Voice Pathology Identification using Deep Neural Networks

C.S.Kanimozhiselvi, M.Balaji Prasath, T.Sathiyawathi

Abstract— The human voice construction is a complex biological mechanism capable of changing pitch and volume. Some Internal or External factors frequently damage the vocal cords and change quality of voice or do some alteration in the voice modulation. The effects are reflected in expression of speech and understanding of information said by the person. So it is important to examine problem at early stages of voice change and overcome from this problem. ML play a major role in identifying whether voice is pathological or normal in nature. Voice features are extracted by implementing Mel-frequency Cepstral Coefficients (MFCC) method, and examined on the Convolutional Neural Network (CNN) to identify the category of voice.

Keywords: Classification, Convolutional Neural Network, MFCC, Voice disorder.

I. INTRODUCTION

When the damage occurs at the vocal cord, it affects the production of voice quality and hence the generated voice called as pathological voice. Voice pathologies affect the larynx and result in uneven vibrations of the vocal folds. Poor voice quality can affect the individual’s ability to communicate both socially as well as in the place of work, thus affects the quality of life, and it has a major impact on economy considering the costs of medical diagnosis and treatment. Voice disorders can be classified as: organic, functional.[1] along with several methods to examine voice disorders, the acoustic analysis have confirmed its effectiveness. Normal voice is produced at larynx and generates good quality of speech sounds.[2] Sometimes, many violent speech, normally called as vocal hyper function, produce a voice disorders. [3] The objective of this paper is to automatic identification of one of the communicative disorder called voice disease based on voice database given to the Deep Neural network. Here we have used our own database of audio files collected from the schools (Erode District, Tamil Nadu) as an input to the neural network model.

LITERATURE REVIEW

Thongluan Laosaphan et al [4], [1] proposed a voice identification by using coefficients extracted from voice signal of spoken words based on the principle of MFCC feature extraction for performing utterance recognition. This method provides better recognition rates when training the words with SVM and provides the improved performance.

Gaganpreet Kaur et al [6] examined the research done in the domain of speaker recognition. The different methods used for feature extraction and feature classification had been discussed. Some methods preferred over others such as MFCC for feature extraction had better performance rather than LPC, because MFCC were most consistent with human hearing due to Mel scale representation. Thus, it was concluded that feature extraction of GMM performs better as they require fewer amounts of data to train the classifier. It also decreases the memory usage of the system.

Aman Ankit et al [5] introduced ASR techniques and had put forth some of the essential information. The voice Recognition System and other methods implemented in ASR developed for various languages. HMM and HMM Toolkit had been used. It describes the methods used and comparative study of the performance system developed.

Daria pane et al [7] proposed a multi dimensional system that can classify voices between pathological and normal. In this work, 28 voice features is examined using PCA, KPCA and NLPCA in some pathological detection methods implemented by testing the A, E, I, O and U vowels, at a high, low and normal pitch. The outcomes from different methods were implemented at 10-fold cross-validation. The outcomes show that, the PCA Techniques used to improve the data and we still have a 90% of the variance.

Al-nasher, A Zulfiqar, [6] implemented a Robot Arm that is used to pick and place an object via recognition of speech sounds. This method implemented at python 2.7 version and works well for all speech sounds and recognize better. The outcomes obtained from the speech recognition system has a high average accuracy rate of speech recognition, which is 80% of the respondents trained data and 70% of the respondents for not trained data.

Vimala.C; Dr.V.Radha et al [7] presented a voice pathology identification system to identify the patient voice quality. The Speech signals are sampled at several samples, and CNN models are implemented to process those speech samples at several layers of neurons. Then, a fusion approach implemented to fuse the features from the CNN models. Another direction is the use of different types of inputs, such as voice and EGG signals, combined by deep fusion strategy. Björn W. Schullere et al [12] proposed a deep-learning based methods to differentiate between unconditional speeches from steady speech and examines its efficiency and utility compared with other data mining algorithms.

Revised Manuscript Received on November 19, 2019

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results evaluated on Several Speech database shows that, DNN perform better than traditional GMM and SVM in steady increase in detection accuracy based on three representative features.

Hou, J.-C.; Wang, S.-S.; Lai [11] presents the deep learning model that can classify the speech sounds based on the generated spectrograms. Ecological sounds of spectrogram images used to train the CNN model and tensor deep stacking network that are proposed to used in sound classification application.

III. AUDIO DATA PROCESSING

These sound files are converted into digital wave form represented as .wav format. These files are sampled at the rate of 44.1kHz. Samples are done at discrete intervals called as sampling rate. Each sample is the amplitude of the wave at a particular time interval, where the bit depth determines how detailed the sample will be also known as the dynamic range of the signal (typically 16 bit which means a sample can range from 65,536 amplitude values). Therefore the data will be analyzed for each sound excerpts is essentially a one-dimensional array. Fig. 1 shows the architecture diagram of voice pathology identification of deep neural network.

IV. BUILDING THE MODEL

Two algorithms are used for building the models.

A. Multi Layer Perceptron Algorithm

A Multi-Layer Perceptron or Multi-Layer Neural Network simulates multiple hidden layers between input and output layer. In Contrast to, single layer Perceptron can learn only linear functions, while a multi-layer Perceptron can learn non-linear functions.

As shown in Fig.2 this model provide an input like X1,X2,...,Xn and outputs f, where f(.) is called as activation function. In order to provide every node with Constant value, Bias is need to implement. The number is given as input to activation function, based on this input it perform some mathematical operation. Many activation function encounter in practice.
B. Convolution Neural Network Architecture

Convolutional Neural Networks is constructed to examine the data through multiple layers of arrays and applied in applications like image recognition or voice recognition. Each parallel layer of a neural network connects some input neurons. Each layer output gives as input to other layers in the CNN. Here weight is associated with each layer. Individuals neurons carry out a move from time to time is called Convolution. The architecture of CNN is shown in Fig. 3.

C. Dataset

The original dataset has been collected from special school children. The reading material to identify different disorders are created and given to school children for reading. The voices are then recorded in an audio file. The following Table.1 shows the members of sound excerpts collected from each child to identify various disorders and Table 2 and 3 shows that experimental setup used in our research. We are used our own dataset here. In future, we will collect more data in both normal and pathological data items.

Table 1. Types of disorder

| Disorders                  | Files |
|----------------------------|-------|
| Normal                     | 20    |
| Phonological Disorder      | 18    |
| Speech and Language disorder| 33    |

D. Experimental Setup

Table 2. Experimental setup of MLP

| Feature Extraction | MLP Layers | Activation Function |
|--------------------|------------|---------------------|
| MFCC               | Dense(256) | Tanh, Sigmoid, Relu |

Table 3. Experimental setup of CNN

| Feature Extraction | CNN Layers                                      | Activation | Optimizer |
|--------------------|-------------------------------------------------|------------|-----------|
| MFCC               | Convolution, filter=16, kernal size=2, max pooling, size=2 | Relu       | ADAM      |
| MFCC               | Convolution, filter=32, kernal size=2, max pooling, size=2 | Relu       | ADAM      |
| MFCC               | Convolution, filter=64, kernal size=2, max pooling, size=2 | Relu       | ADAM      |
| MFCC               | Convolution, filter=128, kernal size=2, max pooling, size=2 | Relu       | ADAM      |

V. RESULTS AND DISCUSSION

The Objective of feature extraction is to select the audio features in more detail and expressive way such that it is easy to deal with when applying CNN and MLP models. MLP Training is completed with three activations function as discussed before. Tanh is correlated to logistic sigmoid activation function but its efficiency is better. Refer Fig 4 for Accuracy comparison of CNN and MLP with different activation functions.

Fig. 4 Accuracy comparison of CNN and MLP with different activation function

The Table 4 shows the performance of MLP with different activation functions are measured and compared with CNN.

Table 4. Overall performance measurement of both CNN and MLP

| Techniques/Architecture Used | Performance |
|-----------------------------|-------------|
| Convolutional Neural Network| 93%         |
| Multi-layer Perceptron      | 80%         |

The MLP performance gets increased with the use of Relu activation function at each layer.

From Table 3, it is obvious that CNN performs well to learn features and predicting the final class.

VI. CONCLUSION

This work is focused on voice pathology detection system was embedded to framework to constantly assess the voice condition of a children. Deep neural architecture can be applied using CNN and MLP to discriminate between normal and pathology subjects. The feature extraction techniques using MFCC explains that voice detection can be done using these features. The results show the CNN outperforms MLP.

VII. FUTURE WORK

Expansion of this work is the classification of many disorders which describe the childhood onset fluency disorder, social communicational disorder and unspecified communication disorder. One of the future works includes more experiments with different hyper parameters to improve the results and to use other feature extraction techniques for further improvement. Both the Multilayer Feed forward...
Network with back propagation algorithm and the Recurrent Neural Network can be implemented in future.

VIII. ACKNOWLEDGMENT

This study is supported by the Indian Council of Social Science Research (ICSSR) (F.No IMPRESS/P1565/36/18-19/ICSSR, Dated: 20.03.2019), Govt of India.

REFERENCES

1. Hamzeh Ghasemzadeh, Mehdi Tajik Khass, Meisam Khalil Arjmandi, Mohammad Pooyan, “Detection of vocal disorders based on phase space parameters and Lyapunov spectrum,” Biomedical Signal Processing and Control, Volume 22, Pages 135-145.

2. Heather C. Nardone, MD1; Thomas Recko, BA2; Lin Huang, “A Retrospective review of the progression of pediatric vocal fold nodules,” JAMA Otolaryngol Head Neck Surg. 2014;140(3):233-236. doi:10.1001/jamaoto.2013.6378

3. Chadawan Ittichaichareon, Siwat Sukshi and Thaweesak Yingshwaromsuk, “Speech Recognition using MFCC”, International Conference on Computer Graphics, Simulation and Modeling (ICGSM’2012) July 28-29, 2012 Pattaya (Thailand)

4. N. J. Nalini, S. Palanivel, “Music emotion recognition: The combined evidence of MFCC and residual phase”, Egyptian Informatics Journal (2016) 17, 1-10

5. Hyeran Byun, Seong-Whan Lee, “Applications of Support Vector Machines for pattern recognition: A Survey”, SVM 2002: Pattern Recognition with Support Vector Machines pp 213-236

6. Jo, Cheolwoo / Wang, Soo-Geon / Yang, Byung-Gon / Kim, Hyung-Soon / Li, Tao (2004): "Classification of pathological voice including severely noisy cases", In INTERSPEECH-2004, 77-80.

7. Prof. (Dr.) Y. P. Singh, Director, Sonany (P.G.) I.T.M., Rewari, "An Approach to Speech Recognition - Challenges & Concept ", International Journal of IT, Engineering and Applied Sciences Research (IJIEASR) Volume 2, No. 12, December 2013

8. Evavan Leer*Robert CPisterfXueZhiWou*. An iOS-based Cepstral Peak Prominence Application: Feasibility for Patient Practice of Resonant Voice, Journal of Voice, Volume 31, Issue 1, January 2017, Pages 131.e9-131.e16

9. Laura Verde ; Giuseppe De Pietro ; Giovanna Sannino, Voice Disorder Identification by Using Machine Learning Techniques, IEEE Access ( Volume: 6 )

10. Shi, S., Wang, Q.; Xu, P.; Chu, X.; “ Benchmarking state-of-the-art deep learning software tools”, In Cloud Computing and Big Data (CCBD), 2016 7th IEEE Int. Conf., pp. 99–104, IEEE, 2016.

11. Zhenzhou Wu1 , Sunil Sivadas2 , Yong Kiam Tan1 , Shih Huang1,2 , Rick Siow Meng Goh, “Multi-Modal Hybrid Deep Neural Network for Speech Enhancement”

12. Björn W Schuller, Speech analysis for health: Current state-of-the-art and the increasing impact of deep learning, Health Informatics and Translational Data Analytics

13. Aditya Khamparia; Deepak Gupta; Nhu Gia Nguyen, Sound Classification Using Convolutional Neural Network and Tensor Deep Stacking Network, New Trends in Brain Signal Processing and Analysis, 2169-3536

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