Voice Pathology Detection Using Decision Tree Classifier

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***Abstract*—Nowadays, the systems of voice disorder detection obtained considerable attention due to the high importance of this field. However, the assessment of voice pathology requires certain tools and well-trained doctors. Moreover, this assessment can be identified by a group of professionals who listen to a patient in order to assess the patient's speech to identify whether the patient's voice is pathological or normal. Nevertheless, this assessment is based on the listener's experience. Consequently, machine learning is the most suitable technique for the detection of voice pathology, where this technique is a cost-effective and non-invasive method. Therefore, this paper presents Decision Tree (DT) algorithm based on the Mel-Frequency Cepstral Coefficient (MFCC) technique for the detection of voice pathology. The voice samples for pathological and healthy classes are collected and taken from the Saarbrucken Voice Database (SVD). The performance of the DT algorithm is assessed in terms of many evaluation measurements such as accuracy, sensitivity, precision, G-mean, F-measure, and specificity.**

Keywords— voice pathology, machine learning, DT, MFCC, SVD

I. Introduction

In the domain of healthcare, specific attributes of speech signals can be utilized to potentially identify certain illnesses [1]. Individuals with particular occupations and unhealthy social behaviors may have an elevated susceptibility to voice-related issues due to the demands of their work, highlighting the significance of studying pathological speech signals within this domain [2, 3]. Within the healthcare sector, the analysis of voice disorders has high importance. Numerous individuals experience voice-related difficulties attributed to various factors, including severe organ damage, air pollution, smoking, and stress [4]. A recent study has revealed that over 7.5 million individuals in the United States grapple with voice disorders [5]. Furthermore, about a quarter of the global population faces voice challenges due to the demands of professions that necessitate speaking louder than normal, such as teachers, singers, auctioneers, lawyers, and actors, who extensively rely on their voices [6]. The significance of monitoring voice pathology has grown in recent years due to the increasing risks associated with such disorders [7]. Moreover, these algorithms present a non-intrusive diagnostic approach that is more patient-friendly, timely, and cost-effective [8].

Machine learning algorithms provide techniques, approaches, and methods that can be used to assist in addressing diagnostic challenges across various medical fields [9]. Several machine learning algorithms have been applied to the analysis of speech in systems of voice pathology detection, including the Extreme Learning Machine (ELM) [10], Support Vector Machine (SVM) [11], and K-Nearest Neighbors (KNN) [12]. Consequently, these machine learning techniques have demonstrated their effectiveness and proficiency in distinguishing between pathological voices and normal voices. Nonetheless, some of machine learning techniques still encounter issues with achieving high classification accuracy [13]. These algorithms are mainly used to classify the pathological class from the healthy class [14]. Along with machine learning algorithms, there are many different feature extraction techniques that are used for the purpose of extracting the voice features and feeding these voice features to the machine learning algorithm in order to classify the voice features with respect to the corresponding class [15].

Mel-Frequency Cepstral Coefficient (MFCC) is considered the most technique used in extracting voice features, as well as it is widely used in systems of voice pathology detection due to its high effectiveness in terms of extracting voice features [16, 17]. Additionally, there are three voice pathology databases which are extensively utilized in the systems of voice pathology. These voice databases are named Saarbrucken Voice Database (SVD) [18], Arabic Voice Pathology Database (AVPD) [19], and Massachusetts Eye and Ear Infirmary (MEEI) [20]. It is worth mentioning that the SVD database is considered the most voice database used in voice pathology detection systems [21]. However, the systems of voice pathology still suffer from low detection accuracy and need more examination and analysis of different machine learning algorithms in the detection of voice pathology. Thus, investigating a machine learning algorithm based on the MFCC technique in the detection of voice pathology is imperative. Therefore, this paper presents

Decision Tree (DT) algorithm based on the MFCC technique for the detection of voice pathology. The voice samples for pathological and healthy classes are collected and taken from SVD database. The performance of the DT algorithm is assessed in terms of many evaluation measurements.

The subsequent sections of this paper are structured as follows: Section II gives the related works in the systems of voice pathology detection. Section III presents the proposed method. Section IV discusses the experimental outcomes of the DT algorithm. Ultimately, Section V presents the conclusion and future works.

II. RELATED WORK

In recent times, the domain of voice pathology surveillance systems has gained high attention from many researchers and developers, whereas the algorithms and techniques of machine learning play an essential role in such systems. In this context, some of the methods and techniques used in the state-of-the-art that concentrate on identifying voice pathologies will be reviewed. The work in [22] is aimed to develop a dependable and efficient system for detecting speech disorders using the long short-term memory (LSTM) technique. Furthermore, the work integrated different feature sets, for instance, MFCCs and Zero Crossing Rate (ZCR) that have not been employed together in the literature. The LSTM technique for vocal pathology detection enhanced the accuracy rate on the SVD samples. The presented approach produced the best results, with an accuracy rate of 99.3% for /u/ vowel samples in neutral pitch, 99.2% for /a/ vowel samples in high pitch, 99% for /i/ vowel samples in neutral pitch, and 99.2% for sentence samples. The work compared the performance of LSTM to that of artificial neural networks (ANNs) and concluded that LSTM performed better.

Another study is proposed and used a technique for identifying dysphonia illness, which is considered one of the voice pathology detection applications [23]. The presented technique employed the Naive Bayes (NB) algorithm as a classifier to distinguish between the dysphonia (pathological) and healthy (normal) classes. The MFCC technique is also used to extract voice features. This work relied on voice data obtained from the SVD database. Several assessment metrics were employed to evaluate the proposed technique. According to the results, the NB algorithm achieved an accuracy of 81.48%, a sensitivity of 65%, a specificity of 91.17%, and a G-mean of 76.98%. In addition, the achieved results of precision and F1-score were 81.25% and 72.22%, respectively.

The authors in [24] have presented a system of voice pathology identification. They used MFCC to extract the voice features and fed these features to the OSELM algorithm to identify the pathological voices from healthy ones. In addition, the voice samples are taken from the SVD database for three different vowels such as /a/, /i/, and /u/. The sentences of the SVD database are also used in the experiment. The experimental outcomes have demonstrated that the OSELM algorithm achieved the highest accuracy of 91.17%, 91% sensitivity, and precision of 94%. Meanwhile, the highest obtained results of specificity, F-measure, and G-mean were 97.67%, 87%, and 87.55%, respectively.

Another study has utilized a variety of techniques for feature extraction for the purpose of extracting voice features. Subsequently, these voice features are combined and fed into the Discriminative Paraconsistent Machine (DPM) algorithm in the detection of voice pathology [25]. These techniques are employed to generate a feature vector from the voice signal, which is then input into the DPM classifier. The voice signals of the SVD database are used to train and test the DPM classifier. The voice samples are categorized into four distinct Classes (Cs): C1 comprises 10 recordings from individuals afflicted with Reinke edema, C2 encompasses 10 samples from patients diagnosed with laryngitis, C3 involves 10 voices affected by both laryngitis and Reinke edema, while C4 contains 10 normal voices. The method obtained the highest accuracy of 95% for the classification of all classes. However, the DPM classifier is trained and tested on a limited set of voice samples.

The evaluation and identification of voice disorders through analysis of glottal signals are studied and discussed in [26]. This approach focuses on deriving glottal signal parameters using the inverse filtering technique. The Aparat Software is employed to acquire these glottal signal parameters, which are then extracted in both the time domain and frequency domain. Additionally, the voice signal is subjected to classification using the k-NN and SVM algorithms. The voice signals used for both classes, pathological and healthy voice samples are collected from the SVD database. The results indicated that the SVM achieved an accuracy of 98.5%, while the K-NN achieved 88.2% accuracy. Nevertheless, this method is based on a limited collection of voice samples used for training and testing the classifiers. Furthermore, Table 1 provides an overview of the machine learning methods showcased in various studies for the purpose of detecting voice disorders.

TABLE I. SUMMARY OF THE RELATED WORK

Classifiers	Features	Databases	Accuracy	References
LSTM	MFCC and ZCR	SVD	99.2%	[22]
NB	MFCC	SVD	81.48%	[23]
OSELM	MFCC	SVD	91.17%	[24]
DPM	SH, ZCR, and SE	SVD	95%	[25]
KNN and SVM	Aparat Software	SVD	SVM = 98.5% K-NN = 88.2%	[26]

III. PROPOSED METHOD

In this study, the proposed method is presented to identify and distinguish voice disorders. Specifically, the goal of this method is to distinguish between pathological voices and those that are healthy. The proposed method is performed based on three main stages. The first stage pertains to the voice pathology database, followed by the subsequent stage which presents the processes of extracting features from voice samples. Lastly, the third stage encompasses the classification algorithm. Each of these stages will be elaborated upon in the following subsections.

A. *Voice Pathology Database*

In the proposed approach, the voice signals have been collected from a German database, which is named Saarbrucken voice database (SVD) [18]. This repository encompasses an extensive collection of voice signals derived from both healthy individuals and patients affected by various pathologies. Notably, the SVD database comprises recordings from over 2,000 individuals, covering more than 71 voice disorders. The samples within the SVD database have been captured acoustically at a 50 kHz sampling rate, with a bit resolution of 16 bits. This database incorporates three vowel sounds: /u/, /a/, and /i/. Each of these vowels is articulated at three different levels of pronunciation such as regular, high, and low. Moreover, the SVD database encloses speech recordings conducted in the German language.

According to the literature, the vowel /a/ is the most commonly utilized vowel in voice pathology detection systems. Thus, in our proposed methodology, we have opted for the /a/ vowel pronounced at the normal level. In the conducted experiments, 140 voice samples were used for each class (i.e., healthy and pathological classes) to differentiate and detect voice pathology. Hence, a total of 280 voice samples were collected for the vowel /a/. From this database, 224 voice samples, accounting for 80% of the whole database, were selected and used for the training phase, which are 112 voice samples for each class. Meanwhile, the testing phase involved 56 voice samples with 28 voice samples for each class, which is about 20% of the whole database

B. *Voice Features Extraction*

The proposed method employs the MFCC technique to extract the voice attributes. In addition, this technique is widely used in terms of voice feature extraction for speech recognition systems [27]. It has also proven effective in voice pathology detection [28]. The MFCC method is rooted in the acoustic mechanisms of the human auditory system. In this method, the computation of actual frequencies is expressed in Hertz (Hz), while subjective pitch is calculated along a linear scale termed the 'Mel Scale' [29]. There are several processes in the MFCC technique as illustrated in Fig. 1.

The pre-emphasis procedure involves routing the voices through a filter to enhance their energy at higher frequencies. Moreover, during the framing stage, the voice signal will be partitioned into segments. Following this, the windowing procedure will be executed, using a window shape for each segment of the voice.

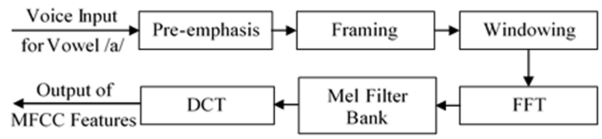

Fig. 1. The MFCC Technique

Subsequently, the Fast Fourier Transform (FFT) procedure is applied to convert all voice frames from their time domain representation to the frequency domain. Additionally, the voice frequencies are transformed from Hertz (Hz) to Mel using the Mel filter bank by employing the following equation:

$$f_{mel} = 2595 \times log\ 10\left(1 + \frac{f_{hz}}{700}\right) \quad (1)$$

The Discrete Cosine Transform (DCT) represents the ultimate procedure of the MFCC technique. It is employed to convert the logarithmic Mel spectrum back into the time domain. As a result, each voice sample undergoes a transformation into a sequence of MFCC features.

C. *Classification Algorithm*

The Decision Tree (DT) algorithm is considered as one of the most powerful methods that has been commonly applied in different domains, such as the identification of patterns [30]. Furthermore, it can be used to make assumptions regarding categorical class names, to classify knowledge based on training sets and class labels, and to classify obtainable data. Additionally, the DT algorithm was efficiently used to solve regression problems. The required computations for the implementation of the DT algorithm were based on a training model. The training model was required to predict the class or value of the given variable based on the learning rules. The DT algorithm uses sample attributes as nodes and sample attribute values as branches. It is a common classification method, and the main learning process is to select relatively important attributes as the middle nodes of the decision tree one by one and to branch with the feature values to build a classification tree with leaf nodes corresponding to specific categories so that the samples can be classified into different categories according to the attribute values. Fig. 2 shows the diagram of the DT algorithm [31].

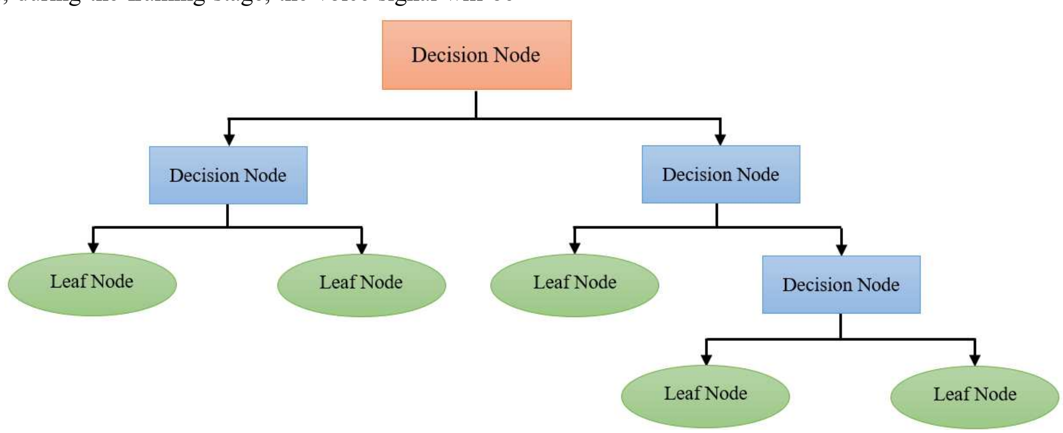

Fig. 2. The diagram of the DT algorithm

In the DT algorithm, entropy is a measure of the database's impurity or randomness. The probability of each decision tree is based on the fraction of entropy of the DT algorithm that is computed by utilizing the following equation [32-34]:

$$E(S) = \sum_{i=1}^{c} - p_i \, log_2 \, p_i \quad (2)$$

where: S refers to the current state of the training example, p_i indicates the percentage of class, and c refers to the number of classes. Moreover, the DT algorithm has many advantages such as simple to comprehend and easy to implement. The algorithm can classify both categorical and numerical outcomes, but the presented features must be categorical, as well as it can present satisfied classification outcomes.

IV. Experimental Results

The voice signals of the vowel /a/ employed in this work were sourced from the SVD database. Furthermore, the database of voice signals with respect to healthy and pathological classes is balanced in terms of the number of samples. In other words, each class has 140 voice samples. We allocated 80% of the database for the training phase and 20% for the testing phase. The experimentation was carried out using the Python 3 programming language within a Google Colaboratory server. The proposed method using the DT classifier was evaluated based on several metrics such as accuracy, sensitivity, precision, G-mean, F-measure, and specificity. The following equations show the computation of these metrics:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (4)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (5)$$

$$\text{G-mean} = \sqrt{\frac{TP}{TP+FN} \times \frac{TN}{TN+FP}} \quad (6)$$

$$\text{F-measure} = \frac{2 * \text{Precision} * \text{Sensitivity}}{\text{Sensitivity} + \text{Precision}} \quad (7)$$

where: TP and TN refer to True Positive and True Negative, respectively. Meanwhile, FP denotes False Positive and FN indicates False Negative. Fig. 3 demonstrates the experimental results of the DT algorithm in differentiating pathological voices from healthy voices.

According to the experimental results of the DT algorithm, the achieved detection accuracy result is 67.857% in detecting voice pathology. In addition, the achieved results of sensitivity, specificity, and precision that have been obtained by the DT algorithm were 68.966%, 66.667%, and 68.966%, respectively. Meanwhile, the DT algorithm achieved 67.806% G-mean and 68.966% F-measure. Additionally, Fig. 4 illustrates the confusion matrix for the experimental results of the presented DT algorithm in the detection of voice pathology. The presented DT algorithm correctly classified 20 voice samples as TP and 18 voice samples as TN. However, the DT algorithm misclassified 18 voice samples, where 9 and 9 voice samples were identified as FP and FN in the detection of voice pathology, respectively.

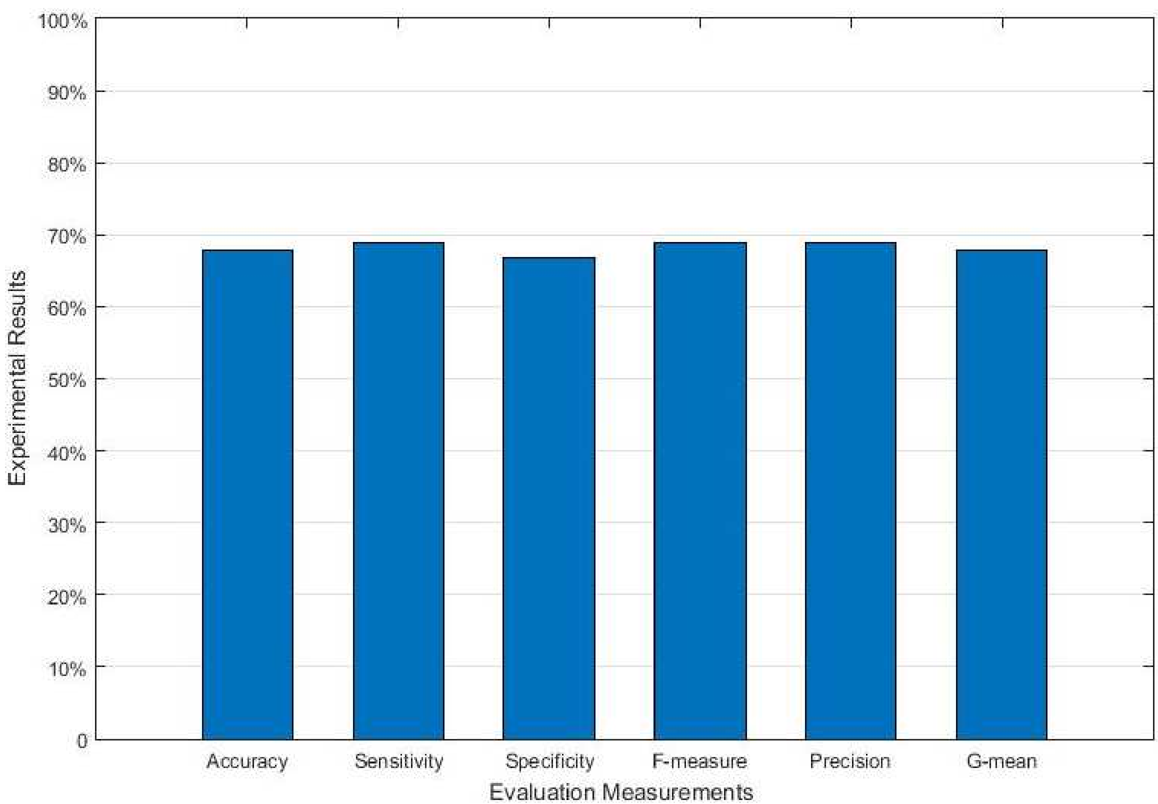

Fig. 3. The experimental results obtained by the DT algorithm in the detection of voice pathology using the SVD database

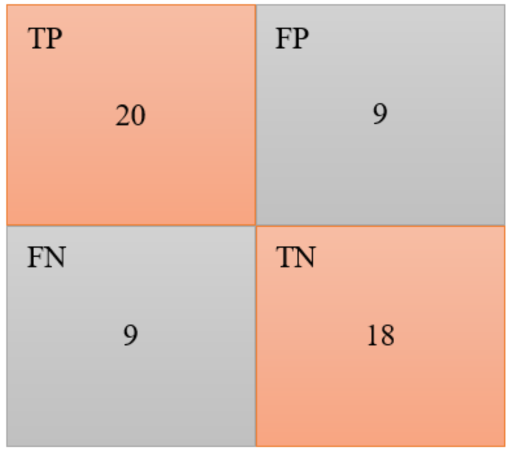

Fig. 4. The confusion matrix for the experimental results of the DT algorithm in the detection of voice pathology

On the other hand, the performance of the proposed DT algorithm is compared with the work in [35] in the detection of voice pathology in terms of accuracy. This work is presented in the identification of voice pathology based on the SVD database using the Gaussian Mixture Modelling (GMM) algorithm. The proposed DT algorithm slightly outperformed the GMM algorithm in the voice pathology detection. Table 2 shows the accuracy comparison between the proposed DT algorithm and the GMM algorithm. Although the DT algorithm obtained 67.857% accuracy and achieved slightly higher performance than the GMM algorithm, the detection accuracy obtained by the DT algorithm is still low. Thus, we concluded that the DT algorithm performed poorly in the detection of voice pathology and needs some improvements in order to elevate its performance. This is considered the main limitation of the proposed method.

TABLE II. ACCURACY COMPARISON BETWEEN METHODS

Method	Accuracy
The proposed DT algorithm	**67.857%**
GMM algorithm [35]	67%

V. CONCLUSIONS AND FUTURE WORK

The detection of voice pathology based on a machine learning algorithm and the voice features is imperative. Therefore, this paper is presented a machine-learning algorithm for the detection of voice disorders. In other words, the DT algorithm is used as a classifier to differentiate pathological samples from healthy ones. In addition, the MFCC technique is employed to extract the voice attributes. The voice signals of each class are gathered from the SVD database for the vowel /a/, where these voices are used to train and test the DT algorithm. The performance of the proposed DT algorithm is assessed in terms of several evaluation metrics. The experimental results showed that the DT algorithm achieved 67.857% accuracy. In addition, the achieved results of sensitivity, specificity, and precision were 68.966%, 66.667%, and 68.966%, respectively. Meanwhile, the DT algorithm achieved 67.806% G-mean and 68.966% F-measure. According to the obtained results, we concluded that the DT algorithm achieved low results in the detection of voice pathology and needs some improvements in order to elevate its performance. In future work, we plan to improve the performance of the DT algorithm in the detection of voice pathology.

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