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# RECOGNITION AND ANALYSIS OF ASTHMA DISEASE BASED ON COUGH SOUND

**Naveen Kumar Vodnala[1], Y. Padma Sai[2], Prathyusha Vilasagaram[3, *]**
[1] Assistant Professor, Department of Electronics and Communication Engineering, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India
[2] Professor, Department of Electronics and Communication Engineering, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India
[3] M.Tech student, Department of Electronics and Communication Engineering, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India
* Corresponding author-E-mail: vilasagaram.prathyusha@gmail.com

**Abstract**
**Objective:** To identify asthma based on cough sounds as the cough is the primary symptom that occurs when the lung airways are being deteriorated.
**Methods:** The cough sound signals are decomposed using the Discrete Wavelet Transform to obtain wavelet coefficients which are used in extracting some spectral and time-domain features. The extracted features are given as input to machine learning-based classifiers that are Decision Tree, Support vector machine and K-Nearest Neighbour to discriminate between Cough sound signals.
**Findings:** The maximum accuracy of 92.3% is obtained from the KNN classifier. The specificity and sensitivity obtained are 100% and 85% respectively. F1-score obtained is also greater for the KNN classifier comparatively.
**Novelty:** This paper includes the Classification of Asthma cough sounds from Normal cough sounds with the combination of wavelet decomposition with comparative of the three different types of classifiers and also computes their performance states the novelty of this research article.
**Keywords:** *Asthma, K-Nearest Neighbour, Raspberry Pi, cough, Support vector machine, Discrete Wavelet Transform, Decision Tree.*

## 1 Introduction:

Currently, there is no cure for pulmonary disorders, which steadily deteriorate a person's health over time. However, if these disorders are found early and given the appropriate care, they can be treated. Asthma is one of them. Therefore, identifying it early on may be one of the most important measures in the medical sector. Developing a portable low-cost system for diagnosing asthma, that combines hardware installed with a machine learning classifier is the novelty of this paper. Cough is the major symptom of asthma, which plays a key role in identifying it and is used as input to the developed diagnosing system. Cough signals are non-invasive and discomfort-free for the patient. Cough sounds are processed to obtain the necessary features, which are then fed into machine learning classifiers. Mother wavelet is considered by selecting the proper features, and finding the best machine learning methods are the main challenges.

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A general classification has been done between Asthma and Non-Asthma using the wavelet packet transform for decomposition of the signals and then are classified by the Wigner distribution (1) with an accuracy of 88% using wavelet packet decomposition. Even if the accuracy of the suggested method is excellent, more research is necessary to identify universal traits that may be used to categorize the unknown signal regardless of age or gender.

Using wavelet transform and the K-NN method, asthma severity may be determined and classified (2). The efficiency of moderate, mild, and severe datasets has been noticed using an ensemble classifier. The wheeze sound frequency band of 100-1600 has been chosen, so A7, D1, and D2 have been disregarded. Tenfold cross-validation was used to validate the KNN classifier. The classification of aberrant (wheeze) noises according to severity levels using 19 features is furthered in this work. Mild, medium, and severe have the highest PPVs at 84%, 77%, and 75%, respectively.

Where in (3) J. KNOCIKOVA has shown the changes in cough characteristics in patients suffering from COPD and Asthma by using discriminant analysis with 5-level Db3 decomposition of signal and classified up to 85-90%. Higher frequencies were detected in Asthma than in COPD. The introduction to wavelets is explained clearly in (4) The Qualitative and Quantitative approaches for selecting mother wavelets are discussed.

Analysis and differentiation of asthma and pneumonia in children are shown in (5) They have used a 20ms subblock of the sliding window to get the data samples decomposed with 5 features in feature extracting and then classified using the Artificial Neural Network (ANN)**.** The Kappa, specificity, and sensitivity of 0.89, 100%, and 89% respectively. This technique extracted audio properties like Shannon entropy, non-Gaussianity, and Mel-frequency cepstral coefficients. However, the study included pneumonia and different feature extraction techniques. Signal-based multimodal classification has been performed by Machine learning (ML) and Deep Neural Networks (DNN) architectures using Continuous Wavelet Transform (CWT)(6) has low values of sensitivity and specificity.

A detailed review of 77 articles considered the analysis of asthma, COPD, and pneumonia depending on the cough sounds is given by(7) Comparatively SVM model and KNN model have achieved consistently highest accuracy than ANN. A detailed study report of cough acoustics with different data set collection, feature extraction, and diagnosis by applying ML, Artificial Intelligence (AI), and Deep Learning techniques (8) non-linear ML algorithms, such as DT and KNN classifiers are free to assume any functional form of the training data.

The classification of massive data sets is done easily by using neural networks (NN). The classifier training process takes longer (due to their hidden layers) and the implementation becomes highly expensive and complex. While machine learning classifiers are quick to train, inexpensive to deploy, and environmentally friendly to utilize. Hence a quick and cheap method can be developed using machine learning classifiers.

## 2 Methodology:

### 2.1 Data set:

The cough sounds are recorded under the supervision of physicians and doctors expertized in pulmonary diagnosis from reputed hospitals. These cough sounds are collected from Subjects in the age group of 18 to 58 years in a controlled and noise-free environment. Each cough sound signal duration is limited to between 1 to 2 seconds. A total of 130 asthma cough sounds and 130 normal cough sounds are collected and used for investigation. The cough sounds are recorded using a Zoom H5 hand recorder with a sampling frequency of 22KHz, 16-bit, and in .wav format.

**2.2 Wavelet decomposition of the cough sound signals:**

The Wavelet decomposition technique is a technique that decomposes the signal in multi-low-resolution levels in the time and frequency domain. There are 2 types of wavelet decompositions they are Discrete wavelet transformation (DWT) and Continuous wavelet transform (CWT). In this model, DWT is used (due to its less complex and ease of implementation and understanding) to decompose the cough sound signals(9) and obtain approximation and detailed coefficients. The decomposition levels are chosen in a way that the wavelet coefficients retain their signal components that relate well with the frequencies required for signal identification(10). Here, Signals are decomposed into seven levels as shown in figure 1. The signal decomposition into sub-bands has been thoroughly detailed (11,12).

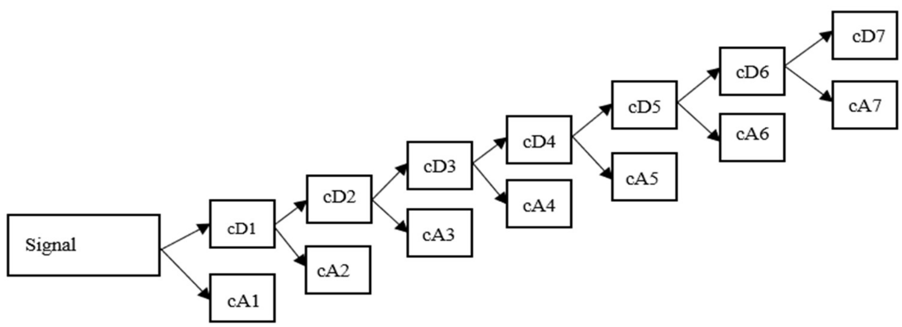


Fig 1 : 7-layer DWT

As a result, eight coef[illegible] (cA7(0-172Hz)) and seven detailed coefficients (cD7(172-344Hz), cD6(344-689Hz), cD5(689-1378Hz), cD4(1378-2756Hz), cD3(2756-5512Hz), cD2(5512-11,025Hz), and cD1(11,025-22,050Hz) are obtained, and then combine all these coefficients in a data frame.

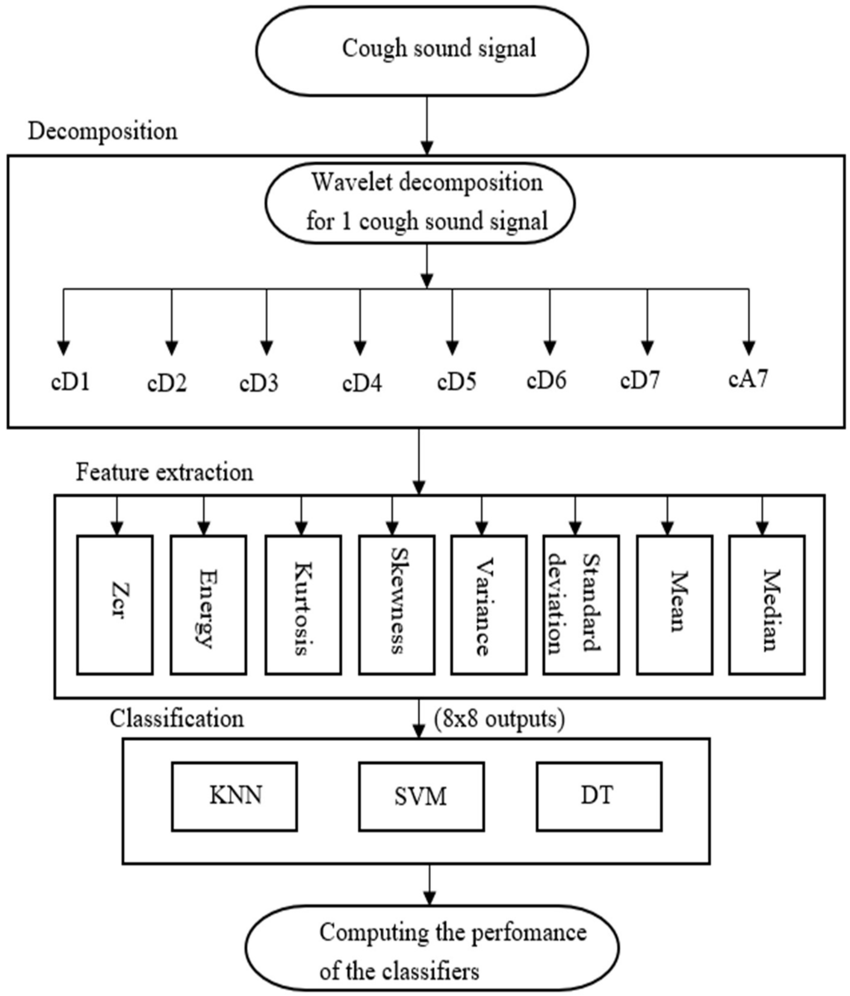


Fig 2: Flow diagram of Methodology

The 7-layer Wavelet decomposition of the Normal cough signal is shown in Figure 3 whereas Figure 4 represents the Wavelet decomposition of the Asthma cough signal. It is observed that the Asthmatic cough bust duration is more than the normal cough bust.

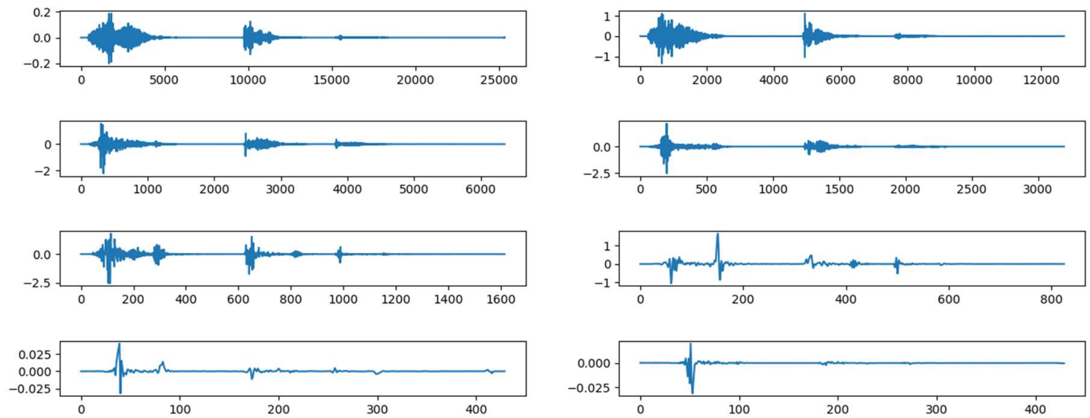

Fig 3: Wavelet decomposition of Normal cough

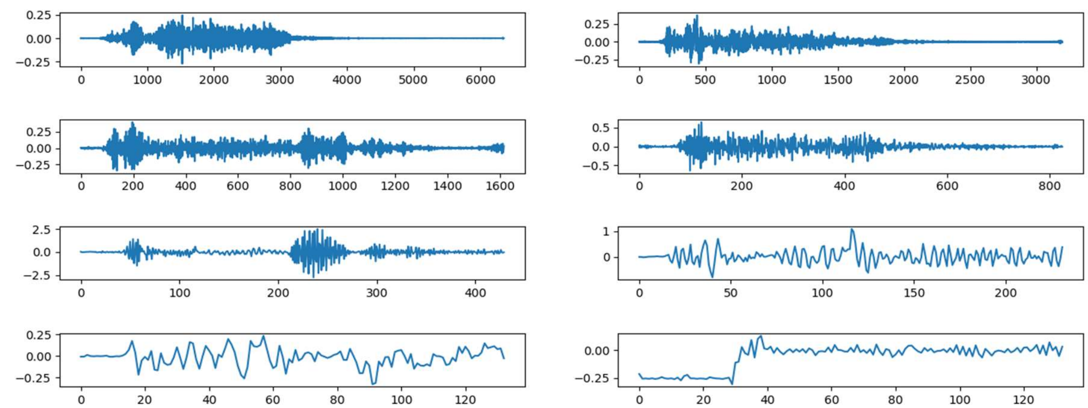

Fig 4: Wavelet decomposition of Asthma cough

**2.3 Feature extraction from the cough sound signals:**

Feature extraction is the significant stage while processing the acoustic signals as features represent the properties of the signal. Zero crossing rate (ZCR), Energy, Median, Kurtosis, Variance, Standard deviation, Skewness, and Mean are the features used.

*ZCR:* It represents how many times the input signal crosses the axis. It is considered that the smoothness of the signal can be predictable with the number of zero crossings. Lesser the zero crossings more the smoothness of the signal and vice versa.

$$zcr = \frac{1}{T-1}\sum_{t=1}^{T-1} 1_{\mathbb{R}_{<0}}(s_t s_{t-1})$$

Where S is a signal, of length T and $1_{\mathbb{R}_{<0}}$is an indicator function.

*Mean*: Mean is the average of two or more values. It represents the value of the signal's average value in the dataset.

$\mu = \frac{1}{N}\sum_{i=0}^{N} x_i$, Where $x_i$ is the signal.

*Median*: Median is used to remove the noise ratio in the signal. It is the middle value in a list when the values are arranged in ascending order.

*Variance*: Variance is the measure of variability. It measures how far the signal fluctuates from the mean. It is calculated as the square of the standard deviation.

$$\sigma^2 = \frac{1}{N-1} \sum_{i=0}^{N-1} (x_i - \mu)^2$$

Where the mean is represented by μ, the signal is represented by $x_i$.

*Standard Deviation (SD)*: It is a measurement of how significantly the information deviates from its mean.

*Skewness*: Skewness indicates the distortion that deviates from the normal distribution in a set of data. It is a dimensionless quantity.

$$skewness = \frac{\Sigma_i^n (X_i - \bar{X})^3}{(n-1) * s^3}$$

Where s is the SD, $\bar{X}$ is the mean, and n is the no. of observations

*Kurtosis*: Kurtosis measures the peakedness of a signal, i.e., its value is high when the peaks in the signal are more. It also represents the Gaussian components in the signal.

*Energy*: Energy is the measure of signal strength and also it is the sum of squares of the amplitude of the signal, normalized by its frame length.

$$the\ E_x = \int_{-\infty}^{\infty} |x(t)|^2 \, dt$$

Where x(t) is a complex signal.

**2.4 Machine learning classifiers:**

A classifier is a method used in machine learning that automatically organises or classifies data into one or a number of a collection of "classes." The testing and training data sets are created from the retrieved feature samples. The classification is carried out based on the features that were extracted. KNN is the simplest supervised machine learning algorithm for solving regression and classification issues. This method is a non-parametric, lazy method that requires no training and makes no assumptions about the data. This method requires no training data set instead it just stores the data and directly performs the classification on new data when provided. The k nearest training observations in the feature space identify the class membership of an unobserved data item. The Euclidean distance formula is used to calculate the distance between two points in a Euclidean space.

$$D(u,v) = \sqrt{\sum_{i=1}^{N} (u_i - v_i)^2}$$

Where u and v are two points in the plane.

Support Vector Machine (SVM) is one of the most popular supervised machine learning techniques used for solving regression and classification issues. This classifier usually acts as a dividing line between the two classes. The Binary classification of the data with a hyperplane and with the support vectors is described (15). Radial Basis Function (RBF) Kernel type SVM is used here to classify the distributed data. It can be calculated by the following formula.

$$SVM(h, h^{/}) = \exp\left(-\frac{\|h-h^{/}\|^2}{2\sigma^2}\right)$$

Where $\|h-h^{/}\|^2$ is the squared Euclidean distance, $\sigma$ is a free parameter.

The Decision tree classifier in machine learning works on the principle of decision-making, which consists of a tree-like structure for representing the decisions and their results. It's one method of showing an algorithm made up of completely conditional control statements. The tree-like structure consists of nodes, branches, and leaf nodes which significantly represent the features, decision rules, and the outcome of the classifier. The branches are divided based on simple questions with yes or no as answers. The logic can be easily understood to make the right decision with the help of this classifier.

**3 Results and Discussion:**

The cough sounds which are taken as input are decomposed using wavelet decomposition(9). The wavelet transform decomposition is widely used in studying time series and signals as they are dynamic signals. Also, different mother wavelets were tried to decompose the signal, resulting in varying accuracies as seen in the table below.

Table 1: Performance (Accuracies) of the classification models with various mother wavelets

| S. No | Mother Wavelet | *KNN* | *SVM* | *DT* |
|---|---|---|---|---|
| 1 | Db2 | 92.30 | 84.61 | 82.69 |
| 2 | Sym7 | 94.23 | 84.61 | 75.00 |
| 3 | Db7 | 92.30 | 88.46 | 84.61 |
| 4 | Db8 | 84.61 | 84.61 | 88.46 |
| 5 | Sym8 | 92.30 | 84.61 | 80.76 |
| 6 | Sym4 | 92.30 | 88.46 | 84.61 |
| 7 | Db4 | 90.38 | 86.53 | 86.53 |

Symlet and Daubechies wavelets are taken into consideration because they resemble the cough sound signals. In Table 1, the KNN classifier exhibits great accuracy when compared to SVM and DT utilising various mother wavelets. Even though KNN produces excellent accuracy with the Sym7 mother wavelet, it is not considered a mother wavelet because it depicts symmetric signals rather than asymmetric signals. Db2 is therefore regarded as the mother wavelet because of its asymmetrical form and great precision. The SVM classifier shows an accuracy of 88.46% with Db7 and Sym4 wavelets. Whereas, DT gives an accuracy of 88.46% with Db8 wavelet.

**3.1 Hardware:**

The Raspberry Pi 4 (RPI4) is a quad-core, 1.2GHz, 64-bit ARM processor with integrated graphics processing unit and 1 GB of random-access memory. For storing data and loading the operating system, it supports Micro SD port. The RPI4 consists of modules for Wi-Fi and ethernet which are used for work with google Collaboratory and thus run python programs to build classification models. The developed classification model is deployed on the RPI4 model-B board as shown in the figure 5. In this paper, three machine learning classifiers i.e., DT, SVM, and KNN are deployed on RPI4. The training data is given to the classifiers to build the model and is tested using test data. The results are predicted using the performance metrics and the AUC-ROC graph. The performances of the classifiers are also compared.

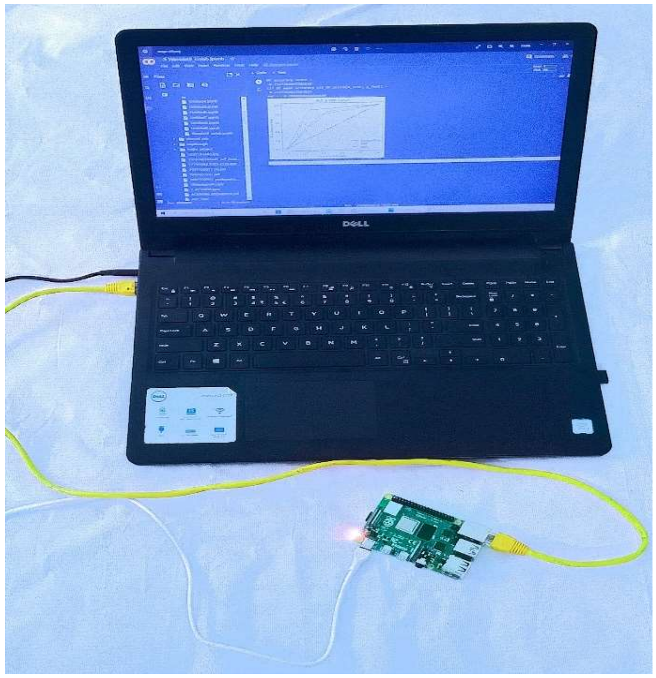

Fig 5: Deployment of the model on Raspberry pi 3

**3.2 Performance metrics:** The attributes used to determine output are confusion matrix, precision, F1-score, sensitivity, accuracy, and specificity(16). KNN obtained the best accuracy of 92.03% with the Db2 mother wavelet compared with others. Table 2 summarizes the confusion matrix and Table 3 shows the performance metrics of the classification models.

*Sensitivity*: It predicts how correctly identify people with the disease.

*Specificity*: It predicts how correctly identify patients are without the disease.

*Accuracy*: It is the degree of closeness to the true value.

*Confusion matrix*: It is the table that is used to describe the performance of a classifier algorithm.

*F1-score*: It is the harmonic mean of recall and precision.

*Precision*: It is the degree to which an instrument will repeat the same value.

Table 2: Confusion matrix of classifiers

| Classifiers | Confusion matrix |
|---|---|
| KNN | [[ 25 0]<br>[4 23]] |
| SVM | [[19 6]<br>[2 25]] |
| DT | [[22 3]<br>[6 21]] |

Table 3: Performance metrics of classifiers

| | KNN(%) | SVM(%) | DT(%) |
|---|---|---|---|
| Precision | 86.20 | 90.47 | 78.50 |
| Sensitivity | 100.0 | 76.00 | 88.00 |
| Specificity | 85.18 | 92.59 | 77.70 |
| Accuracy | 92.30 | 84.61 | 82.60 |
| F-1 score | 92.59 | 82.60 | 82.97 |

**3.2.1 AUC-ROC Curve:**

AUC (Area under Curve Receiver Operator Characteristic) is a measure of how well a model can distinguish among classes. ROC is the plot between the False positive rate (FPR) and the True positive rate (TPR).

$$TPR/Sensitivity/\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP+FN}}$$

FPR= 1-Specificity

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP+T}}$$

The AUC value of a classifier can be used to predict how well that would perform. The AUC value for a good model will be close to 1, indicating good separation. AUC value approaching 0 indicates a bad model, which means it has the lowest measure of separability(17). The AUC values of the classifiers are shown in the below table.

Table 4: AUC values of the classifier

| Classifier | AUC-value |
|---|---|
| KNN classifier | 0.925 |
| SVM classifier | 0.842 |
| DT classifier | 0.828 |

Table 4 summarizes the AUC value of the classifiers, the KNN-AUC value is 0.925 which is near 1 when compared to other classifiers, it can be concluded that the KNN classifier performs well in separation with this method. The AUC – ROC graph for the classifiers is shown in figure 6.

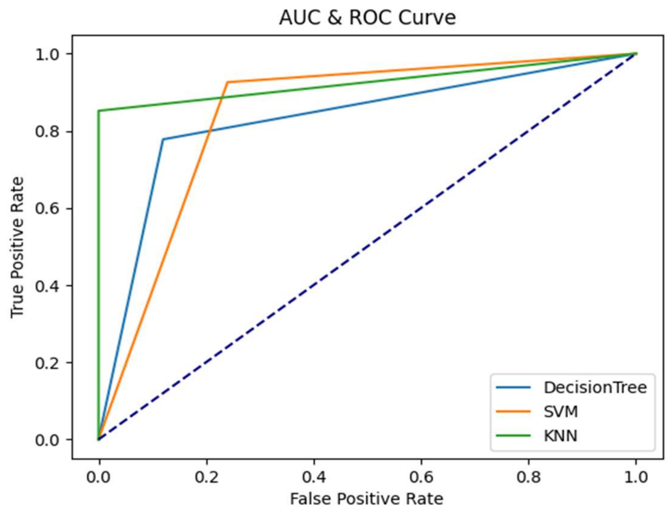


Fig 6: AUC-ROC Curve

Table 5: Comparison with previously published works

| Paper | Disease | Method used | Accuracy | samples |
|---|---|---|---|---|
| Knocikova et al., 2008**(3)** | Asthma | Mann- Whitney, Pearson chi-square tests with 5-level wavelet decomposition | 85-90% | 65 |
| Al-Khassaweneh & Bani Abdelrahman, 2013**(1)** | Asthma, non-Asthma | Wigner distribution with wavelet packet decomposition | 88% | 24 |
| **Amrulloh et al., 2015 (5)** | Asthma, pneumonia | ANN | 94.4% | 18 |
| Pramono et al., 2016(18) | Asthma, Pertussis, croup, bronchiolitis, cough detection | Logistic Regression Model (LRM) | 85% | 38 |
| Alvarez et al., 2018 (19) | Asthma, COPD, Bronchitis | K-NN | 95.28% | 13 |
| Kadambi et al., 2018 (8,20) | Asthma, Chronic cough, COPD | DNN | 92.3% | 9 |
| **Hee et al., 2019 (21)** | Asthma | GMM-UBM | 91% | 176 |
| **Schuller et al., 2020 (22)** | Asthma, COVID-19 | CNN | 67.7% | 1427 |
| **Xu et al., 2021 (23)** | Asthma, COPD | CNN & Mobile Net | 94.9% | 200 |

| | | | | |
|---|---|---|---|---|
| **Proposed model** | Asthma, Normal | KNN, SVM, DT, DWT | 92.03% | 260 |

The previous researchers considered different features and classification methods to classify various respiratory diseases along with Asthma and achieved good results. But when compared to the proposed method, the other researchers (with good accuracy) used very small datasets comparatively. Whereas the proposed model consists of an adequate number of cough sounds in the dataset.

## 4 Conclusion:

The optimum accuracy is 92.30% for the proposed model with 260 samples using KNN classifier. The developed asthma diagnosis models are deployed on a RPI4 model-B board which is handy and patient friendly. The cough sound signals are nonstationary and asymmetrical in nature. Because of this similarity, the Db2 is considered as the mother wavelet. The simultaneous extraction of local spectral and temporal information by wavelets aids in a better understanding of the signal and makes the extraction of features simpler and more precise. The accuracy of the KNN, SVM, and DT classifiers varies depending on the wavelet used, falling between 94.23%-84.61%, 88.46%-84.61%, and 88.46%-75.00%, respectively. SVM has the highest specificity of 92.59%, KNN has the highest F1-score of 92.59%, and KNN performs the best of all the classifiers.

*Conflicts of interest:* The Authors declare no conflicts of interest.

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