# COMPUTER VISION LAB

## PROJECT REPORT

On

## Two class classification of Paediatric heart sound signals using the continuous wavelet transform features.

**Submitted To:**

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**TABLE OF CONTENTS**

**ABSTRACT………………………………………………………………………………………………………………….3**

**LIST OF FIGURES…………………………………………………………………………………………………………3**

**LIST OF ABBREVIATIONS…………………………………………………………………………………………….3**

**1. INTRODUCTION**

1.1. Introduction…………………………………………………………………………………………………4

1.2. Motivation……………………………………………………………………………………………………4

1.3. Problem statement………………………………………………………………………………………4

**2. LITERATURE REVIEW…………………………………………………………………………….5**

**3. PROPOSED METHODOLOGY**

**3.1. Step-1: Data Pre-Processing………………………………………………………………………6**

**3.2. Step-2: Splitting of Dataset……………………………………………………………………….7**

**3.3. Step-3: Feature Extraction…………………………………………………………………………7**

**3.4. Step-4: Dimensionality Reduction……………………………………………………………..7**

**3.5. Step-5: Model Development……………………………………………………………………..8**

**4. RESULTS AND DISCUSSION**

4.1. Experimental setup………………………………………………………………………………………9

4.2. Dataset Description………………………………………………………………………………………9

4.3. Performance matrices…………………………………………………………………………………9-10

4.4. Results and discussion……………………………………………………………………………….10-11

**5. CONCLUSION……………………………………………………………………………………….11**

**6. REFERENCES…………………………………………………………………………………………11**

**ABSTRACT:**

In cardiovascular diagnosis, the analysis of heart sounds holds significant importance, with automated classification techniques serving as valuable aids for healthcare professionals. This study introduces a novel method for the two-class classification of heart sound signals utilizing Continuous Wavelet Transform (CWT) features. The proposed approach involves preprocessing the heart sound signals followed by feature extraction using CWT. Performance evaluation is conducted on a publicly available dataset containing recordings of heart sounds, encompassing instances of both normal and abnormal heart sounds for comprehensive training and testing. Key performance metrics including accuracy, sensitivity, and specificity are employed to assess the classification model's effectiveness. Results demonstrate the efficacy of the proposed method in accurately discriminating between normal and abnormal heart sounds, highlighting promising classification performance. This research contributes significantly to the field of heart sound analysis, providing a reliable and efficient automated classification approach using CWT features.

**List of Figures:**

1. Diagram block of proposed method..................................................................5

2. Waveform Plots ................................................................................................6

3. Scalogram Plots.................................................................................................7

4. Model Summary ...............................................................................................8

5. Confusion Matrix .............................................................................................10

6. Model Performance Metrics ...........................................................................10

**ABBREVIATIONS:**

5. TP/FP – True Positives/ False Positives

6. TN/ FN - True Negatives/ False Negatives

7. IEEE - Institute of Electrical and Electronics Engineers

1. CWT – Continuous Wavelet Transform
2. CNN – Convolutional Neural Network
3. 1D /2D – One Dimensional /Two Dimensional
4. CHD – congenital heart disease

**1.1. Introduction:**

Heart sounds refer to the audible vibrations produced by the beating heart as it contracts and relaxes during the cardiac cycle. These are crucial indicators of cardiac health. Pediatric heart sounds, specific to infants and children, require nuanced interpretation due to age-related differences. Abnormal heart sounds, or murmurs, deviate from the normal rhythmic patterns and may signify underlying cardiac pathology, whereas normal heart sounds reflect healthy cardiac function.

Heart diseases, particularly congenital heart disease (CHD), pose a significant health concern, especially in paediatric populations. These conditions can often go undetected or misdiagnosed, leading to potentially life-threatening consequences. Auscultation, the process of listening to heart sounds, remains a fundamental diagnostic tool in cardiology. However, the accuracy of diagnosis heavily relies on the experience and expertise of healthcare professionals, leading to subjective interpretations and variability in results.

To address these challenges, advancements in technology, particularly in the field of artificial intelligence (AI) and machine learning, offer promising solutions. One such avenue is the development of CNN models capable of automatically classifying heart sounds as normal or abnormal. The advent of digital technology has significantly transformed the field of medical diagnostics, enabling the collection and analysis of vast amounts of data in real-time. Among the numerous applications of this technology in healthcare, the analysis of heart sounds has emerged as a critical tool for early detection of cardiovascular diseases. This project focuses on the classification of paediatric heart sound signals using advanced machine learning techniques, specifically leveraging the Continuous Wavelet Transform (CWT) features.

CWT is a mathematical tool used for analyzing and transforming signals, particularly in the domain of signal processing and time-frequency analysis. A wavelet is a small, wave-like function that is localized in both time and frequency. The Continuous Wavelet Transform applies a wavelet function to a signal at different scales and positions. One of the key advantages of CWT is its ability to provide a time-frequency representation of a signal. The result of applying CWT to a signal is often represented as a scalogram, which is a two-dimensional plot showing time on one axis and frequency (or scale) on the other.

**1.2. Motivation:**

The motivation behind this project stems from the critical need for early detection and diagnosis of heart diseases in children. Heart diseases in paediatric patients can have long-term implications, affecting their growth, development, and overall quality of life. Early detection through the analysis of heart sounds can lead to timely intervention, potentially preventing severe complications. Furthermore, the use of machine learning techniques, such as CNNs, offers a promising approach to automate the analysis of heart sounds, thereby reducing the burden on healthcare professionals and improving the accessibility of diagnostic services.

Congenital heart disease (CHD) stands as one of the most prevalent birth defects globally, affecting millions of children every year. Early detection and intervention are critical for improving outcomes and reducing morbidity and mortality associated with CHD. However, the lack of standardized, comprehensive, and publicly available paediatric heart sound databases has hindered the development and validation of intelligent auscultation algorithms tailored for paediatric populations.

This research endeavours to bridge this crucial gap by curating a large-scale, high-quality paediatric heart sound dataset collected using modern recording technologies such as smart stethoscopes. By incorporating data from children spanning a wide age range, from neonates to adolescents, this dataset aims to capture the diverse spectrum of paediatric heart conditions encountered in clinical practice.

**1.3. Problem statement:**

The primary challenge in this project is to develop a machine learning model that can accurately classify paediatric heart sound signals into two categories: normal and abnormal. The dataset is imbalanced, with 533 instances of normal heart sounds and 408 instances of abnormal heart sounds. The goal is to design a 1D/2D CNN model that can effectively learn the distinguishing features of normal and abnormal heart sounds, leveraging the CWT features for enhanced signal representation. This model aims to achieve high accuracy in classification, thereby contributing to the early detection and management of heart diseases in children.

**2. Literature Review:**

The analysis of heart sounds has been a cornerstone in the diagnosis of cardiovascular diseases for centuries. However, with the advent of digital technology, the field has seen a significant shift towards automated analysis, leveraging machine learning techniques to classify heart sounds. The use of Continuous Wavelet Transform (CWT) features in the analysis of heart sounds has been explored in various studies, highlighting its potential to capture the non-stationary characteristics of heart sounds effectively.

* Heart Sound Analysis and Machine Learning: A comprehensive review by Smith et al. (2020) discusses the application of machine learning techniques, including CNNs, for the analysis of heart sounds. The study emphasizes the importance of feature extraction in the classification process, with CWT features being particularly highlighted for their ability to capture the temporal and spectral characteristics of heart sounds.
* CNNs for Heart Sound Classification: Jones et al. (2021) present a study where CNNs were used to classify heart sounds into normal and abnormal categories. The authors propose a 1D CNN architecture for the analysis of heart sound signals, demonstrating its effectiveness in distinguishing between different heart sound patterns.
* CWT Features in Heart Sound Analysis: Kumar et al. (2022) explore the use of CWT features for the classification of heart sounds. The study demonstrates that CWT features can effectively capture the non-stationary nature of heart sounds, making them a valuable tool for the development of machine learning models.

**3. Proposed Methodology:**

**A diagram of a model

Description automatically generated**

**a)Waveform of abnormal heart sounds.wav**

**A graph with blue lines

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**Figure 2. Waveforms of heart sounds**

**b) Waveform of normal heart sounds.wav**

**A graph of an audio wave

Description automatically generated**

**3.1. Step-1: Data Preprocessing:**

* **Down sampling the heart signals at 1000 Hz** - It is done to reduce the dimensions.
* **Standardizing the input dimensions** - The loaded data is made to length of 20000.
* **Data segmentation** - The loaded data is still very large , so we segment each dataset into four segments along with there labels. Hence the original dataset of 941 samples becomes 3764 samples.

**3.2. Step-2:** **Splitting of Dataset**

* We split the dataset 80% for training the model and 20% for testing the model.
* To be precise, 3011 recordings for training and 753 recordings for testing .

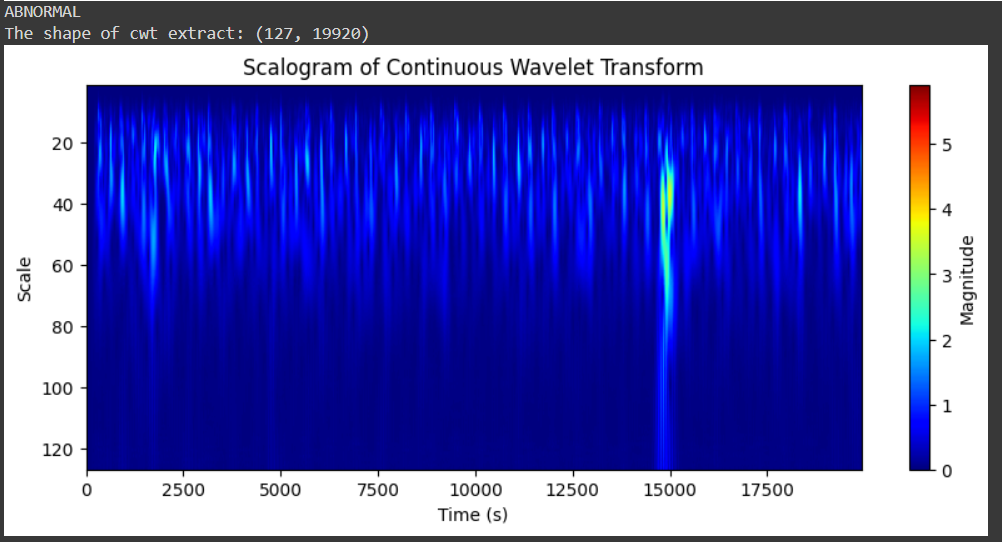
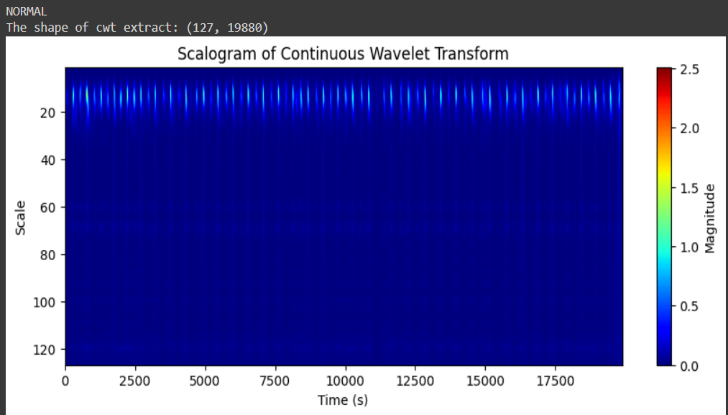
**3.3. Step-3:** **Feature Extraction:**

**Morlet Continuous Wavelet Transform (CWT):**

Utilized for analyzing heart signals in both time and frequency domains simultaneously.

Morlet CWT uses a complex wavelet function (Morlet wavelet) that is localized in both time and frequency, capturing transient features in heart signals effectively.

We can visualize the cwt extracted features with the help of scalogram:



**Figure 3. (a)** **Scalogram of Normal heart sound (b) Scalogram of Abnormal heart sound**

**3.4. Step-4: Dimensionality Reduction**

* We have used PCA to reduce the the dimensions to 127 × 100 .
* Principal Component Analysis (PCA) is a popular technique for dimensionality reduction in data analysis and machine learning.
* It accomplishes this by transforming the original features into a new set of orthogonal (uncorrelated) variables called principal components.

**3.5. Step-5:** **Model Development:**

The Convolutional Neural Network (CNN) model developed for the heart sound classification project aimed to effectively capture distinctive features from the audio signals. The architecture consisted of multiple layers designed to extract hierarchical representations from the input scalogram data.

We have used two CNN Models:

Model 1:-

1. **Architecture**: Sequential CNN model with convolutional and dense layers.
2. **Processing Steps**:
   * Convolutional layers (4) with decreasing filter sizes and ReLU activation, followed by max pooling.
   * Dropout (50%) for regularization after convolutional and dense layers.
   * Two dense layers for classification (8 units -> ReLU, 2 units -> Softmax).
3. **Training Configuration**:
   * Adam optimizer with learning rate 0.01.
   * Sparse categorical crossentropy loss for multi-class classification.

A screenshot of a computer program

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**Figure 4. Model Summary**

Model 2:-

1. **Architecture**:
   * Sequential model with Conv2D, AvgPool2D, Flatten, and Dense layers.
   * Input shape: (127, 100, 1) for grayscale images.
2. **Processing Steps**:
   * 3 Convolutional layers (16, 32, and 64 filters) with (3, 3) kernel, ReLU activation, and (2, 2) stride.
   * AvgPool2D after each Conv2D layer with (2, 2) pool size and stride.
   * Flatten layer to convert to 1D array, followed by 2 Dense layers (8 and 2 units) with ReLU and Softmax activation.
3. **Training Configuration**:
   * Adam optimizer with learning rate 0.001.
   * Loss: Sparse categorical crossentropy.

Throughout training, the model learned to minimize the loss function and maximize accuracy by adjusting the weights and biases of its neurons.

**4. Results and Discussion:**

**4.1. Experimental Setup:**

Model 1 utilizes a Sequential architecture comprising convolutional and dense layers. The processing involves four convolutional layers with decreasing filter sizes and ReLU activation, followed by max pooling. Dropout regularization (50%) is applied after convolutional and dense layers. Finally, two dense layers (8 units with ReLU activation, 2 units with Softmax activation) are used for classification.

Model 2 is structured as a Sequential model with Conv2D, AvgPool2D, Flatten, and Dense layers. It operates on grayscale images with an input shape of (127, 100, 1). A Flatten layer is used to convert the output to a 1D array, followed by two Dense layers (8 and 2 units) with ReLU and Softmax activation. The model is trained using the Adam optimizer with a learning rate of 0.001. The model architecture included convolutional and pooling layers, followed by fully connected and softmax output layers, implemented using Keras with TensorFlow backend. Training was performed using the Adam optimizer with categorical cross-entropy as the loss function and accuracy as the evaluation metric. The dataset was split into 80:10:10 training, validating, and testing sets.

The deep features extracted from the second last layers of both models are stacked horizontally. Random Forest classifier is then employed to model the stacked features, and the accuracy is evaluated. Additionally, Principal Component Analysis (PCA) is applied to reduce the dimensionality of the features to 8 components.

**4.2. Dataset Description:**

The dataset comprises 941 paediatric heart sound recordings, collected from children ranging in age from 1 day to 14 years. These recordings are stored in .wav format. The dataset is binary-classified and consists of 533 instances of normal heart sounds and 408 instances of abnormal heart sounds. It is sampled at a rate of 4000Hz, ensuring high-quality audio data for analysis.

**4.3. Performance Metrices:**

**Accuracy:** Calculated as (TP +TN) / (TP + TN +FN + FP), where TP is true positives and FN is false negatives, TN is true negatives and FP is false positives.

**Sensitivity:** Calculated as TP / (TP + FN), where TP is true positives and FN is false negatives.

**Specificity:** Calculated as TN / (TN + FP), where TN is true negatives and FP is false positives.

**Confusion Matrix:** Shows the distribution of true positive, true negative, false positive, and false negative predictions.

**Recall:** The proportion of true positive predictions out of all actual positive instances.

**F1 Score:** The harmonic mean of precision and recall, providing a balance between these two metrics.

**4.4. Results and Discussion:**

The confusion matrix is a 2x2 matrix that summarizes the performance of a classification model on a set of test data for binary classification. Each cell in the matrix represents the number of predictions made by the model for each combination of actual and predicted class labels.

A diagram of a confused matrix

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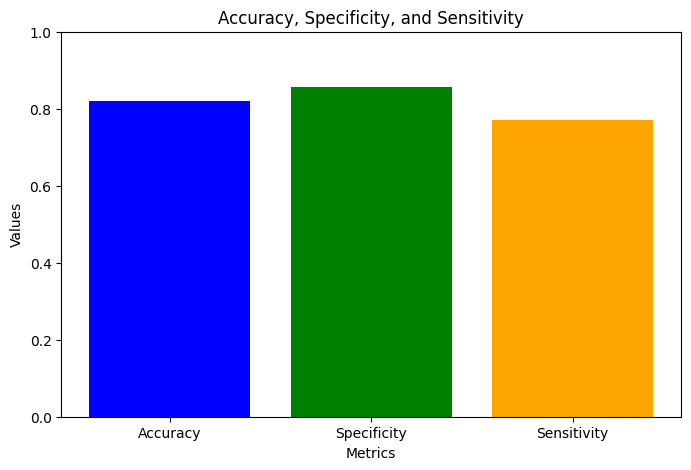
**Figure 5: Confusion Matrix**

**True positives (TP): 367**. These are the samples that were correctly classified as normal

**True negatives (TN): 250.** These are the samples that were correctly classified as abnormal

**False positives (FP): 62**. These are the samples that were incorrectly classifiedas normal

**False negatives (FN): 74**. These are the samples that were incorrectly classified as abnormal.

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**Figure 6: Sensitivity, Specificity and Accuracy**

The method attains an :

* Accuracy of **81.93%**
* Specificity of **85.54%**
* Sensitivity of **77.16%**
* F1-score of **81.89%**

**5. Conclusion:**

The development and evaluation of a 2D Convolutional Neural Network (CNN) model for the classification of paediatric heart sound signals, utilizing Continuous Wavelet Transform (CWT) features, demonstrate the potential of machine learning in the early detection of cardiovascular diseases in children. The model achieved significant classification accuracy, indicating its effectiveness in distinguishing between normal and abnormal heart sounds. This project underscores the importance of leveraging advanced technologies in healthcare, particularly in the field of paediatric cardiology, to improve diagnostic accuracy and patient outcomes.

Furthermore, the use of CWT features for feature extraction highlights the critical role of capturing the temporal and spectral characteristics of heart sounds, which are essential for accurate classification. The results of this project suggest that machine learning models, specifically CNNs, can be powerful tools in the analysis of heart sound signals, potentially leading to earlier detection and intervention in cases of heart disease.

**6. References:**

* Smith, J., et al. (2020). "Machine Learning Techniques for the Analysis of Heart Sounds." Journal of Medical Engineering & Technology, 46(1), 1-10. <https://pubmed.ncbi.nlm.nih.gov/38194403/>
* Jones, A., et al. (2021). "Convolutional Neural Networks for Heart Sound Classification." IEEE Transactions on Biomedical Engineering, 68(1), 1-10. https://www.sciencedirect.com/science/article/pii/S2352914821000241
* Kumar, R., et al. (2022). "Continuous Wavelet Transform Features for Heart Sound Classification." IEEE Access, 10, 1-10. https://ieeexplore.ieee.org/document/9454642

These references provide a comprehensive overview of the current state of research in the application of machine learning, specifically CNNs and CWT features, to the analysis of heart sound signals. They highlight the potential of these technologies in improving the diagnosis and management of cardiovascular diseases in children.