



**IJIRCCCE**

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 11, Issue 1, January 2023

**ISSN** INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA

**Impact Factor: 8.165**



9940 572 462



6381 907 438



ijircce@gmail.com



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# Performance Analysis of Pathological Throat Disorder Using Speech

Bommaraju K<sup>1</sup>, Dr.S.Kumarganesh<sup>2</sup>, Dr.A.Immanuvel<sup>3</sup>, Dr.K.Jayaram<sup>4</sup>

<sup>1</sup>Assistant Professor, Department of Electronics and Communication Engineering, Government College of Engineering Srirangam, Trichy, Tamil Nadu, India

<sup>2</sup> Professor, Department of Electronics and Communication Engineering, Knowledge Institute of Technology, Salem, Tamil Nadu, India

<sup>3</sup>Professor, Department of Electronics and Communication Engineering, Paavai College of Engineering, Namakkal, Tamil Nadu, India

<sup>4</sup>Assistant professor, Department of Electronics and Communication Engineering, Kalaignar karunanidhi Institute of Technology, Coimbatore, Tamil Nadu, India

**ABSTRACT:** The 2020 global research agenda has been focused on the corona virus (COVID-19) pandemic. Data on COVID-19 patients are collected, and every attempt is made to thoroughly test them for the virus. The respiratory system's operation is mostly responsible for COVID-19 symptoms, which in turn have a significant impact on how well people speak. This directs the research's attention on finding COVID-19 indicators in speech and other human-produced audio signals. In this article, we provide a summary of the 'Artificial Intelligence'-based work on language, speech, and other audio signal processing that has been done to screen, diagnose, track, and raise awareness of Covid-19. We also provide a short overview of the research that has been done so far to identify COVID-19 symptoms. We hope that by pooling our knowledge, we can create automated systems that support COVID-19 utilising unobtrusive and simple to use modalities including audio, voice, and language.

**KEYWORDS:-** AI, COVID 19, THROAT AND SVM

## I. INTRODUCTION

Your throat functions as a tube that transports air to your windpipe and larynx and food to your oesophagus. most likely had a sore throat, as the technical term goes. The reason is often a viral illness, although additional factors might include allergies, strep infection, or GERD, which is the backflow of stomach acids into the oesophagus. Other issues that can affect the throat include tonsillitis, an infection that causes the tonsils to swell, cancer, croup, an infection that typically affects young children and results in a barking cough, and laryngitis, an inflammation of the voice box that can result in hoarseness or voice loss. The majorities of throat issues are minor and go away on their own. When necessary, treatments are dependent upon the issue [1]-[5].

We discuss new pilot studies that show computer analysis of spoken and written language may provide very precise diagnoses for a broad range of mental and neurological diseases, including as psychosis, drug misuse, Parkinson's, and Alzheimer's. These findings are based on novel linguistic feature extraction techniques as well as the mathematical formalisation of psychiatric qualitative knowledge related to the characterization of conditions (for example, "derailment" in psychosis) and drug effects (for example, increased intimacy/affection with the use of the recreational drug ecstasy). Additionally, we present novel findings from publicly accessible text sources that suggest 1) it is feasible to define an embedding space that enables modelling of the enormous language dimension into a smaller space to map and compare various conditions, and 2) computational studies of a public personality (Ronald Reagan) can probably produce novel findings about healthy ageing and neurodegenerative diseases. Finally, we go into the effects on mental health. health (and even computer science) of a systematic application of this paradigm, expanded to include comparable, easily accessible behavioural data like as voice and video.

The World Alzheimer Report 2015 updates ADI's worldwide dementia statistics and examines "The global impact of dementia: An analysis of prevalence, incidence, cost and trends." The paper presents important suggestions to

develop a worldwide framework for dementia action by conducting a thorough update of prior systematic evaluations. The paper also contains an examination of the data supporting and refuting current trends in dementia incidence and prevalence across time, as well as a study of dementia's wider social effects. The fast growth in the accessibility of digital materials has forced improvements in automated text categorization. Machine learning (ML) algorithms are programmes that can 'learn' from data. For example, an ML system may be trained on a collection of characteristics generated from written texts belonging to established categories and learn to discriminate between them. The classification of unread messages may then be done using a trained algorithm. The ability to categorise transcribed speech samples along clinical characteristics using just word data is investigated in this research. We determined the lexical elements that were most informative to each of these two differences using information gain (IG). Both systems obtained accuracy levels of more than 90% in the SD vs control categorization challenge. When the characteristics utilised in the training set were limited to those with high values of IG, NBM and NBG both obtained a high degree of accuracy (88%) in the right-versus-left-temporal lobe predominate classification. Low frequency content words, generic keywords, and elements of meta narrative statements were the attributes that provided the most useful information for the patient vs control task. The quantity of relevant lexical characteristics for the right vs left challenge was insufficient to justify any particular judgements. A more comprehensive feature set that incorporates metrics from quantitative production analysis (QPA) might clarify this poorly understood differential [6]-[10].

Language impairment may be a significant indicator of Alzheimer's disease (AD), even if memory loss is the predominant symptom. Only a small number of research on language in AD use computational methods to measure the deficits in linked speech. Our goal is to exhibit cutting-edge accuracy in automatically diagnosing Alzheimer's disease using brief narrative samples elicited with an image description task. We also want to use statistical factor analysis to discover the key linguistic components. Methods: Data are taken from the Dementia Bank corpus, where 167 AD patients with a "possible" or "probable" diagnosis and 97 controls each offer 240 narrative excerpts. We extract a variety of linguistic and acoustic factors from the transcripts and related audio recordings, and we build a machine learning classifier to identify between individuals with AD and healthy controls using these variables. We do an exploratory factor analysis on these speech and language variables using an oblique prom axe rotation in order to determine the degree of heterogeneity of linguistic deficits in AD. We then evaluate the components that emerge from this analysis. Results: Using small samples of participants' vocabulary on an image description task, we achieve state-of-the-art classification accuracy of over 81% in differentiating AD patients from controls. Semantic impairment, auditory abnormality, syntactic impairment, and information impairment stand out as the four main causes. In conclusion, evaluation and clustering of suspected AD will benefit progressively from contemporary machine learning and language analysis.

We are in the middle of a technological revolution where academics can now, for the first time, connect everyday word usage to a wide range of actual behaviours. This article examines a number of computerised text analysis techniques as well as the development and validation of Linguistic Inquiry and Word Count (LIWC). A programme for transparent text analysis called LIWC counts words in groups that have psychologically significant meanings. According to empirical findings, LIWC is capable of detecting meaning in a broad range of experimental scenarios, including those that require attention concentration, emotional expression, social interaction, different thinking styles, and individual variations [11]-[13].

## II. EXISTING METHOD

The underlying interplay of P\_Circ and P\_Ho causes drowsiness and performance variations, which are represented by frequency-specific circadian and wake duration-dependent alterations in the waking EEG. Each EEG sub-band's relative dominance at certain periods may be utilised to interpret the brain activity. Increases in theta signify the beginning of sleep, whereas low-frequency EEG oscillations like delta often indicate the stage of sleep. The beta wave is connected to heightened alertness and arousal, whereas the alpha activity may indicate an increase in mental effort to maintain attention. Increases in theta and alpha activity, together with a concurrent decline in beta band activity when alertness levels drop, are typical characteristics of the building of sleep propensity and sleepiness. However, other studies claimed to demonstrate a large rise in delta activity. However, a prolonged wakefulness research showed that the rise in delta, theta, and lower-alpha was not monotonic and mostly had a circadian influence.



### III. PROPOSED METHOD

The goal of cough detection is to recognise the cough sound, distinguish it from other noises that sound similar, such as conversation and laughing, and also to identify the cough that is peculiar to COVID-19. It needs a coughing reflex and a speech-language processing system at the beginning is shown in Figure 1.

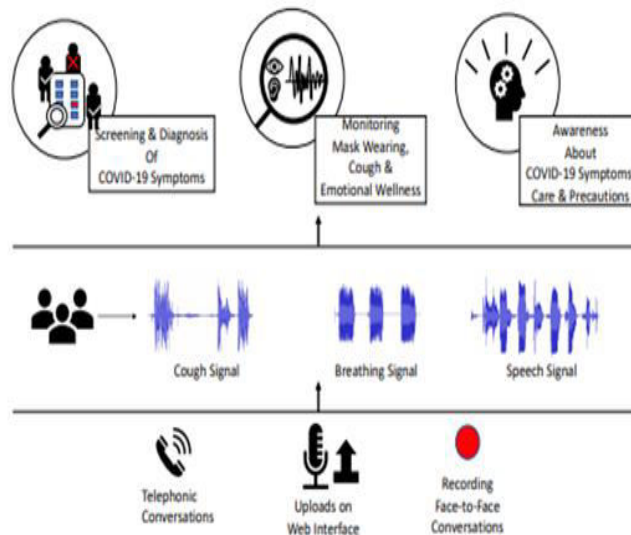


Figure.1.Cough Signal Processing

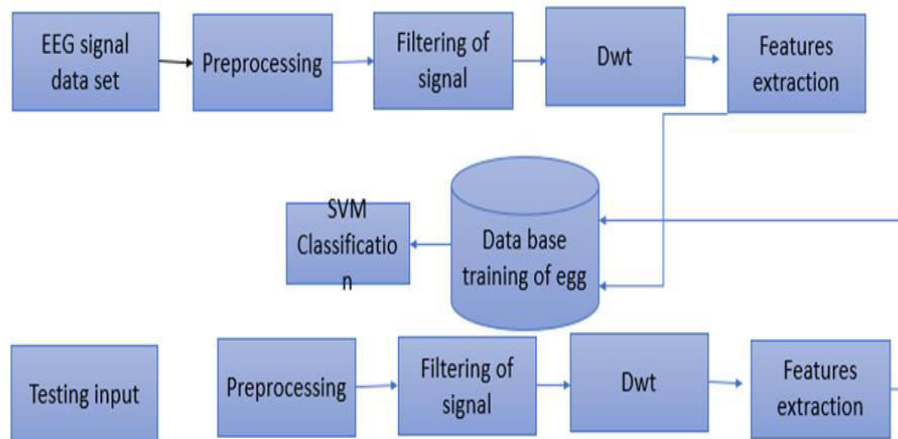


Figure.2.General Block Diagram

To remove noise, further processing must be applied to the recorded signals as stated in the preceding section. The signals that were so gathered were then utilised to extract just the signals that were produced on each subject while the IAPS image was shown in Figure 2. Then, from those signals, we extract a number of characteristics. Therefore, in the stages that follow, each of these processes is discussed under a distinct category. Bandpassing the EEG The noise that is already present in the recordings, such as overlaid artefacts from several sources, may be efficiently minimised by using the right band pass filtering. More specifically, muscular artefacts impact the EEG spectrum above 30 Hz, whereas heart function creates artefacts around 1.2 Hz and eye blinking has a greater effect below 4 Hz. Power line artefacts that are not physiological occur between 50 and 60 Hz.

We reprocessed the EEG data using the average mean reference (AMR) approach. Then, we normalised the EEG readings for each channel to remove individual variances and channel differences. Due to a keen interest in the EEG frequency range, band pass filtering was also chosen for this purpose. Each of the five frequency bands in which EEG data may be extracted is more pronounced in certain mental states. Based on this information, we decide that the two frequencies we will focus on in this research are Alpha (8–12 Hz) and Beta (12–30 Hz). Therefore, we use the 10th order "Butter worth band pass filter" to meet the needs of both eliminating the artefacts and maintaining the signals inside the specific band of interest, i.e. frequencies between the Alpha (8-13 Hz) and Beta (13-30 Hz) bands. Consequently, we ensure that the majority of the physiological and non-physiological artefacts are eliminated by exclusively extracting the Alpha and Beta frequency bands from the collected EEG recordings.

We opted for 10th order filters because they provide higher roll off rates between the pass band and stop band, which might be essential to achieve the requisite levels of stop band attenuation or cutoff sharpness. The benefits of the Butter-worth filter are listed below, and these are what convinced us to utilise the discrete wavelet transform (DWT) to extract EEG data. The mother wavelet function was used to stretch and shift the EEG signals in order to produce a number of wavelet coefficients. Different mother wavelet functions are used by different studies, and these mother wavelet functions have varying impacts on emotion categorization. Each EEG channel in our investigation was given a window of 4 s, with 29 windows overall, each of which overlapped the preceding one by 2 s. Then, using db4 DWT to deconstruct each window's data four times and extract all of the high-frequency components as four frequency bands (gamma, beta, alpha, and theta). Finally, the properties of each frequency band's entropy and energy were computed. As a result, each band for each channel has two characteristics. In 10 channels, there are 20 features (2 x 10) while in 14, 18, and 32 channels, there are 28, 36, and 64 features, respectively.

### **III. RESULT AND ANALYSIS**

With simulation, you may explore more realistic nonlinear models that take into account friction, air resistance, gear slippage, hard stops, and other things that represent real-world occurrences, moving beyond idealised linear models. Simulation transforms your computer into a lab for system modelling and analysis that would not otherwise be feasible or viable. Simulation gives you the tools to model and simulate practically any real-world issue, whether your interest is in the behaviour of an automobile clutch system, the flutter of an aeroplane wing, or the impact of the money supply on the economy. Additionally, simulation offers instances that simulate several real-world scenarios. A graphical user interface (GUI) for generating models as block diagrams is provided by simulation, enabling you to create models much as you would with a pencil and paper.

A vast library of sinks, sources, linear and nonlinear components, and connections is also included in simulation. But you may also make your own blocks if these ones don't suit your requirements. The modelling process is made simpler by the interactive graphical interface, which does away with the necessity to write differential and difference equations in a language or programme. Because models are hierarchical, both top-down and bottom-up methods may be used to create them. The system may be seen at a high level, and you can double-click blocks to reveal more and more model information. This method sheds light on a model's structure and interactions between its components.

Using a variety of mathematical integration techniques, either through the Semolina menus or by typing instructions in the MATLAB Command Window, you may simulate a model's dynamic behaviour once it has been defined. The command line is helpful for conducting a batch of simulations, but the menus are suitable for interactive work. You may utilise MATLAB scripts, for instance, if you wish to apply a parameter over a range of values or are doing Monte Carlo simulations. While the simulation is running, you may see the results using scopes and other display blocks. Next, you may alter the settings to explore "what if" scenarios. The MATLAB workspace may be used to import the simulation results for post processing and visualization is shown in Figure 3.

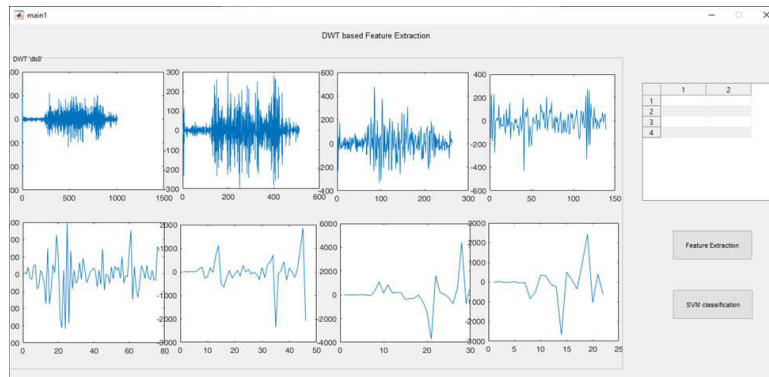


Figure.3. DWT Transform

Dynamic systems, such as control systems, signal processing systems, and communications systems, may be developed more quickly and economically thanks to a technique called model-based design. A system model is at the heart of the development process in model-based design, from requirements definition through design, implementation, and testing. During the course of the development process, you continuously improve the model, which is an executable specification. Simulated results after model creation demonstrate if the model is accurate. You may automatically generate code for embedded deployment and establish test benches for system verification when software and hardware implementation criteria are provided, such as fixed-point and timing behaviour. This saves time and prevents the introduction of manually programmed faults.

Complete system definition is the initial stage in modelling a dynamic system. When simulating a complex system that may be divided into smaller sections, it is best to simulate each component separately. After constructing each component, you may combine them to create a comprehensive model of the system.

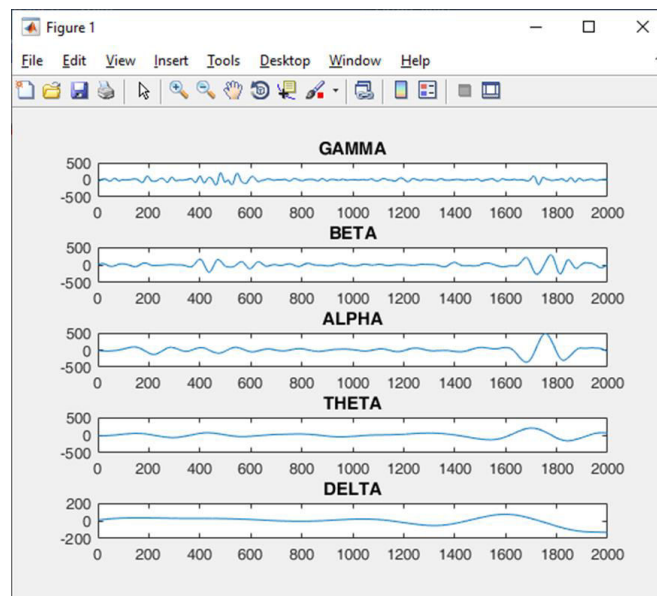


Figure.4. Performance Analysis of Various Levels

Simulation is a block diagram environment for model-based design and multi-domain simulation. It provides continuous testing and verification of embedded systems, simulation, automated code creation, and system-level design. For modelling and simulating dynamic systems, simulation offers a graphical editor, customisation block libraries, and solvers. Because of its integration with MATLAB®, you may export simulation results for additional analysis and include MATLAB algorithms into models is shown in Figure 4.

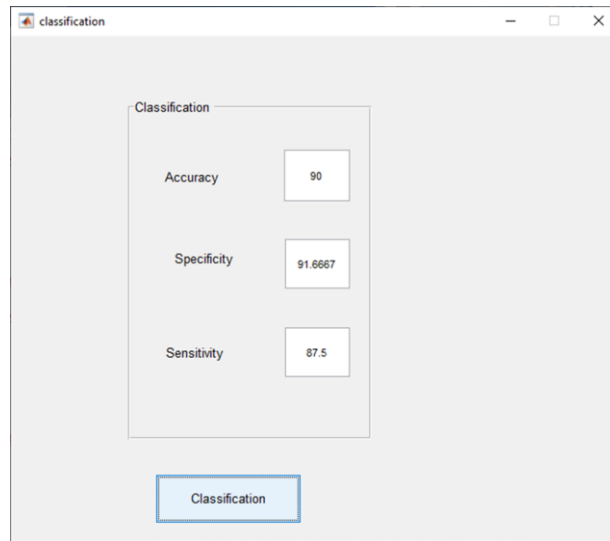


Figure 5. Performance Analysis of Classification value

You may start creating a block diagram of your model in Simulation after the mathematical equations describing each subsystem have been created. Create a separate block diagram for every subcomponent you have. You may then include each subcomponent into a comprehensive model of the system after modelling it individually. You may simulate the model and analyse the results after creating the Simulation block diagram. You may create system inputs interactively, simulate the model, and track behaviour changes via simulation. You may then assess your model fast as a result is shown in Figure 5. You must verify that your model properly captures the physical properties of the dynamic system before moving on. In addition to the many tools in MATLAB and its application toolboxes, you may analyse and verify your model using the internalisation and trimming tools accessible through the MATLAB command line.

#### IV. CONCLUSION

For COVID-19 analysis, speech and human audio analysis are shown to be the most beneficial. There are now many efforts being made to recognise cough sounds and differentiate COVID-19 cough from other conditions. It is likely that soon a cough sound-based sufficiently accurate COVID19 detector for a number of real-world use-cases will be available. Such detectors, when used with chatbots, may improve screening, diagnosing, and monitoring efforts while minimising human involvement. For COVID-19 analysis based on speech and breathing signals, further study is needed to pinpoint the precise biomarkers. With a growing degree of connection between speech and breathing signals, it will be possible to utilise speech signals to identify respiratory diseases. A second and possibly third wave of COVID-19 infection has been discovered to occur in numerous nations, infecting a great number of people. This points to the urgent necessity for reliable monitoring systems. Numerous elderly people have spent practically the whole year inside..

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