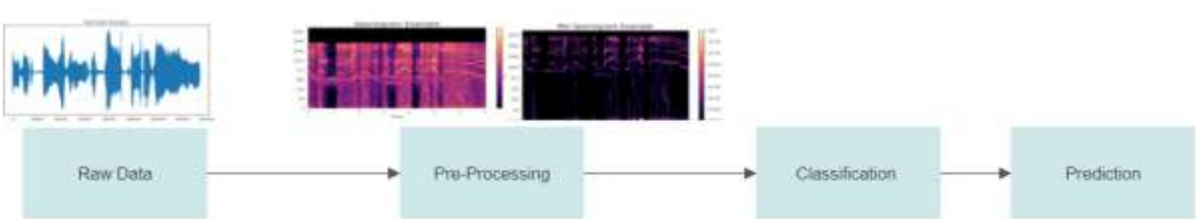


Fig 3 Working

a. Data set

Audio data from Donate a cry corpus is taken for the research. A baby cry audio corpus that was created as a result of the Donate-a-cry initiative. The dataset consists of the input audio files which are in .wav format which are the infant cry sounds. The following data is divided as 70% training set and 30% testing set. A total of five categories are being considered: Hunger, Burp, Pain, Discomfort, Burp and Tiredness.

b. Pre-processing

An audio file containing the unknown baby cry and whose reason is to be classified is uploaded. Unwanted noise and empty audio frames are removed from the input audio file during pre-processing. The characteristics are then extracted from the audio by converting it to cepstral coefficients (in this case, the MFCC approach is employed to get cepstral coefficients). The mean of the coefficients is used for additional processing once the cepstral coefficients have been computed. Figure 2 shows the raw audio sample of hunger cry. The spectrogram and the Mel spectrogram is visualized in python as shown in figure 6 and figure 7.

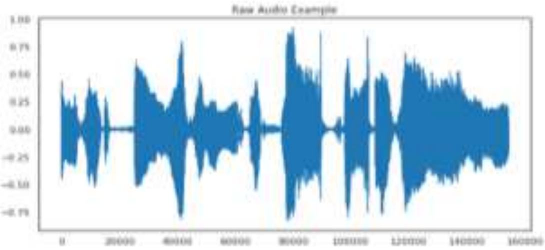


Fig 4: Raw audio sample

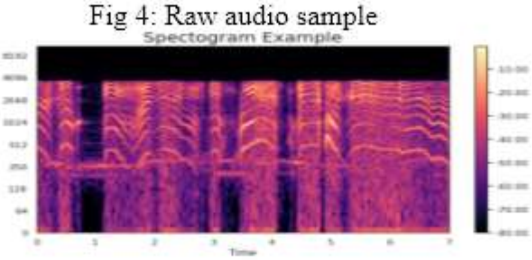


Fig 6: Spectogram

c.
Classification
The data set is split into training set and testing set in 70:30 ratio. In this work, the cry sound signals are recognised using the MFCC characteristics. We extract MFCC characteristics for different crying sound like hunger, pain, discomfort, and burp. Various machine learning algorithms are trained on the training dataset of cry recordings to identify patterns that are associated with a particular cry. The algorithms include K-nearest neighbour, Gaussian Naïve Bayes and Decision Tree, Convolution Neural Network (CNN). These algorithms can then be used to classify new cry recordings into hunger, pain, discomfort,

3. Result And Analysis

a. Performance Matrix

In this work, we used metrics that are established as guiding principles, such as the F1-score (F1), recall rate (RR), and precision rate (PR), and accuracy to evaluate the effectiveness of our techniques.

When the model accurately predicts the positive class, it is said to be a true positive (TP).
When the model accurately predicts the negative class, it is said to be true Negative (TN).
When the model forecasts the positive class inaccurately, it is called a false positive (FP).
When the model forecasts the negative class inaccurately, it is known as a false negative(FN).

(a) Precision Rate (PR) = $\frac{\text{TP}}{\text{TP+FP}}$

(b) Recall Rate (RR) = $\frac{\text{TP}}{\text{TP+FN}}$

(c) F1 score = $\frac{\text{precision}*\text{recall}}{\text{precision+recall}}$

(d) Accuracy = $\frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}$

4.2 Performance Comparison

Table 1 shows comparison of various machine learning algorithms. According to evaluation CNN outperforms the other classifiers for all frame durations in terms of class-wise accuracy. The F1-scores for the CNN, KNN, Naïve Bayes and Decision tree methods for recognising cry sounds for were 94.10%, 88.06%, 82 %, and 80 % respectively.

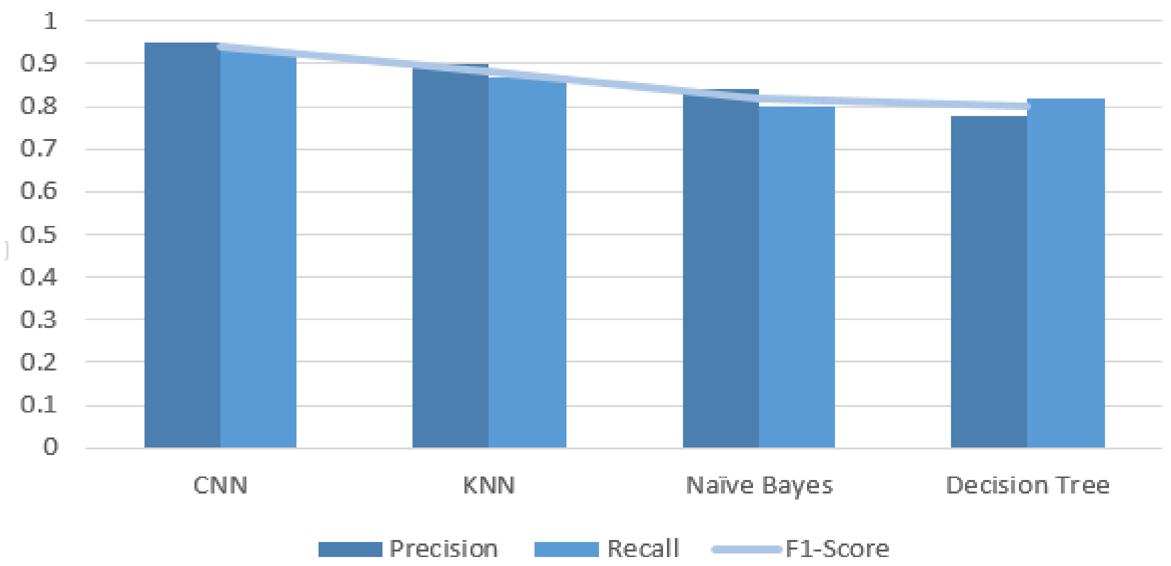
Model	Precision	Recall	F1-Score

CNN	0.95	0.93	0.94
KNN	0.90	0.87	0.88
Naïve Bayes	0.84	0.80	0.82
Decision Tree	0.78	0.82	0.80

Table 1 Comparison of various models

The experimental outcomes of approaches based on deep learning for determining newborn discomfort from noises are encouraging. Figure 7 shows the comparison of overall accuracy obtained from various Machine learning algorithms. CNN with spectrogram images achieved the highest performance (94.10% accuracy). The second highest assessment performance (88% accuracy) was obtained using K-nearest neighbours. Using Naïve Bayes for classifying neonatal and infant cry achieved an accuracy of 82 % while using Decision tree achieved an accuracy of 80.66%.

Fig 4: Result



4. Conclusion

Cry analysis is a promising approach for neonatal pain assessment in infants. The recent advances in machine learning have led to significant improvements in the accuracy of algorithms used in analyzing infant crying signals. Despite the challenges in developing a standard classification scheme for infant crying signals, machine learning algorithms have shown promising results for both neonatal pain assessment and SIDS prevention.

The proposed system for neonatal pain assessment through the analysis of infant crying signals will require further research and validation before widespread adoption in clinical practice. However, it is evident that cry analysis, combined with machine learning, has the potential to revolutionize neonatal care and improve the outcomes of neonates and infants.

5. References

J. J. Parga et al., “Defining and distinguishing infant behavioral states using acoustic cry analysis: is colic painful?” *Pediatric research*, vol. 87, no. 3, 2020.

A. Gorin, C. Subakan, S. Abdoli, J. Wang, S. Latremouille, and C. C. Onu, "Self-supervised learning for infant cry analysis," *in ICASSP Workshop SASB. IEEE*, 2023.

R. Cohen, Y. Lavner, "Infant cry analysis and detection*", IEEE 27th Convention of Electrical and Electronics Engineers in Israel*, (2012), 1–5.

I. A. Banica, H. Cucu, A. Buzo, D. Burileanu, C. Burileanu, "Automatic methods for infant cry classification", *International Conference on Communications (COMM),* (2016), 51–54

I. A. Banica, H. Cucu, A. Buzo, D. Burileanu, C. Burileanu, "Baby cry recognition in real-world *conditions", in 39th International Conference on Telecommunications and Signal Processing, TSP 2016*, (2016), 315–318.

Valente, M., Slevin, M., & Krishnan, R. (2018). "Machine learning for infant cry classification." *IEEE Reviews in Biomedical Engineering*, 11, 219-234.

Basu, S., Kumar, A., Kumar, A., & Mahajan, P. (2020). "Convolutional neural network-based pain detection in infant cries", *Journal of Medical Systems*, 44(6), 118.

Li, X., Zhang, Y., Huang, D., & Xu, W. (2019). "Deep belief network-based pain recognition from infant facial expression and cry signals", *International Journal of Neural Systems*, 29(7), 1950007.

G. Zamzmi, C.-Y. Pai, D. Goldgof, R. Kasturi, Y. Sun, and T. Ashmeade, "Automated Pain Assessment in Neonates", *20th Scandinavian Conference in Image Analysis (SCIA 2017)*, 2017, pp. 350–361.

Salekin, M.S., Zamzmi, G., Paul, R., Goldgof, D., Kasturi, R., Ho, T., Sun, Y., 2019b. "Harnessing the power of deep learning methods in healthcare: Neonatal pain assessment from crying sound", in: 2019 *IEEE Healthcare Innovations and Point of Care Technologies, (HIPOCT), IEEE*. pp. 127–130. doi:10.1109/HIPOCT45284.2019.8962827.

S. Brahnam, C.-F. Chuang, F. Y. Shih, and M. R. Slack, "Machine recognition and representation of neonatal facial displays of acute pain," *Artificial Intelligence in Medicine*, vol. 36, no. 3, pp. 211 – 222, 2006.

B. Gholami, W. M. Haddad, and A. R. Tannenbaum, "Relevance vector machine learning for neonate pain intensity assessment using digital imaging," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 6, pp. 1457–1466, June 2010

D. Ververidis and C. Kotropoulos, "Fast and accurate sequential floating forward feature selection with the bayes classifier applied to speech emotion recognition," *Signal Processing*, vol. 88, no. 12, pp. 2956 – 2970, 2008.

L. Adde, J. L. Helbostad, A. R. Jensenius, G. Taraldsen, and R. Sten, "Using computer-based video analysis in the study of fidgety movements," *Early Human Development*, vol. 85, no. 9, pp. 541 – 547, 2009

Gan, T.J., 2017. Poorly controlled postoperative pain: prevalence, consequences, and prevention. Journal of pain research 10, 2287. doi:10.2147/JPR.S144066.

Hudson-Barr, D., Capper-Michel, B., Lambert, S., Palermo, T.M., Morbeto, K., Lombardo, S., 2002. "Validation of the pain assessment in neonates (pain) scale with the neonatal infant pain scale (nips)". *Neonatal Network* 21, 15–22. doi:10.1891/0730-0832.21.6.15

M. Ranger, C. C. Johnston, and K. Anand, "Current controversies regarding pain assessment in neonates," in *Seminars in perinatology*, vol. 31, no. 5. Elsevier, 2007, pp. 283–288.