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Respiratory Sound classifications in clinical field using deep. Learning

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Abstract: Respiratory disease, any of the diseases and disorders of the airways and the lungs that affect human respiration. Diseases of the respiratory system may affect any of the structures and organs that have to do with breathing, including the nasal cavities, the pharynx (or throat), the larynx, the trachea (or windpipe), the bronchi and bronchioles, the tissues of the lungs, and the respiratory muscles of the chest cage and also most affected organ in the body by COVID-19 is lungs which damages the alveoli (tiny air sacks). This paper presents the detection of respiratory diseases based on breathing sound parameter by using deep learning. The objective of paper is state deep learning-based lungs disease detection model. taking consideration of recent work and future work we are here collect sound data of different respiratory disease from online repository i.e., URTI, LRTI, Bronchiectasis, Bronchiolitis and COPD and also have healthy patients sound records. In methods and procedure, we are using MFCC concept for sound feature extraction Here we will be using Mel-Frequency Cepstral Coefficients (MFCC) from the audio samples. The MFCC summarizes the frequency distribution across the window size, so it is possible to analyze both the frequency and time characteristics of the sound. These audio representations will allow us to identify features for classification. The presented information can be used by other researchers to plan their research contributions and activities. The potential future direction suggested could further improve the efficiency and increase the number of deep learning aided lung disease detection applications.

Index Terms - Respiratory disease, Deep learning, Mel-Frequency Cepstral Coefficients (MFCC).

I. Introduction

Nowadays we see the percentage of respiratory disease are increasing rapidly. People are suffering from different kinds of diseases that's affects the lungs and other parts of respiratory disease which is mainly caused by infection or by smoking tobacco, other second-hand tobacco, radon, asbestos also due to the chemicals and increasing pollution. Respiratory disease includes URTI, LRTI, COPD, Bronchiectasis, Bronchiolitis, Pneumonia, Asthma and lung cancer also lung disorder pulmonary disease. When we are healthy, we take our breathing for granted, never fully appreciating that our lungs are essential organs for life. But when our lung health is impaired, we realize that nothing else but our breathing is what really matters. That is the painful reality for those suffering from lung disease a condition that affects people of all ages in every corner of the world. Lung diseases kill millions and cause suffering to millions more. Threats to our lung health are everywhere, and they start at an early age when we are most vulnerable. Fortunately, many of these threats are avoidable and their consequences treatable. So, to overcome on this disease or to avoid before it gets severe condition, I have collected the respiratory sound recording waves from online repositories which contains URTI, LRTI, COPD, Bronchiectasis, Bronchiolitis, Pneumonia and healthy patient's respiratory sound. Based on that creating a model which will detect the disease respiratory disease as we will give new sound recording. Using MFCC (Mel Frequency Cepstral Coefficient) concept which will be using Mel-Frequency Cepstral Coefficients from the audio samples. The MFCC summarizes the frequency distribution across the window size, so it is possible to analyze both the frequency and time characteristics of the sound. These audio representations will allow us to identify features for classification. The main aim of Deep learning model is it will allow us to show graphically the pattens of respiratory track and severity by sound records, that we can also store that data and it will detect of disease.

II Motivation of Project

Respiratory diseases are leading causes of death and disability in the world. About 65 million people are suffering from COPD and 3 million died from per year Also the percentage of smokers are increasing day by day from the age of 13 to 15 and 15 onwards and mostly in corporate society.

The Impact of Covid-19 on the People, who are already suffering through respiratory diseases.

III Methodology

Data Collection

Data collection is the procedure of collecting, measuring and analyzing accurate insights for research using standard validated techniques. A researcher can evaluate their hypothesis on the basis of collected data. In most cases, data collection is the primary and most important step for research, irrespective of the field of research. The approach of data collection is different for different fields of study, depending on the required information.

The most critical objective of data collection is ensuring that information-rich and reliable data is collected for statistical analysis so that data-driven decisions can be made for research. Applications areas of Electrical, Mechanical, Fluid, Acoustic, Chemical, Multipurpose, and Interfacing. Data is a type of data that has already been published in books, newspapers, magazines, journals, online portals etc. There is an abundance of data available in these sources about your research area in business studies, almost regardless of the nature of the research area. Therefore, application of appropriate set of criteria to select secondary data to be used in the study plays an important role in terms of increasing the levels of research validity and reliability.

These criteria include, but not limited to date of publication, credential of the author, reliability of the source, quality of discussions, depth of analyses, the extent of contribution of the text to the development of the research area etc. Secondary data collection is discussed in greater depth in Literature Review chapter. Secondary data collection methods offer a range of advantages such as saving time, effort and expenses. However, they have a major disadvantage. Specifically, secondary research does not make contribution to the expansion of the literature by producing fresh (new) data.

Common challenges in data collection:

Data quality issues. Raw data typically includes errors, inconsistencies and other issues. Ideally, data collection measures are designed to avoid or minimize such problems. That isn't foolproof in most cases, though. As a result, collected data usually needs to be put through data profiling to identify issues and data cleansing to fix them.

Finding relevant data. With a wide range of systems to navigate, gathering data to analyze can be a complicated task for data scientists and other users in an organization. The use of data curation techniques helps make it easier to find and access data. For example, that might include creating a data catalog and searchable indexes.

Deciding what data to collect. This is a fundamental issue both for upfront collection of raw data and when users gather data for analytics applications. Collecting data that isn't needed adds time, cost and complexity to the process. But leaving out useful data can limit a data set's business value and affect analytics results.

Dealing with big data. Big data environments typically include a combination of structured, unstructured and semi structured data, in large volumes. That makes the initial data collection and processing stages more complex. In addition, data scientists often need to filter sets of raw data stored in a data lake for specific analytics applications.

Low response and other research issues. In research studies, a lack of responses or willing participants raises questions about the validity of the data that's collected. Other research challenges include training people to collect the data and creating sufficient quality assurance procedures to ensure that the data is accurate.

IV Preprocessing Data for Machine Learning

Data preprocessing in Machine Learning is a crucial step that helps enhance the quality of data to promote the extraction of meaningful insights from the data. Data preprocessing in Machine Learning refers to the technique of preparing (cleaning and organizing) the raw data to make it suitable for a building and training Machine Learning models. In simple words, data preprocessing in Machine Learning is a data mining technique that transforms raw data into an understandable and readable format.

1. Acquire the dataset

Acquiring the dataset is the first step in data preprocessing in machine learning. To build and develop Machine Learning models, you must first acquire the relevant dataset. This dataset will be comprised of data gathered from multiple and disparate sources which are then combined in a proper format to form a dataset. Dataset formats differ according to use cases

For instance, a business dataset will be entirely different from a medical dataset. While a business dataset will contain relevant industry and business data, a medical dataset will include healthcare-related data.

There are several online sources from where you can download datasets like https://www.kaggle.com/uciml/datasets and https://archive.ics.uci.edu/ml/index.php. You can also create a dataset by collecting data via different Python APIs. Once the dataset is ready, you must put it in CSV, or HTML, or XLSX file formats.

2. Import all the crucial libraries

Since Python is the most extensively used and also the most preferred library by Data Scientists around the world, we'll show you how to import Python libraries for data preprocessing in Machine Learning. Read more about Python libraries for Data Science here. The predefined Python libraries can perform specific data preprocessing jobs. Importing all the crucial libraries is the second step in data preprocessing in machine learning. The three core Python libraries used for this data preprocessing in Machine Learning are:

NumPy – NumPy is the fundamental package for scientific calculation in Python. Hence, it is used for inserting any type of mathematical operation in the code. Using NumPy, you can also add large multidimensional arrays and matrices in your code.

Pandas – Pandas is an excellent open-source Python library for data manipulation and analysis. It is extensively used for importing and managing the datasets. It packs in high-performance, easy-to-use data structures and data analysis tools for Python.

Matplotlib – Matplotlib is a Python 2D plotting library that is used to plot any type of charts in Python. It can deliver publication-quality figures in numerous hard copy formats and interactive environments across platforms (IPython shells, Jupyter notebook, web application servers, etc.).

3. Import the dataset

In this step, you need to import the dataset/s that you have gathered for the ML project at hand. Importing the dataset is one of the important steps in data preprocessing in machine learning. However, before you can import the dataset/s, you must set the current directory as the working directory.

4. Identifying and handling the missing values in data preprocessing, it is pivotal to identify and correctly handle the missing values, failing to do this, you might draw inaccurate and faulty conclusions and inferences from the data. Needless to say, this will hamper your ML project.

Basically, there are two ways to handle missing data:

Deleting a particular row – In this method, you remove a specific row that has a null value for a feature or a particular column where more than 75% of the values are missing. However, this method is not 100% efficient, and it is recommended that you use it only when the dataset has adequate samples. You must ensure that after deleting the data, there remains no addition of bias.

Calculating the mean – This method is useful for features having numeric data like age, salary, year, etc. Here, you can calculate the mean, median, or mode of a particular feature or column or row that contains a missing value and replace the result for the missing value. This method can add variance to the dataset, and any loss of data can be efficiently negated. Hence, it yields better results compared to the first method (omission of rows/columns). Another way of approximation is through the deviation of neighboring values. However, this works best for linear data

5. Encoding the categorical data

Categorical data refers to the information that has specific categories within the dataset. In the dataset cited above, there are two categorical variables – country and purchased. Machine Learning models are primarily based on mathematical equations. Thus, you can intuitively understand that keeping the categorical data in the equation will cause certain issues since you would only need numbers in the equations.

6. Splitting the dataset

Splitting the dataset is the next step in data preprocessing in machine learning. Every dataset for Machine Learning model must be split into two separate sets – training set and test set.

7. Feature scaling

Feature scaling marks the end of the data preprocessing in Machine Learning. It is a method to standardize the independent variables of a dataset within a specific range. In other words, feature scaling limits the range of variables so that you can compare them on common grounds. When it comes to creating a Machine Learning model, data preprocessing is the first

V RELATED WORK

The related work section describes automation methods and physical systems to ease the detection of respiratory diseases. Physical devices like the Breath Monitoring System (Radogna et al., 2019) propose a smart breath analysis device that can be used to detect COPD. A classifier based on combination of ANN and backpropagation based Multi-Layer Perceptron algorithm to predict patient’s respiratory audio crucial event with certain respiratory diseases, predominantly asthma and COPD, was examined (Khatri & Tamil, 2018). Because ANN is a nonlinear method, its output is better than commonly used classification or regression techniques. Further analysis can be performed along similar lines by refining the classifier’s parameters or using specific machine learning techniques such as deep learning. The precision and recall were 77.1% and 78.0% for the peak event level, respectively, and those for the non-peak events were 83.9% and 83.2%. The average machine performance is 81.0%. An articulate system for chronic illness was proposed that offers an integrated platform for successful diagnosis and real-time appraisal of patients’ health status with COPD disease (Bellos et al., 2014). A machine/device is being put together to observe a patient’s condition in real-time. A hybridized classifier was developed on a personalized digital assistant consisting of a machine learning algorithm such as SVM, random forest, and a predicate-based approach to include a more complex classification scheme to classify a COPD series early and in real-time. The classification quality obtained was calculated at 94%.

A computer-based approach to automatically interpret stethoscope recorded respiratory sounds, which has several possible use cases such as telemedicine and self-screening, has also been proposed (Liu et al., 2017). One custom-built test tool collects three forms of respiratory sounds from 60 patients. A deep model of Convolutional Neural Networks that consisted of 6 convolution layers, three max-pooling layers, and three wholly linked layers are deployed ahead. Via time-frequency transformation, 60 bands of Log-scaled Mel-Frequency Spectral features were collected framewise which were present in the dataset and segmented as model inputs in a size of 23 consecutive frames. Finally, the developed model was evaluated with a new dataset of 12 subjects measured in precision and recall to 5 respiratory physicians’ mean results.

A simple and cost-effective digital stethoscope to record respiratory sounds on a monitor, which can be used on any unit, was proposed by Aykanat et al. (2017), using which 17,930 lung sounds were recorded from 1,630 subjects. The study used two forms of machine learning algorithms: Mel frequency cepstral coefficient features in the Convolutional Neural Network (CNN) and SVM along with spectrogram images. While the usage of MFCC functionality for an SVM algorithm is a widely agreed approach for audio classification, the patrons used its tests to assess the CNN algorithm performance. With each CNN and SVM algorithm, four data sets were prepared for classification of respiratory audio: safe versus unhealthy; rale, rhonchus, and standard classification of speech; singular classification of respiratory speech form; and classification of the audio form of all sound forms. Experimental accuracy findings were 86% CNN, 86% SVM, 76% CNN, 75% SVM, 80% CNN, 80% SVM and 62% CNN, 62% SVM respectively. Consequently, it was found that spectrogram picture classification works well with both the CNN and the SVM algorithms. Given a vast proportion of input, CNN and SVM algorithms can correctly identify and pre-determine COPD through respiratory audio. In research, for the classification of spirometry results, ANFIS, MANFIS, and CANFIS models with different membership functions were employed (Asaithambi, Manoharan & Subramanian, 2012). ANFIS algorithm achieves better recognition accuracy compared to the neural network approach previously employed. This may be because ANFIS incorporates neural networks' learning capacities and the fuzzy inference system's logic capacities. CANFIS achieves 97.5% higher classification accuracy relative to the standard ANFIS and MANFIS, as observed. Chamberlain et al. (2016), focused on wheezes and crackles (two most frequent lung sounds), and their algorithm achieved ROC curves with AUCs of 0.86 and 0.74 for wheezes and crackles, respectively. Another research was carried out in which the COPD disease dataset consisted of 155 samples which were belonging to two distinct categories, classified into Class 1: COPD containing 55 samples and Class 2: Standard containing 100 samples (Er & Temurtas, 2008).

Results achieved with a two hidden layer based MLNN (95.33% accuracy) were higher as compared to single hidden layer based MLNN system. A study conducted to categorize data samples used a feed-forward NN architecture with a secret layer running on the log sigmoid transfer feature (Asaithambi, Manoharan & Subramanian, 2012). This network had a range of plain, layer-organized neuron-like processing units. The network testing was carried out with the error propagation backward. Neural networks that operate radial bases are often focused on supervised learning. RBF networks can be used effectively to model nonlinear data, as they can be trained in one-step instead of using a repetitive method similar to Multiple Layer Perceptron. Radial base networks learn quickly. The hidden layer outputs are combined linearly in response to an input vector to form the network answer, which is interpreted with a desired solution to the output layer. The weights are conditioned using a standardized linear system in a controlled manner.

Machine-learning techniques have tremendous potential to aid the early detection of COPD exacerbations (Fernandez-Granero, Sanchez-Morillo & Leon-Jimenez, 2018). Prediction of exacerbations may reduce inevitable adverse consequences and minimize the high costs associated with patients with COPD. Acute exacerbations are one of the critical factors of declining qualities of a healthy life and accord to sustained obstructive pulmonary disease (COPD) patients being hospitalized. The established model could detect early searing COPD exacerbations 4.4 days before its initiation. For automatic symptom-based exacerbation predictions, a decision tree forest classifier was trained and validated with recorded data. Deep learning-based algorithms such as CNN and LSTMS are getting lots of attention in real life critical learning systems (Bai et al., 2020).

CONCLUSION

In this study, we have proposed a simple and less resource-intensive deep learning assistive model, which can assist medical experts in detecting respiratory diseases using respiratory sounds. In the conducted experiments, we have used a machine learning library feature such as MFCC, Mel-Spectrogram, Chroma, Chroma (Constant-Q), and Chroma CENS to perform a detailed analysis of respiratory sounds Dataset. Based on the conducted experiments, it has been found that "mfcc" has provided better accuracy in detecting respiratory diseases in machine learning library features. For the future scope, we can extend its functionalities to aid doctors in detecting various other diseases such as probability of occurrence of heart attack/cardiac arrest based on the heart beats sounds, detection of Asthma based on lung sounds etc. We can also enhance the current system to detect the severity of the disease.

REFERENCES

1) Ahmed J, Vesal S, Durlak F, Kaergel R, Ravikumar N, Rémy-Jardin M, Maier A, Tolxdorff T, Deserno T, Handels H, Maier A. 2020. COPD classification in CT images using a 3D convolutional neural network. In: Maier-Hein K, Palm C, eds. Bildverarbeitung für Die Medizin 2020—Informatik Aktuell. Wiesbaden: Springer Vieweg, 39–45.
2) Altan G, Kutlu Y, Allahwardi N. 2019. Deep learning on computerized analysis of chronic obstructive pulmonary disease. IEEE Journal of Biomedical and Health Informatics 24(5):1344–1350 DOI 10.1109/JBHI.2019.2931395.
3) Altan G, Kutlu Y, Pekmezci AÖ, Nural S. 2018. Deep learning with 3D-second order difference plot on respiratory sounds. Biomedical Signal Processing and Control 45:58–69 DOI 10.1016/j.bspc.2018.05.014.
4) Amaral JL, Lopes AJ, Jansen JM, Faria AC, Melo PL. 2012. Machine learning algorithms and forced oscillation measurements applied to the automatic identification of chronic obstructive pulmonary disease. Computer Methods and Programs in Biomedicine 105(3):183–193 DOI 10.1016/j.cmpb.2011.09.009.
5) Asaithambi M, Manoharan SC, Subramanian S. 2012. Classification of respiratory abnormalities using adaptive neuro-fuzzy inference system. In: Pan J-S, Chen S-M, Nguyen NT, eds. Intelligent Information and Database Systems. Berlin: Springer, 65–73.

6) Aykanat M, Kılıç Ö, Kurt B, Saryal S. 2017. Classification of lung sounds using convolutional neural networks. EURASIP Journal on Image and Video Processing 2017(1):65 DOI 10.1186/s13640-017-0213-2.
7) Badnjevic A, Gurbeta L, Custovic E. 2018. An expert diagnostic system to automatically identify asthma and chronic obstructive pulmonary disease in clinical settings. Scientific Reports 8(1):11645 DOI 10.1038/s41598-018-30116-2.
8) Bai Z, Li Y, Woźniak M, Zhou M, Li D. 2020. DecomVQANet: decomposing visual question answering deep network via tensor decomposition and regression. Pattern Recognition 110:107538 DOI 10.1016/j.patcog.2020.107538.
9) Bellos CC, Papadopoulos A, Rosso R, Fotiadis DI. 2014. Identification of COPD patients' health status using an intelligent system in the CHRONIOUS wearable platform. IEEE Journal of Biomedical and Health Informatics 18(3):731–738 DOI 10.1109/JBHI.2013.2293172.
10) Chamberlain D, Kodgule R, Ganelin D, Miglani V, Fletcher RR. 2016. Application of semi-supervised deep learning to lung sound analysis. In: 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). Piscataway: IEEE, 804–807.
11) Du R, Qi S, Feng J, Xia S, Kang Y, Qian W, Yao YD. 2020. Identification of COPD from multi-view snapshots of 3D lung airway tree via deep CNN. IEEE Access 8:38907–38919 DOI 10.1109/ACCESS.2020.2974617.
12) Er O, Temurtas F. 2008. A study on chronic obstructive pulmonary disease diagnosis using multilayer neural networks. Journal of Medical Systems 32(5):429–432 DOI 10.1007/s10916-008-9148-6.
13) Fernandez-Granero MA, Sanchez-Morillo D, Leon-Jimenez A. 2018. An artificial intelligence approach to early predict symptom-based exacerbations of COPD. Biotechnology & Biotechnological Equipment 32(3):778–784 DOI 10.1080/13102818.2018.1437568.
14) ICBHI. 2017. ICBHI challenge. Available at https://bhichallenge.med.auth.gr/ICBHI_2017_ Challenge (accessed 21 May 2020).
15) Khatri KL, Tamil LS. 2018. Early detection of peak demand days of chronic respiratory diseases emergency department visits using artificial neural networks. IEEE Journal of Biomedical and Health Informatics 22(1):285–290 DOI 10.1109/JBHI.2017.2698418.
16) Kingma DP, Ba J. 2017. Adam: a method for stochastic optimization. arXiv. Available at http://arxiv.org/abs/1412.6980.
17) Librosa. 2020. Feature extraction—Librosa 0.8.0 documentation. Available at https://librosa.org/ doc/latest/feature.html (accessed 20 May 2020).
18) Librosa. 2019. Librosa 0.8.0 documentation. Available at https://librosa.org/doc/main/generated/ librosa.feature.chroma_stft.html (accessed 21 May 2020).
19) Liu Y, Lin Y, Gao S, Zhang H, Wang Z, Gao Y, Chen G. 2017. Respiratory sounds feature learning with deep convolutional neural networks. In: 2017 IEEE 15th International Conference on Dependable, Autonomic and Secure Computing, 15th International Conference on Pervasive Intelligence and Computing, 3rd International Conference on Big Data Intelligence and Computing and Cyber Science and Technology Congress (DASC/PiCom/DataCom/CyberSciTech). Piscataway: IEEE, 170–177.
20) Manoharan S, Veezhinathan M, Ramakrishnan S. 2008. Comparison of two ANN methods for classification of spirometer data. Measurement Science Review 8(3):535 DOI 10.2478/v10048-008-0014-y.
21) Patil S, Shashank J, Deepali P. 2020. Enhanced privacy preservation using anonymization in IoT-enabled smart homes. In: Smart Intelligent Computing and Applications. Singapore: Springer, 439–454.
22) Perna D. 2018. Convolutional neural networks learning from respiratory data. In: 2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM). Madrid: IEEE, 2109–2113.
23) Perna D, Tagarelli A. 2019. Deep auscultation: predicting respiratory anomalies and diseases via recurrent neural networks. arXiv. Available at http://arxiv.org/abs/1907.05708.
24) Pham L, McLoughlin I, Phan H, Tran M, Nguyen T, Palaniappan R. 2020. Robust deep learning framework for predicting respiratory anomalies and diseases. arXiv. Available at http://arxiv.org/abs/2002.03894.
25) Radogna AV, Fiore N, Tumolo MR, De Luca V, De Paolis LT, Guarino R, Leo CG, Mincarone P, Sabato E, Satriano F, Capone S, Sabina S. 2019. Exhaled breath monitoring during home ventilo-therapy in COPD patients by a new distributed tele-medicine system. Journal of Ambient Intelligence and Humanized Computing 5:1–9.
26) Rocha BM, Filos D, Mendes L, Serbes G, Ulukaya S, Kahya YP, Jakovljevic N, Turukalo TL, Vogiatzis IM, Perantoni E, Kaimakamis E, Natsiavas P, Oliveira A, Jácome C, Marques A, Maglaveras N, Pedro Paiva R, Chouvarda I, De Carvalho P. 2019. An open access database for the evaluation of respiratory sound classification algorithms. Physiological Measurement 40(3):035001.
27) Shaikh A, Patil S. 2018. A survey on privacy enhanced role based data aggregation via differential privacy. In: 2018 International Conference On Advances in Communication and Computing Technology. Piscataway: IEEE, 285–290.
28) Weese J, Lorenz C. 2016. Four challenges in medical image analysis from an industrial perspective. Medical Image Analysis 33:44–49 DOI 10.1016/j.media.2016.06.023.
29) Wierenga R. 2020. An empirical comparison of optimizers for machine learning models. Available at https://heartbeat.fritz.ai/an-empirical-comparison-of-optimizers-for-machinelearning-models-b86f29957050.