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HUMAN SOUND-BASED DISEASE DETECTION SYSTEM USING MACHINE LEARNING

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***Abstract:* :** A human sound-based disease detecting system leveraging machine learning involves collecting diverse audio samples capturing specific human sounds related to diseases or health conditions. Through signal processing and feature extraction methods like spectrograms or MFCCs, meaningful features are derived from these audio signals. Supervised machine learning models, such as CNNs or RNNs, are trained on these extracted features to learn patterns and correlations between audio characteristics and particular diseases. After validation and performance assessment, the trained model is integrated into an application or system to analyze incoming audio input and predict potential diseases or health issues, and ethical use of health data remain pivotal throughout the development process. Employing signal processing techniques and feature extraction methods like spectrograms or MFCCs, the system abstracts meaningful patterns from the audio data. Through supervised learning algorithms such as CNNs or RNNs, the model learns to correlate these sound features with specific diseases during the training phase. Validation and fine-tuning ensure its accuracy and generalizability, following which it gets integrated into an interface for real-time audio input processing and disease prediction. Ethical considerations, data privacy, and collaboration among medical professionals and AI experts are essential throughout the development to responsibly deploy this system, potentially enabling early disease detection and remote healthcare accessibility.

***Index Terms* - Sound Detection, Machine Learning, Image Processing**

I. INTRODUCTION

Voice analytics uses a voice recognition tool to analyze and record an audio. Voice analytics program not only converts speech to text, but can also recognize the sentiments and intent of the speaker by interpreting audio signals. There is an abundance of research showing that a person's speech can be affected by multiple physical and mental health conditions. Also, during the speaking, there are 6300+ parameters which become active from which some set of the parameters are affected in each health condition. They could also make your voice creak or jitter so briefly that it’s not detectable to the human ear. For example, speaking in a more nasal accent, elongating noises, slurring words or even noises that are not audible to the human ear. So in the proposed system we develop a machine learning architecture to classify the diseases based on human sounds.

1.1 DESCRIPTION

A human sound-based disease detecting system employing machine learning utilizes audio data to identify potential health conditions. This system collects a wide array of sound samples related to specific diseases or health issues, encompassing coughs, breath sounds, heart murmurs, or speech patterns 4 indicative of various ailments. Through sophisticated signal processing techniques and feature extraction methods such as spectrograms or Mel- frequency cepstral coefficients (mfccs), significant patterns and features are abstracted from the audio data. Machine learning algorithms, including convolutional neural networks (cnns) or recurrent neural networks (rnns), are then trained on these extracted features to recognize correlations between sound patterns and specific diseases. The model undergoes rigorous validation and refinement to ensure its accuracy and robustness, or indicate potential diseases or health conditions. Collaboration among medical experts, data scientists, and ethical considerations are pivotal in developing and deploying this system responsibly, potentially revolutionizing early disease detection and enabling accessible remote healthcare

1.2 PROBLEM DEFINITION

The problem definition for a human sound-based disease detecting system using machine learning involves creating an automated and accurate method to analyze audio samples and identify patterns associated with various diseases or health conditions. This encompasses the challenge of developing algorithms capable of recognizing specific sound features correlated with diseases, such as coughs, breath sounds, or speech patterns indicative of 5 certain ailments. The key goal is to build a robust and reliable model that can accurately predict or detect diseases based on audio inputs, enabling early diagnosis and potentially facilitating remote healthcare. Challenges include sourcing diverse and comprehensive datasets, implementing effective signal processing and feature extraction techniques, and training machine learning models to generalize well across different diseases while ensuring ethical handling of sensitive health data. The primary aim is to create a system that contributes to early disease detection, enhancing healthcare accessibility and potentially improving health outcomes.

The problem at hand is the development of a disease prediction system using voice recognition and analytics. Despite the potential of voice analytics to detect health conditions by analyzing subtle changes in speech, the absence of a standardized text for sample collection remains a significant challenge. The goal is to create a machine learning model capable of classifying diseases based on voice patterns, offering early warnings, point-of-care screening, and disease surveillance. This system aims to provide rapid, accurate, and language-independent health assessments, bridging the gap between patient symptoms and timely medical intervention while reducing the subjectivity of traditional diagnosis methods.

I. LITRETURE SURVEY

Human voice as well as the sound of the body is used as a clinical method to assess the health condition of an individual. The evaluation of the human voice has risen as a critical field of exploration. Speech analysis fundamentally involves the extraction of certain features from voice signals for generation of voice in alluring pertinence by using reasonable techniques. This paper brings up normal ailments that sway understanding voice patterns in proof for driving research that have affirmed voice modifications as demonstrative manifestations in their respective ailments and also the technique by which voice analysis can be done.

Depression is a common mental health problem leading to significant disability world wide. Depression is not only common but also commonly co- occurs with other mental and neurological illnesses. Parkinson's Disease gives rise to symptoms directly impairing a person's ability to function. Early diagnosis and detection of depression can aid treatment, but diagnosis typically requires an interview with a health provider or structured diagnostic questionnaire. Thus, unobtrusive measures to monitor depression symptoms in daily life could have great utility in screening depression for clinical treatment. Vocal biomarkers of depression are a potentially effective method of assessing depression symptoms in daily life, We have a database of 921 unique patients with Parkinson's disease and their self assessment of whether they felt depressed or not. Voice recordings from these patients were used to extract paralinguistic features, which served as inputs to machine-learning and deep learning techniques to predict depression.

2.1 VOICE-BASED DETECTION

. A human sound-based disease detecting system using machine learning for voice-based detection involves leveraging audio data to identify potential health issues through speech patterns and characteristics. This system would collect and analyze voice samples, extracting features from speech such as pitch, tone, rhythm, and articulation. These extracted features could be processed using machine learning algorithms to detect anomalies or patterns associated with specific diseases or health conditions, like Parkinson's disease, depression, or vocal disorders. Challenges include creating algorithms that can effectively interpret variations in speech due to different languages, accents, or individual vocal traits, as well as ensuring the system's accuracy and reliability across diverse populations. Developing such a system holds promise for non-invasive, accessible early detection of various health issues through voice analysis, potentially aiding in remote healthcare and timely interventions.

This system involves collecting voice samples and extracting relevant features such as pitch, intensity, frequency, and articulation using signal processing techniques. Machine learning models, such as neural networks or support vector machines, can then be trained on these voice features to recognize 9 patterns associated with various diseases or health issues, like Parkinson's disease, Alzheimer's, or respiratory disorders. Challenges include ensuring accuracy across different languages and accents, handling variations in speech due to age or individual differences, and addressing ethical considerations regarding health data privacy. Such a system has the potential to offer non- invasive, accessible early detection of health conditions through voice analysis, supporting timely interventions and remote healthcare.

2.2 SYMPTOM-BASED DETECTION

A human sound-based disease detecting system using machine learning for symptom-based detection involves analyzing specific sounds related to bodily symptoms for potential disease identification. This system captures and processes sounds like coughs, breath patterns, or heart murmurs to extract symptom-specific features using signal processing techniques. Machine learning algorithms, like deep neural networks or decision trees, are then trained on these features to associate sound patterns with particular symptoms or diseases, such as pneumonia, asthma, or heart conditions. Challenges 10 include obtaining a comprehensive dataset covering diverse symptom manifestations, ensuring the model's accuracy across different populations and conditions, and integrating ethical considerations for responsible data handling. Such a system holds promise for aiding in early symptom-based disease detection, potentially enabling quicker diagnoses.

Natural language processing (NLP) and automatic detection of the disease have become popular in the recent era. Several research work show disease detection system in several languages. We present a disease detection system from the clinical text which is in Bengali language consisting of a numerous set of diacritic character, at a sentence-level classification.

2.3 CORONARY HEART DISEASE DETECTION

Detecting coronary heart disease (CHD) using a human sound-based disease detection system with machine learning involves analyzing specific sound patterns associated with the heart to identify potential indicators of CHD. This could include analyzing heart murmurs, abnormal rhythms, or other cardiac sounds captured via auscultation. Signal processing techniques, such as 11 filtering and spectral analysis, may be employed to extract relevant features from these sounds, focusing on frequency variations, intensity, or temporal characteristics. Challenges include obtaining diverse and extensive datasets of cardiac sounds, ensuring accuracy and reliability in differentiating normal heart sounds from those indicative of CHD, and integrating the system into clinical practice for effective diagnosis and patient care.

Coronary Heart Disease (CHD) is one of the major causes of death now-a- days. Due to increased stress level and many other reasons the heart disease are common in human. The heart problems affect the larynx and breathing and consequently the quality of speech. The current work is aimed at understanding the variation of voice parameter in the CHD patients. For processing the voice signal CSL (Computerized Speech Lab) model 4500 is used, it also contains MDVP (Multi Dimensional Voice Program), that analyzes and displays up to 22 voice parameters from a single voice analysis.Establish the cascade classifier for both left and right eyes, subsequently initiating the eye detection process. The next step involves extracting exclusive eye data from the entire image by delineating the eye's boundary box. Utilizing the cascade classifier facilitates the extraction of the eye image from the frame, where the left eye comprises solely the eye's image data. This information is then inputted into our CNN classifier, predicting the status of the eyes regarding openness or closure. The same process is applied to the right eye, creating a dataset for analysis.

To prepare the image for the model, essential operations are conducted to ensure the correct dimensions. This includes converting the color image to grayscale and resizing it to 24x24 pixels, aligning with the model's training specifications. Normalization is applied to optimize data convergence, scaling all values between 0 and 1. Additionally, the dimensions are expanded to align with the classifier's input requirements. Loading the model is accomplished using the command `model = load_model('models/cnnCat2.h5')`.

III.DESIGN

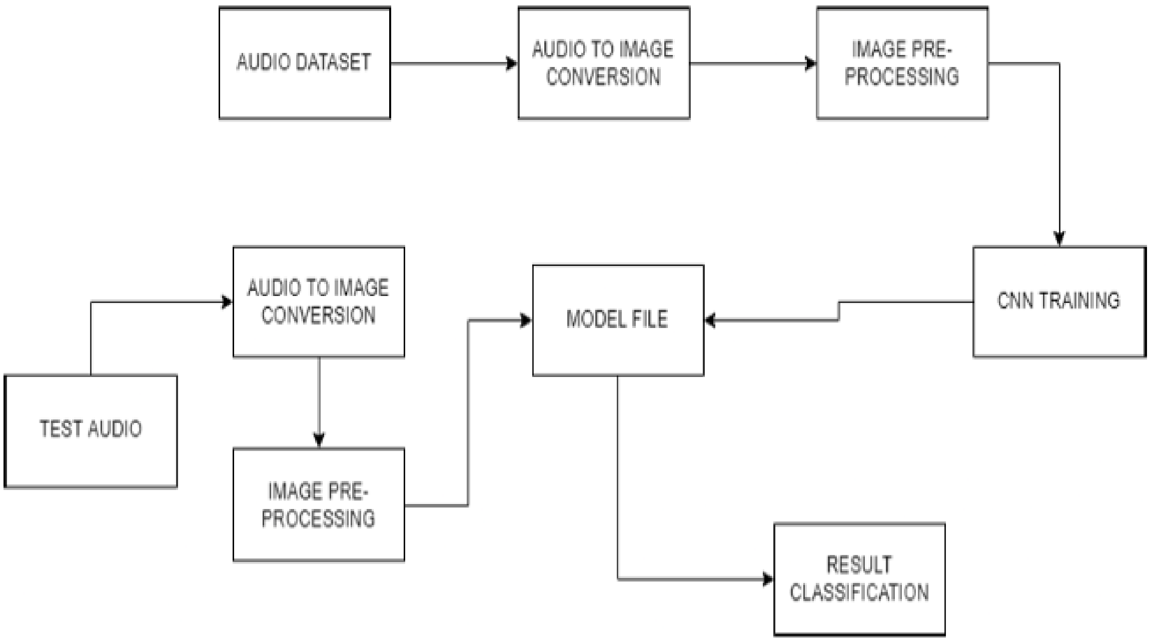


Fig 3.1 Block diagram

The audio dataset is converted in to image using spectrogram technique and all the images are pre-processed To enhance the image and sent for convolution neural network training.After the training process the model file is created And during testing process the test audio is converted in to image and evaluated with model file using cnn and final result is classified.

IV.TENSORFLOW

TensorFlow is an interface for expressing machine learning algorithms, and an implementation for executing such algorithms. A computation expressed using TensorFlow can be executed with little or no change on a wide variety of heterogeneous systems, ranging from mobile devices such as phones and tablets up to large-scale distributed systems of hundreds of machines and thousands of computational devices such as GPU cards. The system is flexible and can be used to express a wide variety of algorithms, including 24 training and inference algorithms for deep neural network models, and it has been used for conducting research and for deploying machine learning systems into production across more than a dozen areas of computer science and other fields, including speech recognition, computer vision, robotics, information retrieval, natural language processing, geographic information extraction, and computational drug discovery.

This paper describes the TensorFlow interface and an implementation of that interface that we have built at Google. The TensorFlow API and a reference implementation were released as an open-source package under the Apache 2.0 license in November, 2015 and are available at www.tensorflow.org. Based on our experience with Disbelief and a more complete understanding of the desirable system properties and requirements for training and using neural networks, we have built TensorFlow, our second-generation system for the implementation and deployment of largescale machine learning models. TensorFlow takes computations described using a dataflow-like model and maps them onto a wide variety of different hardware platforms, ranging from running inference on mobile device platforms such as Android and iOS to modest sized training and inference systems using single machines containing one or many GPU cards to large-scale training systems running on hundreds 25 of specialized machines with thousands of GPUs.

Having a single system that can span such a broad range of platforms significantly simplifies the real-world use of machine learning system, as we have found that having separate systems for large-scale training and small-scale deployment leads to significant maintenance burdens and leaky abstractions. TensorFlow computations are expressed as stateful dataflow graphs (described in more detail in Section 2), and we have focused on making the system both flexible enough for quickly experimenting with new models for research purposes and sufficiently high performance and robust for production training and deployment of machine learning models. For scaling neural network training to larger deployments,

TensorFlow allows clients to easily express various kinds of parallelism through replication and parallel execution of a core model dataflow graph, with many different computational devices all collaborating to update a set of shared parameters or other state. Modest changes in the description of the computation allow a wide variety of different approaches to parallelism to be achieved and tried with low effort [14, 29, 42]. Some TensorFlow uses allow some flexibility in terms of the consistency of parameter updates, and we can easily express and take advantage of these relaxed synchronization requirements in some of our larger deployments.

V.DATA PARALLEL TRAINING

One simple technique for speeding up SGD is to parallelize the computation of the gradient for a mini-batch across mini-batch elements. For example, if we are using a mini-batch size of 1000 elements, we can use 10 replicas of the model to each compute the gradient for 100 elements, and then combine the gradients and apply updates to the parameters synchronously, in order to behave exactly as if we were running the sequential SGD algorithm with a batch size of 1000 elements. In this case, the TensorFlow graph simply has many replicas of the portion of the graph that does the bulk of the model computation, and a single client thread drives the entire training loop for this large graph.

The TensorFlow system shares some design characteristics with its predecessor system, Disbelief , and with later systems with similar designs like Project Adam and the Parameter Server project . Like Disbelief and Project Adam, TensorFlow allows computations to be spread out across many computational devices across many machines, and allows users to specify machine learning models using relatively high-level descriptions. Unlike DistBelief and Project Adam, though, the general-purpose dataflow graph model in TensorFlow is more flexible and more amenable to expressing a wider variety of machine learning models and optimization algorithms.

VI .IMPLEMENTATION

6.1 PYTHON:

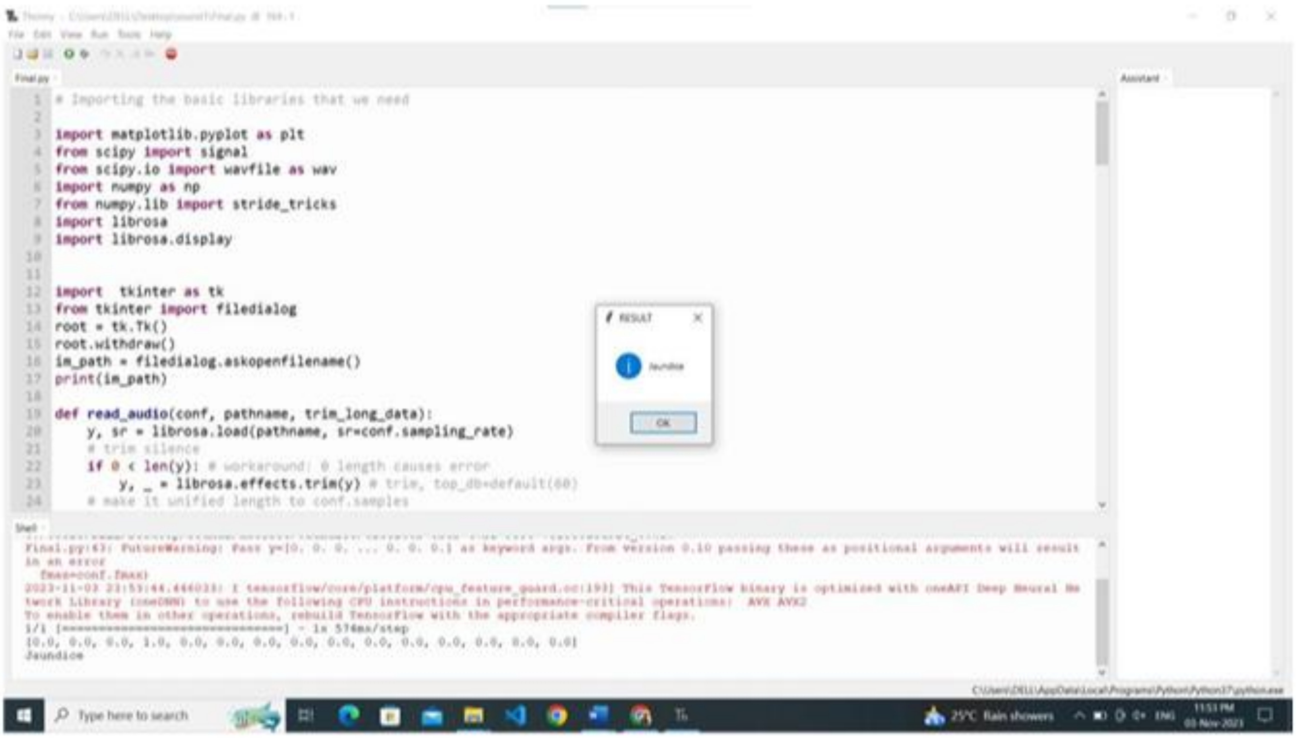
PYTHON 3.7:

Python is an interpreter, high-level, general-purpose programming language. Created by Guido van Rossum and first released in 1991, Python's design philosophy emphasizes code readability with its notable use of significant whitespace. Python is an easy to learn, powerful programming language. It has efficient high-level data structures and a simple but effective approach to object- oriented programming. Python's elegant syntax and dynamic typing, together with its interpreted nature, make it an ideal language for scripting and rapid application development in manya reason most platforms and may be freely distributed. The same site also contains distributions of and pointers to many free third party Python modules, programs and tools, and additional documentation. The Python interpreter is easily extended with new functions and data types implemented in C or C++ (or other languages callable from C). Python is also suitable as an extension language for customizable applications. This tutorial introduces the reader informally to the basic concepts and features of the Python language and system. It helps to have a Python interpreter handy for hands-on experience, but all examples are self-contained, so the tutorial can be read off- line as well. For a description of standard objects and modules, see library-index. Reference-index gives a more formal definition of the language. To write extensions in C or C++, read extending-index and c-api-index.

There are also several books covering 32 Python in depth. This tutorial does not attempt to be comprehensive and cover every single feature, or even every commonly used feature. Instead, it introduces many of Python's most notes worthy features, and will give you a good idea of the language's flavor and style. After reading it, you will be able to read and write Python modules and programs, and you will be ready to learn more about the various Python library modules described in library- index. If you do much work on computers, eventually you find that there's some task you'd like to automate.

For example, you may wish to perform a search-and-replace over a large number of text files, or rename and rearrange a bunch of photo files in a complicated way. Perhaps you'd like to write a small custom database, or a specialized GUI application or a simple game. If you're a professional software developer, you may have to work with several C/C++/Java libraries but find the usual write/compile/test/re-compile cycle is too slow. Perhaps you're writing a test suite for such a library and find writing the testing code a tedious task. Or maybe you've written a program that could use an extension language, and you don't want to design and implement a whole new language for your application.

VII.RESULT



VIII.CONCLUSION

The human sound-based disease detecting system employing machine learning represents a pioneering approach towards early disease identification through sound analysis. By integrating data acquisition, signal processing, and machine learning models, this system enables non-invasive, real-time disease detection, offering potential benefits in remote healthcare and proactive intervention. Despite challenges in data diversity and ethical considerations, its potential impact on timely diagnosis and accessible 46 healthcare underscores its significance in transforming disease detection paradigms, promising a future where sound analysis becomes a valuable tool in improving health outcomes.

The problem remains in the absence of a doctor-to-patient recommendation system that alerts the doctor to the patient's condition and provides excellent care to the patient, since they have access to a doctor at all times. The problematic statement is building a model for disease prediction using voice recognition. Since the lack of a normalized text for sample collection is a significant issue, our project aims to make it language independent. In future this system can be implemented in mobiles which can detect the person diseases while the person uses the mobile and intimates them instantly**.**

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