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Lung Sound Based Disease Detection with Deep Learning Technique

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Abstract: *In recent times, technologies such as machine learning and deep learning have played a vital role in providing assistive solutions to a medical domain's challenges. They also improve predictive accuracy for early and timely disease detection using medical imaging and audio analysis. Due to the scarcity of trained human resources, medical practitioners are welcoming such technology assistance as it provides a helping hand to them in coping with more patients. Apart from critical health diseases such as cancer and diabetes, the impact of respiratory diseases is also gradually on the rise and is becoming life-threatening for society. The early diagnosis and immediate treatment are crucial in respiratory diseases, and hence the audio of the respiratory sounds is proving very beneficial along with chest X-rays. The presented research work aims to apply Convolutional Neural Network based deep learning methodologies to assist medical experts by providing a detailed and rigorous analysis of the medical respiratory audio data for Chronic Obstructive Pulmonary detection This study proposes a computerized method for classifying asthma and chronic obstructive pulmonary disease (COPD) based on lung sound (LS) analysis using the ICBHI dataset. The approach involves denoising LS recordings to enhance data quality, followed by Empirical Mode Decomposition (EMD) for effective signal processing and feature extraction. We will leverage GoogLeNet deep convolutional neural networks (CNNs) to classify LS recordings as either healthy or diseased, employing backpropagation and Stochastic Gradient Descent with Momentum (SGDM) for training. The model's performance will be evaluated using metrics such as True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN), accuracy, sensitivity, specificity, and the Area under the Curve (AUC) of the Receiver Operating Characteristic (ROC) curve, aiming to enhance automated detection and diagnosis of respiratory condition.*

Keywords: *Asthma COPD,Lung Sound Analysis EMD,Deep Learning Convolution Neural Networks (CNNs)*.

1. INTRODUCTION

Lung diseases are a major cause of global morbidity and mortality, including asthma, COPD, lung infections like pneumonia, lung cancer, bronchitis, and other breathing problems [1, 2]. Lung sounds can be indicative of most lung and respiratory diseases [3]. When there is no

Respiratory disorder, normal breathing sounds are heard, whereas abnormal breathing sounds such as wheezing or crackling are detected when there is a lung disease [4, 5]. For this reason, regular or routine monitoring of breathing sounds is essential for symptom prevention and alleviation, as well as for the early detection of various respiratory diseases Typically, respiratory abnormalities are diagnosed by spirometry and auscultation [86]. While spirometry is impossible for certain groups, such as children, and is difficult to use practically to monitor a long-term pattern of patient condition in non-clinical settings [7], auscultation is non-invasive, inexpensive, and easy to use [8]. Medical professionals listen to these sounds to evaluate and diagnose patients however, conventional auscultation requires considerable training and expertise, and its quality depends on the doctor's experience and hearing. The misunderstanding of breathing sounds and making incorrect diagnoses is not rare among medical students.To overcome the limitation of conventional auscultation, various methods such as neural networks classifiers and NMF are suggested in many cases in order to assist in the automatic detection and classification of adventitious lung sounds .Among them, deep learning algorithms train the machine to automatically learn the characteristics of the signals or waveforms of lung sounds to recognize abnormal lung or breathing sounds (wheezing, crackling) [8]. The most common deep learning algorithm used for lung sound classification is a convolutional neural network (CNN) or recurrent neural network (RNN) model that extracts breathing sound features from a two-dimensional spectrogram image, or a combination of the two, a convolutional-recurrent neural network (CRNN).The accuracy of the models ranges from 63% to 99% and in general, the CNN-based model has the highest accuracy. Incorporating AI-based lung sound analysis into automated diagnosis systems has been suggested to determine the degree of airway inflammation [9] or the risk of a number of lung diseases .Recently, efforts have been made to collect breathing sounds from smartphones or real-time lung sounds from wearable devices to develop automated AI-based solutions for lung sound analysis and classification. Through this technological advancement, abnormal respiratory and asthmatic symptoms could be detected or diagnosed at an early stage via real-time self-monitoring or telemedicine [10].However, most existing models focus on the automatic diagnosis of single recorded data, and applications to real-time monitoring data are still limited .They tended to be developed based on the learning data collected by auscultation for a short period of 10 to 70 s and labeled by clinicians [11]. Much of the previous work focused on addressing methodological challenges associated with noise cancellation or reduction detection of the breathing section, or binary classification of an individual cycle of respiration. Due to a lack of adaptability for real-time, continuous long-term signals, most lung sound classification algorithms have not been widely implemented in practice, with limited applicability in self-symptom management or telemedicine [12]. Considering that respiratory patterns represent the holistic physical and psychological state of humans, not only the presence of abnormal sounds but also the location, duration, and relationships of a sequence of respiration cycles, including atypical breathing activities, could serve as important reference data for clinicians and patients to diagnose and monitor lung diseases.To provide comprehensive information about the lung's breathing functionality, which may not be well noticed or recognized in a clinical setting, the pattern and frequency of abnormal lung sounds within a relatively long time must be analyzed rather than most of the existing models for determining the presence or absence of abnormalities at each respiratory unit.

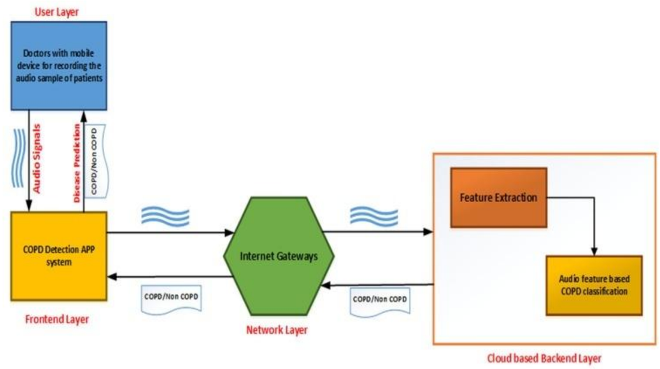

Figure 1: shows the overall training and testing methodology and is explained as given below:

Data Acquisition: the lung sounds that are offered as input was recorded from normal as well as abnormal male and female patients with various kinds of respiratory dysfunctions such as: COPD, Asthma, lower and upper respiratory tract infection (LRTI, URTI). Two research teams from Portugal and Greece created a database of respiratory sounds from where 126 input recordings has been taken (ICBHI, 2017 Challenge). The data samples include both respiratory sounds of healthy individuals as well as of patients who were having the repiratory ailments. The patients span from all age groups, including young children, adults, and senior citizens. The dataset consists of a total of 5.5 h of recordings containing 6898 respiratory cycles, of which 1,864 contain crackles, 886 contain wheezes and 506 contain both crackles and wheezes, in 920 annotated audio samples from 126 subjects. The cycles were annotated by respiratory experts as including crackles, wheezes, a combination of them, or no adventitious respiratory sounds. The recordings were collected using heterogeneous equipment and their duration ranged from 10 s to 90 s. The chest locations from which the recordings were acquired is also provided. Noise levels in some respiration cycles is high, which simulate real life conditions.

Data Preprocessing: the dataset contained a lot of irregularities and unstructured data. To normalize the data, we trimmed/padded the audio files to a length of 20 seconds using a Python library Librosa (Librosa, 2020).

Feature Extraction: for the feature extraction, we calculated five features. The features were Mel-Frequency

Cepstral Coefficients (mfcc), melspectrogram (Mel-Spectrogram), Chromagram calculated from the waveform/power spectrogram (chroma_stft), Constant-Q Chromagram (chroma_cqt) and chroma_cens (Chroma Energy Normalized Variant (CENS)). MFCCs are coefficients that collectively make up an mel-frequency cepstrum (MFC). An MFC is a representation of the short-term power spectrum of a sound, based on a linear cosine transform of a log power spectrogram on a non-linear mel scale of frequency. These features represent phonemes (which are the distinct units of sound) as the shape of the vocal tract (which is responsible for sound generation) is manifest in them. This makes MFCC a great feature to consider for respiratory audio analysis. In order to obtain the Mel-Spectrogram, we take samples of air pressure over time, map it from the time domain to the frequency domain using the fast Fourier Transform and we convert the freuqnecy to a mel scale and the color dimension to the amplitude. It represents short-term power spectrum of a sound. Chroma-based features (like the ones we mentioned above) are also referred to as “pitch class profiles”, are a powerful set of features for analysing music whose pitches can be categorized. Since the respiratory sounds also vary quite distinctly in pitch, Chroma makes it a great feature for our user case.CENS features are robust to dynamics, timbre, and articulation, making these commonly used in audio matching and retrieval applications. We gave each of the features the “n” value (like n_mfcc’s in mfcc and n_chroma bins in chroma features) as 40 to maintain consistency across the features.

Augmentation: we used different audio augmentation methods on the samples to increase the number of non-COPD samples since the number of COPD samples was almost four times the number of non-COPD samples. We applied the following techniques for the audio augmentation.

1. **Lung Sound Waveforms**
2. **The Regular Lung Sound**

The regular lung sound waveforms can be divided into:

Vesicular breath or normal lung sound: The sound is more high-pitched during inhalation than exhalation, and more intense; it is also continuous, rustling in quality, low-pitched, and soft.

Bronchial sound breathing: The sound is high-pitched, hollow, and loud. However, it could be a sign of a health problem if a doctor hears bronchial breaths outside the trachea.

Normal tracheal breath sound: It is high-pitched, harsh, and very loud.

A sample of a normal lung sound waveform is shown in **Figure 2**.

Figure 2. Sample of a normal lung sound waveform [**6**]: vesicular—normal (**upper**), bronchial (**middle**), normal tracheal (**lower**).

3. **The Wheezing Lung Sound**

The wheezing sound is a continuous and high-pitched sound and is distinguished into:

Squawks: A squawk is a momentary wheeze that happens while breathing in.

Wheezes with numerous notes are called polyphonic wheezes, and they happen during exhalation. The pitch of them may also rise as exhalation nears its conclusion.

Monophonic wheezes can last for a long time or happen during both phases of respiration. They can also have a constant or variable frequency.

4. **Crackles Sound**

Generally speaking, crackles can be heard while inhaling. They may have a bursting, bubbling, or clicking sound to them.

Coarse: Coarse crackles are louder, lower in pitch, and linger longer in the larger bronchi tubes than fine crackles do. Although they usually occur during inhalation, they can also occur during exhalation.

Medium: These are brought on by mucus bubbling up in the two tiny bronchi, which carry air from the trachea to the lungs. The bronchi are divided into progressively smaller channels that ultimately lead to alveoli, or air sacs.

Fine: These delicate, high-pitched noises are particular to narrow airways. Fine crackles may occur more frequently than coarse crackles during an intake than during an exhalation.

5. **Rhonchi Sound**

Low-pitched, continuous noises called rhonchi have a snoring-like quality. Rhonchi can happen when exhaling or when exhaling and inhaling, but not when inhaling only. They take place as a result of fluid and other secretions moving about in the major airways.

6. **. Stridorand Pleural Rub Sounds**

A high-pitched sound called stridor forms in the upper airway. The sound is caused by air squeezing through a constricted portion of the upper respiratory system.

The rubbing and cracking sound known as "pleural rub" is caused by irritated pleural surfaces rubbing against one another.

For efficient respiratory infection therapy, early diagnosis and patient monitoring are critical. In clinical practice, lung auscultation, or paying attention to the patient’s lung sound by means of stethoscopes, is used to diagnose respiratory disorders. Lung sounds are typically characterized as normal or adventitious. The majority of frequent adventitious lung noises heard above the usual signals are crackles, wheezes, and squawks, and their presence typically suggests a pulmonary condition [**7**, **8**, **9**].

2. RELATED WORK

Fan Wanget.al. (2023) [13] when it comes to diagnosing a respiratory disorder, lung sound is an essential reference factor with significant importance. Automatic lung sound classification systems, in particular, have the potential to be of tremendous use in circumstances in which health care personnel are absent. During the course of this work, we perform a preprocessing step on the initial lung sound signal in order to subtract noise interference from the signal. After the sound signal has been processed, a spectrogram is produced by applying a Fourier transform with a limited temporal dimension. A deep learning network that is based on ResNet is used to classify the spectrogram, which causes the respiratory cycle to be classified into four distinct categories: normal, crackle, wheeze, and both. The breathing cycles are extended to a uniform fixed time in order to address the problem of different time scales in spectrograms. Validation of the suggested method was accomplished through the utilization of the official benchmark standards of the ICBHI 2017 challenge as well as the dataset partitioning strategy. The classification of the respiratory cycle is a promising area for the suggested method, as demonstrated by the results of experiments and comparisons.

Wei-Bang Ma (2022)[14] The diagnostic process for respiratory disorders can be accomplished in a straightforward, low-cost, and non-invasive manner with the use of lung sound therapy. However, the experience of each individual physician may vary, which then leads to diagnostic results that are not consistent with one another. A deep learning model for identifying lung sounds was developed by us in order to address this issue. This model has the potential to offer medical professionals a more reliable reference for accurate diagnosis. They suggested a classification system that was equipped with efficient pre-processing methods and a DenseNet169 CNN model. This system was based on a lung sound dataset that was gathered from children ranging in age from one month to eighteen years old. 89.0% for task 1.1, 90.9% for task 1.2, 83.8% for task 2.1, and 67.3% for task 2.2 are the outcomes of four separate categorization tasks, each of which is calculated according to a total score specified rule.

3. PROPOSED METHODOLOGY

The suggested methodology seeks to create a computational technique for categorizing instances of asthma and chronic obstructive pulmonary disease (COPD) by analyzing lung sound (LS) patterns. We will utilize the publicly available ICBHI dataset to gather the necessary LS recordings. Firstly, to enhance the quality of the LS data, we will perform denoising techniques. This step is crucial for removing unwanted noise and artifacts from the recordings, ensuring the accuracy of subsequent analyses. Next, we will employ Empirical Mode Decomposition (EMD) analysis for signal processing. EMD is particularly useful for decomposing non-stationary and nonlinear signals like LS recordings into intrinsic mode functions, facilitating feature extraction and classification. To perform classification, they will employ the GoogLeNet architecture, a deep Convolutional Neural Network renowned for its efficacy in picture categorization assignments. We will utilize ResNet-50 for our LS data, capitalizing on its capacity to acquire discriminative features from intricate data. To train the network, we will employ a neural network (NN) approach, utilizing backpropagation and SGDM optimization algorithms to minimize classification errors. The dataset will be split into 70% for training and 30% for testing; ensuring robust evaluation of the model's performanceThe classification output will categorize LS recordings as either healthy or diseased, providing valuable insights into the presence of asthma or COPD.

Dataset description

https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/HT6PKI The ICBHI 2017 respiratory sound database is utilized for the purpose of training and evaluating the deep learning model. The compilation was initially created to provide assistance for the scientific challenge held at the International Conference on Biomedical Health Informatics - ICBHI 2017. The present iteration of this database is provided without charge for the purpose of research.[15]

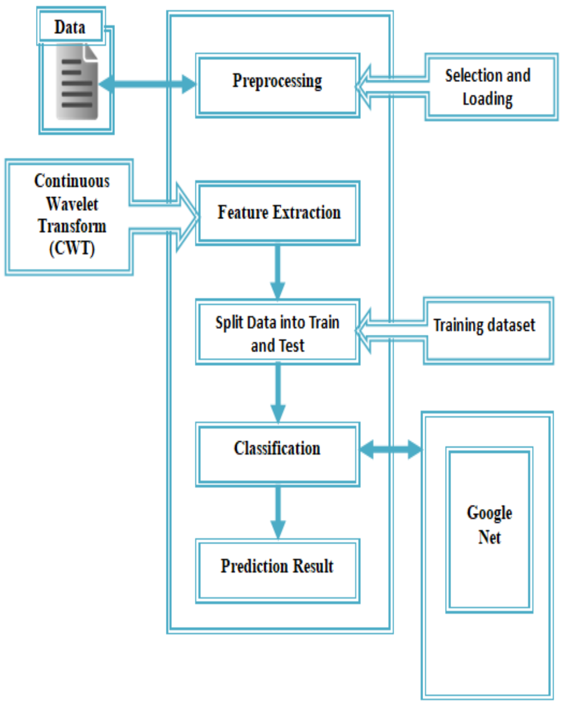

Figure 3: proposed flow diagram

GoogLeNet

The original GoogLeNet (Inception-v1) architecture, detailing each component's purpose and characteristics:

1. **Input Layer**:
   - Shape: Input images with dimensions typically standardized to a fixed size (e.g., 224x224x3 for RGB images).
2. **Convolutional Layers**:
   - Several convolutional layers are stacked at the beginning of the network to extract low-level features.
   - These layers employ small receptive fields (e.g., 3x3) and are followed by rectified linear unit (ReLU) activations to introduce non-linearity.
3. **Inception Modules**:
   - The fundamental components of GoogleNet are the inception modules, which enable the network to efficiently capture characteristics at various spatial scales.
   - Each inception module consists of parallel convolutional and pooling operations of varying sizes (1x1, 3x3, 5x5), followed by concatenation.
   - These modules enable the network to learn diverse and rich representations of the input data while optimizing computational efficiency.
   - The output of each inception module typically undergoes batch normalization and ReLU activation.
4. **Pooling Layers**:
   - Max pooling layers are interspersed throughout the network to reduce spatial dimensions and introduce translation invariance.
   - These layers downsample the feature maps, helping to gradually increase the receptive field of the network.
5. **Fully Connected Layers (FC)**:
   - Towards the end of the network, global average pooling is often employed to reduce the spatial dimensions of the feature maps to a vector.
   - The resulting vector is then fed into one or more fully connected layers, which serve as the classifier.
   - These fully connected layers typically have a large number of parameters and are responsible for learning high-level representations of the input data.
6. The last fully linked layer often employs softmax activation to generate class probabilities.

Output Layer:

- The output layer consists of a softmax function, which converts the raw scores produced by the previous layers into class probabilities.
- Each node in the output layer corresponds to a specific class in the classification task.
- During training, the network's predictions are compared to the ground truth labels using a loss function (e.g., cross-entropy loss), and the parameters are optimized using backpropagation.

Continuous Wavelet Transform (CWT)

The Continuous Wavelet Transform (CWT) is a mathematical technique employed in signal processing and analysis to express a signal in relation to its time-frequency characteristics. The Continuous Wavelet Transform (CWT) [16]enables simultaneous analysis of time and frequency, making it valuable for discovering localized characteristics in signals that exhibit variations in both time and frequency domains. The mathematical formula representing the Continuous Wavelet Transform (CWT) of a signal (t)x(t) in relation to a wavelet function $\psi(t)$ψ(t) is expressed as:

$$CWT_x(a,b) = \int_{-\infty}^{\infty} x(t) \cdot \frac{1}{\sqrt{|a|}} \cdot \psi^* \left(\frac{t-b}{a}\right) \, dt$$

Where:

CWTx(a,b) is the Continuous Wavelet Transform of the signal x(t) at scale aa and translation b.

a represents the scale parameter, which controls the width of the wavelet and thus the frequency resolution.

b represents the translation parameter, which shifts the wavelet along the time axis.

ψ(t) is the complex conjugate of the analyzing wavelet function.

|a| is a normalization factor to ensure energy conservation.

The CWT is essentially a convolution of the signal with scaled and translated versions of the mother wavelet function. By varying the scale and translation parameters, the CWT provides a time-frequency representation of the signal, revealing how its frequency content evolves over time.[17-18]

In practice, the CWT is often implemented using discretized scales and translations, resulting in a discrete set of CWT coefficients. The discretized CWT can be represented as:

$$CWT_x[n,m] = \sum_{k=-\infty}^{\infty} x[k] \cdot \frac{1}{\sqrt{|a_n|}} \cdot \psi^* \left(\frac{k-mb_n}{a_n}\right)$$

Where:

- nn and mm represent the discrete indices corresponding to the scale and translation parameters, respectively.
- an and bn are the discretized scale and translation values.

The CWT can be computed efficiently using fast algorithms such as the Fast Wavelet Transform (FWT) or the Fast Fourier Transform (FFT)-based methods. These algorithms exploit the convolution theorem and other properties of wavelets to accelerate the computation of the CWT coefficients.

The CWT decomposes the input signal into time-frequency representations at different scales aa and translations bb. By varying the scale and translation parameters, the CWT captures both localized and global features of the signal across different time and frequency resolutions.

COPD Signal Result

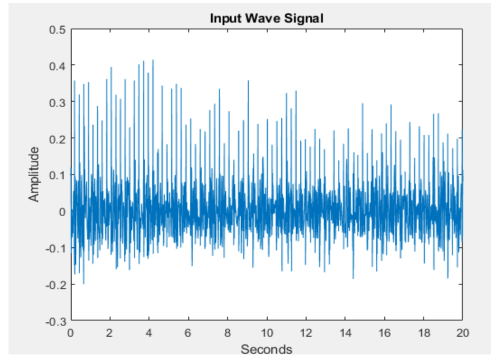

Figure 4: Input signal chronic obstructive pulmonary disease (COPD)

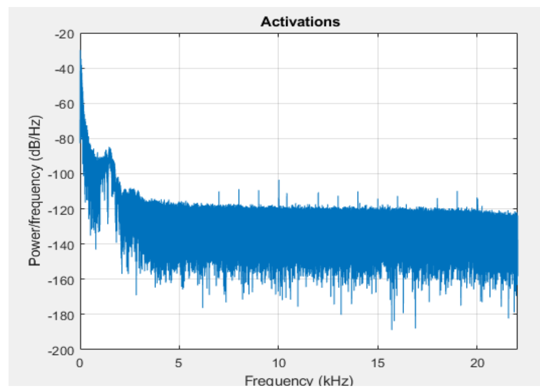

Figure 5: Signal frequencies

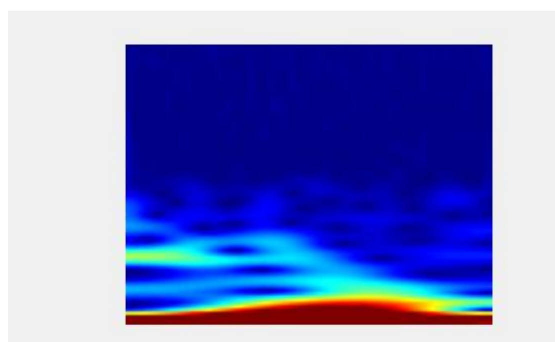

Figure 6: Power of the CWT coefficients

```
ans =

    'The loaded image belongs to the COPD'
```

Asthma signal result

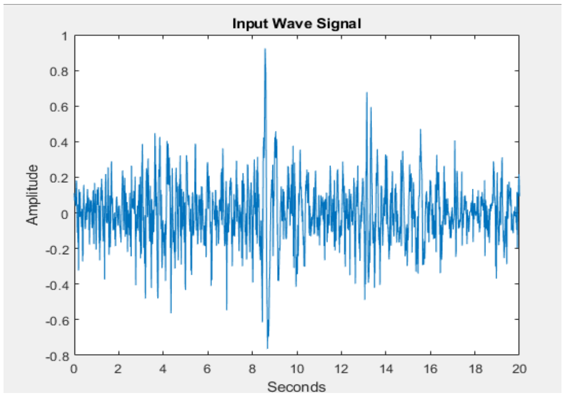

Figure 7: asthma Signal

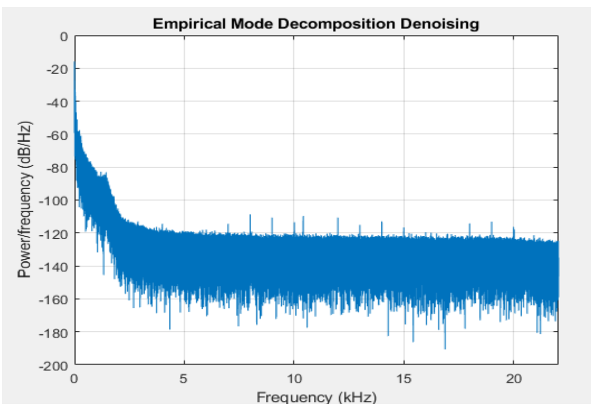

Figure 8: Signal frequency asthma signal

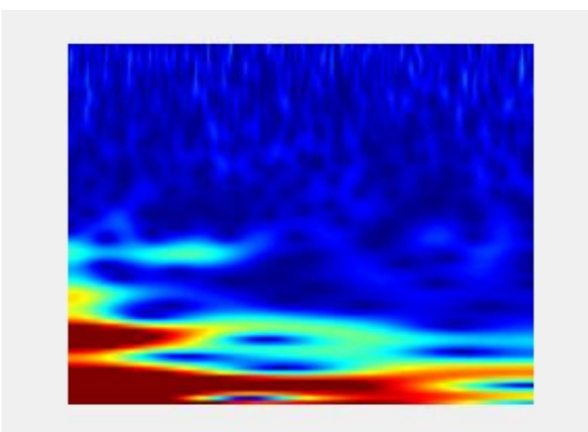

Figure 9: Power of the CWT coefficients

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ans =

    'The loaded image belongs to the Asthma'
```

4. EVALUATION MATRIX

A confusion matrix is essential for evaluating the efficacy of the classifier. This matrix provides the count of accurate and inaccurate predictions based on the known values. The observed outcome is indeed true, and the model correctly predicted it as true; this is known as a true positive (TP). A true negative (TN) occurs when both the actual values and the anticipated values are erroneous. On the other hand, a false positive (FP) refers to a situation where the actual value is false, but the model incorrectly predicted it as true. A "False Negative" (FN) occurs when the model incorrectly predicts that a true value is false.[19-20]

Intersection over Union (IOU): IOU, If one just wish to quantify the extent of overlap between two bounding boxes or masks in a segmented image, simply can utilize the Jaccard Index, also referred to as the Jaccard Index. The region where the predicted segmentation and the ground truth overlap is called the area of utility, also known as Intersection over Union (IoU). This region is separated by the area where the anticipated segmentation and the ground truth do not overlap, which is called the area of union. The range of this specific statistic spans from 0 to 1, where 0 represents no overlap and 1 represents perfect overlap. With a threshold of 0.5, our goal is to achieve an IOU value that is at least 97% greater than the present value

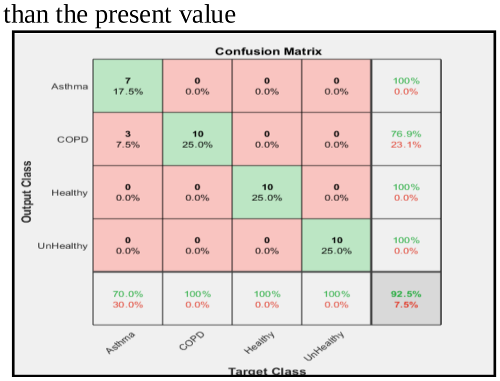

Figure 10: confusion matrix

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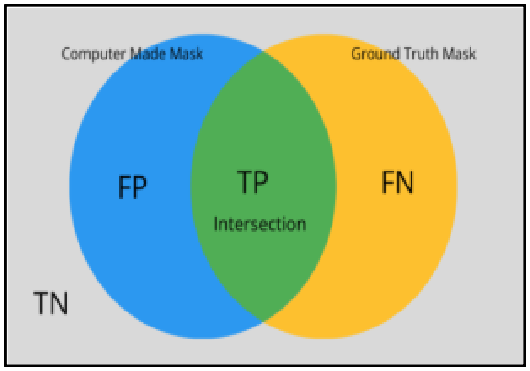

Figure 11: Model evaluation parameters

Green region: Our model estimates 1 (lesion mask) and the ground truth is 1. (True Positive, TP)

Blue region: Our model estimates 1 (lesion mask) but the ground truth is 0. (False Positive, FP)

Yellow region: Our model estimates 0 (absence of lesion) but the ground truth is 1. (False Negative, FN)

Gray region: Our model estimates 0 (absence of lesion) and the ground truth is 0. (True Negative, TN)

Accuracy: A model's accuracy can be defined as the frequency with which it has correctly predicted the value based on the information that was provided. When it comes to FP and FN, however, it does not provide any specific information. There are certain applications in which the F1 score and recall play a very significant role. These applications involve FP and FN that are significant. [21]The formula that is described in Equation 1 is used to determine the accuracy of the calculation.

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}} \qquad \text{equation 1}$$

Precision: This evaluation parameter provides information regarding the frequency with which a model predicts true positives. A low accuracy value indicates that there are a significant number of false positives. The precision calculation formula is shown in Equation 2, which may be found here.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \qquad \text{equation 2}$$

Recall: It is possible to obtain information on the frequency with which a model predicts false negatives by monitoring this parameter. The model predicted a significant amount of false negatives, as seen by the low recall value. Recall can be calculated using the formula that is provided in Equation 3.

$$\text{Recall} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN}} \qquad \text{equation 3}$$

Dice Coefficient (F1 Score): The dice coefficient is a measurement that determines how much overlap there is between two masks. One means that there is no overlap, whereas zero suggests that there is a perfect overlap. Two times the Area of Overlap should be divided by the total number of pixels in both images in order to arrive at the Dice Coefficient estimate. There is a correlation between this statistic and IOU. In order to accomplish our objective, we need to earn an F1 score of 95% or above.

F1 Score: Both precision and recall are taken into consideration when determining the F1 score. To put it another way, a high F1 score indicates a low number of false positives and false negatives, which further suggests that the model is accurately recognizing true threats and is not troubled by false alarms. In Equation 4, the formula that is used to calculate the F1 score is presented.

$$\text{F1 score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Presiion} + \text{Recall}} \qquad \text{equation 4}$$

Table 1 Comparison Result for COPD Dataset and Asthma Dataset

COPD Dataset	COPD Dataset	ASTHMA Dataset
Accuracy	99.6	99.9
Sensitivity	95.36	92.36
Specificity	96.23	94.25
Precision	94.23	93.26

Table 2 Comparison Result For COPD Dataset and Asthma Dataset

	Accuracy
Proposed work	99.6
Existing work	99.3

5. CONCLUSION

The suggested methodology offers a thorough approach to creating a computerized system for categorizing asthma and chronic obstructive pulmonary disease (COPD) cases using lung sound (LS) analysis. By leveraging denoising techniques and Empirical Mode Decomposition (EMD) analysis for signal processing, we aim to enhance the quality of LS data and extract discriminative features from non-stationary and nonlinear signals. Utilizing the GoogLeNet architecture adapted to LS data and training the network with a neural network approach using SGDM optimization, we seek to achieve accurate classification of healthy and diseased LS recordings. Evaluation using standard metrics such as True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN), accuracy, sensitivity, specificity, and Area under the Curve (AUC) of the Receiver Operating Characteristic (ROC) curve will provide a robust assessment of the model's performance in distinguishing between asthma and COPD cases based on LS analysis. Overall, this methodology holds promise for advancing computer-aided diagnosis in respiratory diseases and providing valuable insights for clinical decision-making.

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