AJSE

American Journal of Science & Engineering

Volume 2 Issue 4

March 2022

American Journal of Science & Engineering (AJSE)

Society for Makers, Artists, Researchers and Technologists (SMART)

6408 Elizabeth Ave SE, Auburn 98092, Washington, USA

ISSN: 2687-9530 (Print) and 2687-9581 (Online)

Editor-in-Chief

Dr. Izzat Alsmadi

Texas A&M, San Antonio, USA

Research Interest: Cyber Intelligence, Cyber Security, Software Engineering, Social Networks

Bio: Izzat Alsmadi is an Assistant Professor in the department of computing and cyber security at the Texas A&M, San Antonio. He has his master and PhD in Software Engineering from North Dakota State University in 2006 and 2008. He has more than 100 conference and journal publications. His research interests include: Cyber intelligence, Cyber security, Software security, software engineering, software testing, social networks and software defined networking. He is lead author, editor in several books including: Springer The NICE Cyber Security Framework Cyber Security Intelligence and Analytics, 2019, Practical Information Security: A Competency-Based Education Course, 2018, Information Fusion for Cyber-Security Analytics (Studies in Computational Intelligence), 2016. The author is also a member of The National Initiative for Cybersecurity Education (NICE) group, which meets frequently to discuss enhancements on cyber security education at the national level.

A Comparative Study on Different Techniques for Classification of Brain Waves From EEG Signals

Sukanya Roy
Assistant Professor, University of Engineering & Management, Kolkata, India
Email Id: piu.sep.1993@gmail.com

Soumya Bhattacharjee
University of Engineering & Management, Kolkata, India
Email Id: bhattacharjee.soumya018@gmail.com

Bijoy Kumar Mandal
Assistant Professor, NSHM Knowledge Campus, Durgapur, India
Email Id: writetobijoy@gmail.com

Mriganka Saha
University of Engineering & Management, Kolkata, India
Email Id : mrigankas099@gmail.com

Abstract – The latest trends and research in Brain-Computer Interface (BCI) technology have been used for emotional sensing and researchers interested in neurons to analyse brain diseases and disorders. In particular, Brain-Computer Interfaces (BCIs) are used by machine learning approaches to either restore neural pathways or help the patient interact effectively through an electronic prosthetic, showing promising results in impairment and rehabilitation care. Emotion Recognition and prediction of sensations supported by electroencephalography (EEG) have generated interest in a number of ways to implement human-centered services. Emotion is an aspect of how people behave and it is a critical overall performance in BCI. Today, researchers in computational linguistic regions have an interest in emotional attention for the evaluation of feeling. The EEG is moreover extra efficient for the evaluation of brain signal that assists in the analysis of neurological disorder medicinal drug and additionally performs a critical function altogether the neurosurgery related to the mind. This work aims to review reported papers on emotion identification, recognition, and exceptional detection of brain sickness upon that paper, a research analysis is worked out again to outline and illustrate the Brainwave emotion referendum outcome, and the evaluation also covers a few recent works on these degrees such as acquisition of EEG signals, extraction of capacities, emotion category, and prediction of ailment from these degrees. The various techniques of computer vision applied and combined with BCI technologies show that perhaps the treatment of brain disease with the use of BCIs is a promising and constantly evolving field.

Keywords– BCI; EEG; ML; Prediction;

NOMENCLATURE

BCI- Brain Computer Interface, EEG- Electroencephalography, ML- Machine Learning, MRI- Magnetic Resonance Image, SVM- Support Vector Machine

I. INTRODUCTION

Machine learning, with its power to pass around, interpret and identify data easily, is a good approach for EEG analysis in patients with brain disease. The use of technology will lead to a quicker, more open and potentially reliable assessment of patient data, leading towards more timely and efficient treatment. [1] Emotions play a significant and vital role in human creatures' existence. A sign of psychosomatic problems is conveyed through impulsive behaviors. The variations in brain patterns and perceptions can be reflected in these disorders. BCI serves as a human brain channel to connect with a computer device. It facilitates its users to monitor digital signals with cognitive processes which are independent of cortical nerves and muscles. Image is a general representation of an artefact, idea, organisation of patterns, person or thing in art. Figure 1 explains how a EEG signal looks like.

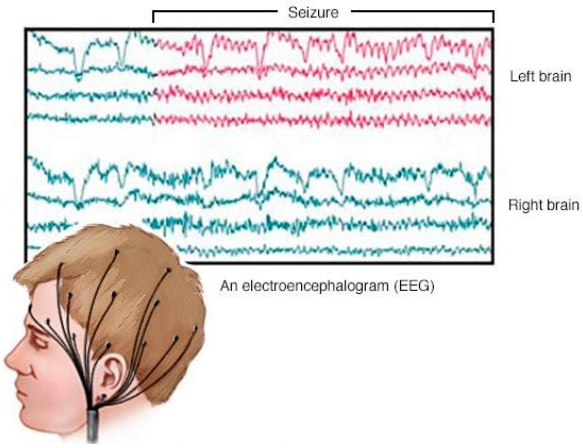

Fig.1. EEG Signal

Well humans have come so far that we have the technology to perceive the images that used be on papers on digital platforms. A digital image is an image that is depicted by the computer systems normally in a binary form generally in the 2-D matrix state. It can also be defined by mathematical function f(x,y) where x and y are axis. Generally, we broadly categorize the digital images in two forms depending on the image resolution is fixed or not, it can be called vector and raster. A vector image is a combination of 2D points connected by lines and curves to create unique polygons and other structures. Whereas raster images are bitmap images that are represented as the dot matrix image generating a series of rectangular dots with respective pixel colors [2].

The human brain is divided into two hemispheres. The left one is known to be "logical brain" which is mainly involved in language and for analysis purpose and the right one is the "creative brain," which involved in daydreaming and imagination. The right part of the body is still dominated by the left one, while the right part of the brain has power over the parts of the left body. Brain produces signals which reach the nervous system and make humans and animals to reciprocate what our brain wants to tell.

II. LITERATURE SURVEY

The human brain is a complicated, interconnected device. Trillions of dollars of nerve fibers (synapses) with complex spatiotemporal neuron dynamics, along with non-invasive brain signal mapping methods, there are several aggressive versions. Among all the approaches to non-invasive. Direct cortical measure for the study of the human brain The temporary resolution of less than one millisecond EEG is provided. [3] The

A very good review on Deep Learning for Segmentation of Brain MRI: State of the Art and Expected Directions [4]. A quantitative analysis was done on MRI brain daily for neurological diseases and for segmentation types. Deep learning plays a vital role in this. A segmentation approach based on deep learning, evolving daily because of its self learning generalization capability. The study in this paper provides an overall overview of different techniques used by deep learning for MRI brain images. It has been concluded that in critical assessment, deep learning plays a vital role effectively.

This dissertation focuses on the automated segmentation of meningioma from the Magnetic Resonance Imagery of the multispectral brain. By proposing a completely automated system hierarchically organized into two stages, the authors address the segmentation task. The initial, unsupervised stage is formulated on the basis of Graph Cut. Initial segmentation outcomes are optimized in the second step using a supervised Support Vector Machine-based classification. The overall segmentation process is fully automated and adapted to non-volumetric information characterized by poor cross separation in an effort to facilitate insertion in clinical practice. The findings of this small survey are promising but indicate that classification profits from either the integrated a use of Graph Cut as well as SVM frameworks. [5].

Various methodologies are used for the image segmentation purpose and clustering is one of them. As far as the complexity of brain image edges is concerned, it is very difficult to perceive three different tissue segments accurately: white matter, grey matter and cerebrospinal fluid as well as different diseases that is affected in the brain. We have implemented a modified approach in this paper to bring forward a new process which means Modified C. The whole algorithm was used for the identification of brain image diseases such as the anomaly detection associated with tumor and gray matter. In this paper, colours are used for the detection of anomaly part. We have merged all the colours to get the final coloured image. With the help of the coloured pixels, we can easily calculate the percentages of white matter, grey matter and the percentage of cerebrospinal fluid. Then according to the colour percentage, we can predict the brain anomaly according to a dataset; which contains the name of the brain disease and the percentage of grey matter and white matter of the affected person. Segmentation of accurate brain tissue from magnetic resonance (MR) images is a crucial step in quantitative brain image analysis [6].

The nature is exclusivist, non-Gaussian, unpredictable, non-correlated, of EEG signals. Electroencephalography (EEG) may be used to identify brain damage, any other illness, or symptoms. In detecting, Many neurology-related conditions, including such psychiatric illnesses like epilepsy, sleep disturbances like crohn's disease, cancer, anxiety, and depression, are also used and numerous trauma (stress)-related issues. The traces are distinct different activities for the brain [7].

III. ANALYSIS

A. Machine Learning Review

Before you can even start to run your algorithm, four key components must be part of each Machine Learning algorithm. These components are the ingredients that the data you want to run, The model, the optimization method, and the algorithm of restriction. The data to be used is normally background information that is available to the public, but to create a data set that is specific to your particular research, you often need to add your own research. The next ingredient was the model we would prepare to be using the sample as part of the machine learning phase in your specific study. The third ingredient is the objective attribute that plays a part once you are

prepared to make your model give you a performance that is as similar as possible to truth. To evaluate the accuracy of the performance that your model has produced, the objective function is used [8].

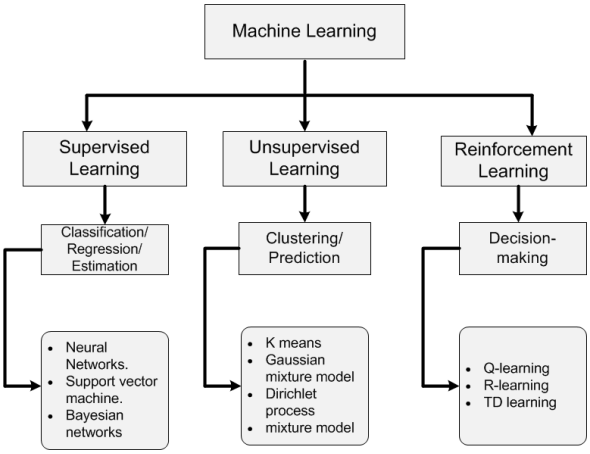

Fig.2. Machine Learning Algorithm Chart (Google Photos)

Figure 2 explains about different algorithms used in Machine Learning. Machine learning algorithms are classified into categories of supervised learning, including the simple implementations shown in this category as well as the unsupervised learning classification, which contains the complex algorithms used for this segment. Issues will often occur for any machine and algorithm-based technology. Machine learning may lead to datasets or algorithms being. More generic and not sufficiently detailed for various topics of study [9]. Compared to the true model, In the general equation, the generalizability may be induced by a prejudice that could then create an error due to incorrect assumptions being made according to how the model appears.

A. EEG Signal & Machine Learning

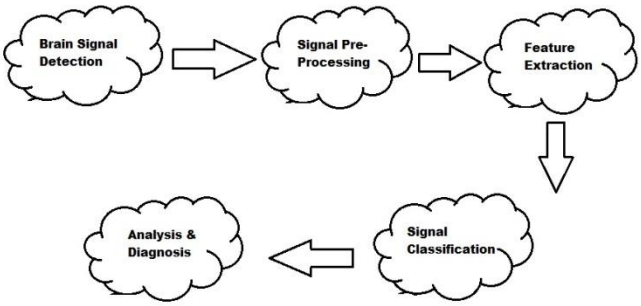

Fig.3. Diagram to describe how a brain signal is processed to detect and predict emotions and diseases respectively.

The above diagram Figure 3, explain clearly about the step by step process how a brain signal in analyzed. In this review paper, we have mainly focused on EEG Signals, how this signal is captured, how pre-processing is done, and then different features extraction methods of machine learning are used to detect the signal type and then moved to the classification processes that is also a part of machine learning and lastly the part goes to the doctor or different researcher for analysis and diagnosis purpose for emotion detection analysis as well as disease prediction.

B. EEG Signal Identification

At first, the brain's EEG is captured by the traditional approach known as the International 10-20 System globally. These signals are first amplified and then digitized within the Digital EEG system. By electric impulses, the neurons connect with each other. To measure the amplitude of electrical impulses, the electrodes are located on the scalp. Frequency range of a standard EG signal is 1 Hz-100 Hz but the 100Hz is very unusual and amplitude varies from 10 µV – 100 µV.

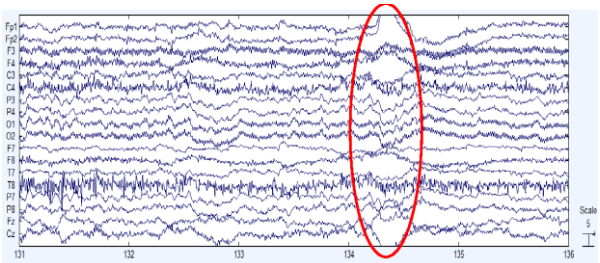

Fig.4. Represents the various types of emotions using EEG brainwaves. The circled area demonstrates the variations in pattern from which we can assess the emotion of any live individual.

EEG signals are an important indicator of the function of the brain and have an immense capacity for diagnosing brain diseases and disorders [10]. Figure 4 represents the various types of emotions using EEG brainwaves. The circled area demonstrates the variations in pattern from which we can assess the emotion of any live individual. Flashing of eyes during the process of signal acquisition, muscle activities, and activities occurring in the background are different forms of objects that influence the signal. Therefore, EEG signals are generated from extremely reliable, de-noised facilities and specialized intervention instruments, objects, and numerous other noise sources. EEGs have outstanding spatial resolution and less than a millisecond, regardless of their actual spatial resolution. The signal has a very low Hertz frequency range when measured. Based on the frequency bands, such signals can be categorized [11]. Our brainwaves shift in line with what we do and experience. When slower brain signals are dominant, we can feel tired,

slow, sluggish, or wistful. The longer wavelengths are dominant, as they sound activated, or neurotic.

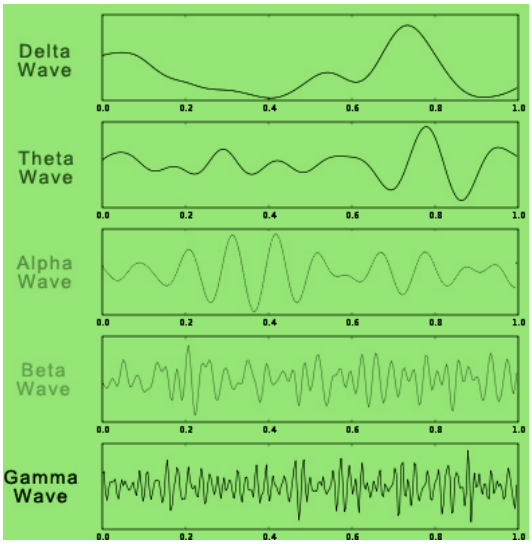

Fig.5. Different Types of Brain Waves.

Figure 5 explains how many types of waves are there that can be used. The EEG signals structure is very complex, random, and non-correlated. The attributes of the EEG rely on several variables, including the person, maturity and psychological condition of the object. Many solutions have been proposed in research to detect the secret performance metrics and unexpected changes that can take place. The study of the signal [12] includes three important factors. All prevailing wavelengths throughout the EEG are calculated by means of signal spectral data.

TABLE I. BRAIN WAVES CLASSIFICATION

Brain Waves Name	Frequency Range	Usually associate With
GAMMA	> 40 Hz	Greater cognitive performance, including perception, problem solving, and awareness
BETA	13–39 Hz	Active, intensive thought, active processing, active focus, awareness and arousal
ALPHA	7–13 Hz	Calm, comfortable but alert condition.
THETA	4–7 Hz	Extreme mindfulness /relaxation, Stage of sleep.
DELTA	< 4 Hz	Extreme restful sleep, lack of consciousness about the body

A number of states of consciousness, from sleep to active thought, are controlled by each type of brainwave. Table 1 describes about the brain waves classification [14].Though all brain signals work collectively, one brainwave may be more powerful and predominant than the others. Your present state of mind will be dictated by the dominant brainwave. So you would be known to be in a "alpha state of mind" if you are awake and comfortable since the maximum intensity of your Alpha brain waves would be the greatest.

C. Brain Computer Interface Model

Under BCI Model we have 3 phases of brain signal processing namely; Signal Preprocessing, Feature Extraction and Classification [13]. Different machine learning algorithms for EEG signals are currently being explored for identification, classification, and analysis. Fig.6. illustrates the working of BCI Model. Diagram is taken from Google images.

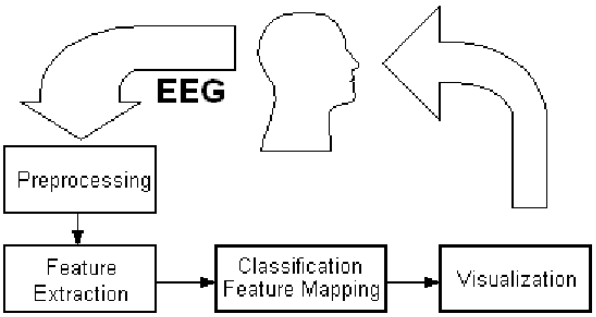

Fig.6. illustrates the working of BCI Model

I. Signal Pre-Processing

In BCI, at the initial level, data collection and filtering is carried out. Data collection is recorded with the aid of electrodes placed on the subject's scalp (EEG signal). In the context of an EEG sample, the 10-20 or Global 10-20 system would be an internationally accepted tool for the identification but application of scalp electrode position, polysomnograph sleep analysis or voluntary laboratory research. This technique was developed to maintain systematic testing procedures to ensure that the findings of the study (clinical or research) of a subject could have been compiled, replicated, and analyzed and compared accurately using the methodology [14]. Figure 7 shows 10-20 International System of Electrodes Placement. The method is focused on the correlation between an electrode's position and the brain's underlying region, specifically the cerebral cortex.

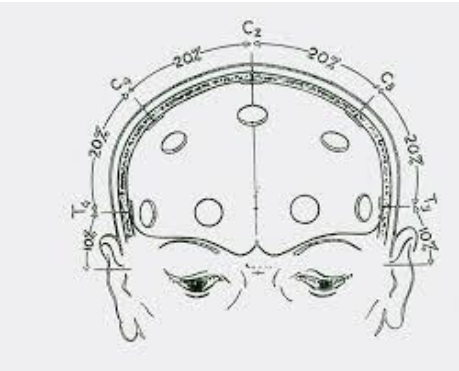

Fig.7. 10-20 International System of Electrodes Placement

Effective identification and removal involves artifacts and noise in the signal. Then the signal obtained serves as an input to the filter. The noise signal is filtered out of the signal by the filter and avoids signal distortion. For rejection of anomalies and noise, Notch filters are used. Medav Filter is also there [15]. To reject components with very low frequencies. With both the aid of low-pass filters with 40-70 Hz as a cut-off frequency, high-frequency noise components are eliminated.

II. Signal Feature Extraction & Classification

A feature reflects a property that is exclusive. Several feature extraction techniques have been developed and the choice of both appropriate characteristics and electrode position is typically based on neuroscientific observations [16]. Many linear and non-linear approaches have been documented in the literature for feature extraction. Linear techniques include ICA, FFT, Eigenvector, AR, Wavelet transform, Wavelet Packet Decomposition, Principal Component Analysis The factor of correlation, Hurst exponent (H), largest exponent of Lyapunov (LLE), different entropies, Higher Order Spectra (HOS), Fractal Dimension (FD), complication charts and spatial stage graphs are non-linear techniques. BCIs depend, through signal processing and other feature analysis, Gathering data and extracting characteristics from EEG impulses from the brain. The input data will gradually be represented as a machine result by operation of extracted data through a predetermined machine learning model.

Collection and measurement by means of a sensor, such as EEG data. To addition to digitally manage things,, these signals are magnified and electromagnetic distortion and other unwanted signal features are extracted out. The signal is analyzed to identify important features until this signal, along with a technique called feature extraction, is changed and transmitted to a computer. Amplitude and latencies of time-triggered EEG response, including such P300 waves, 20 or power within Resonant frequencies, like those from sensor motors patterns, may be commonly derived features of EEG operation. Such collected signal characteristics serve to decipher the intent of the user. The extracted data would undergo function conversion by the use of a supervised machine learning method to convert the features into some kind of function required by the user.

With their merits and de-merits, the EEG signal detection and feature extraction methods have been evaluated in a highly thorough and extensive survey [6-14]. Time-frequency methods for epilepsy detection and assessed frequency analysis (FFT), time-frequency analysis (STFT) over several electrodes were studied by Alexandros et.al. It was found that the classification outcomes were better for STFT. Another paper compared their shortcomings to FFT, AR, TF and WT and according to the author, the WPD approach generates a redundant signal representation and achieves better accuracy. For epileptic seizure detection, a DWT and SVM based expert model has been developed. The issue of improving the extraction of features was discussed in [17]. The adaptive feature extraction process, i.e. adaptive common spatial patterns, was also reviewed in this paper.

D. Diagnosis & Analysis

In the classification of brain diseases, any use of computer intelligence has continued to expand the number of observations of advanced diagnostic imaging identification, their ability to manage the period of occurrence, the optimization of the tumour, the condition of repairable tissue, and eventually the effects of the patients prior. The potentially long-term challenges they will have to endure. The key diagnostic class of disease is focused on medical (two-dimensional) imaging and one-dimensional) signal processing. In the identification, control, and prediction of diseases, certain methods have been used. Machine Learning has been applied to biomedical signal function extraction, such as electroencephalography (EEG), for one-dimensional signal processing. Recent results demonstrate the feasibility of EEG recordings predicting seizures; the transition from preictal to paroxysmal states consists of a "buildup" that can be monitored using advanced techniques of extraction of features and ML.

I. SVM

EEG is a relatively useful method for disability detection, but it can be very difficult to extract features from these signals. For higher dimensional and nonlinear issues, In pattern recognition, the SVM, that utilizes kernels that transfer specimens from one function space to another, has been shown to be extremely strong. All in all, though LDA is an effective classification technique, it is restricted to linear analysis. Consequently, however versatile, neural networks involve large amounts of data. Consequently,

for nonlinear analysis, SVM is a good preference for small data sets. Even then, SVM is a successful approach for accurately classifying stroke-related EEGs, selecting the correct kernel for a given task can be difficult. First to enhance the general efficiency of the signal, raw EEG signals were pre-processed. Next through wavelet packet entropy and Granger causality flow, features were extracted. The defined weights within and kernel are accounted for by this approach to retain a much more effective procedure [18].

Popular spatial pattern performance relies heavily on predetermined spatial-spectral filtering circumstances; but these conditions for brain disease patients are often difficult to recognize. For identification after extracting features, a static SVM has been used, and the analysis revealed that the combination typical spatial-spectral pattern boosted and SVM system surpassed all other techniques and, following a 2month turnaround time, it was able to reach 70% precision.

II. NEURAL NETWORK

To differentiate between EEG and control info, which would be more easily accessible than CT scans, a convolutional neural network has previously been used. The classification model of the community was accelerated by the implementation of early stopping and batch normalization techniques. Using CNN, F ratings are been shown that it contributes to greater performance than the comparative classifiers and is capable of outclassing neural networks with a smaller number of steps than the Naive Bayes model. Compared to the Naive Bayes model, this CNN has a stochastic component [19]. When classifying brain damaged patients, problems occur due to varying stage stages of disease this limits the consistency of categorization throughout the classification of mental disorder for stroke victims.

Accuracy assessment has shown that Deep CNN accuracy has declined with reduced training time, with the maximum attainable performance after one minute. When binary and more fine-tuned diagnoses are still limited, the detection of brain disease, development of a deep CNN to determine EEG signals for disease may help. Enhanced deep CNNs, which could cause normal and patho-physiological changes in EEG to be properly established, can help real-time diagnosis.

III. OTHER ML METHODS

Quantifying the degree Movement disorder in an effective quality management system as this has a direct effect on the individual's subsequent quality of life. One approach to achieve was to use ERS as an exam function for both the level of motion impairment in an injured individual. These were observed that there had been a statistically important difference and in strength of ERS and the frequency of the incidence of ERS between such two groups. For chronic cases, the strength of ERS was smaller, and the timing was delayed. Cerebral system activities then revealed that this delay and low ERS power could be seen as the clinical team would have to devote more work into conducting the hand action, as ERS shows a reduction in cortical activation. Additionally, ERS was again found in stroke patients with mild motor disability and severe cognitive impairments, and the same response was found. GMM (Gaussian Mixture Model) is used for comprehensive feature analysis, since it is a probabilistic model that describes the existence of sub-populations inside a bigger population using Gaussian distribution. In a preprocessing module and as a classifier in a classification module, they implemented the model both as a filter. GMM as a filter and as a classifier outperforms in terms of accuracy as compared to CSPSVM, reaching a high reliability of 80% in the scenario of one of the research subjects.

Sensorimotor rhythms (SMR) paradigms are another technique Used only for assisting with stroke diagnosis in machine learning. The need for a sensorimotor rhythm paradigm has become one of the most popular motor imagery concepts. [20]. The movement that is being imagined in an SMR paradigm is characterized in the interpretation of large parts of the body's kinesthetic motions, such as our arms, that can be interpreted as harmonics of cognitive function. In studies between healthy patients and patients who have had brain disorders, this model was also used.

IV. CONCLUSION

EEG is a non-invasive procedure, i.e. The signals are collected via the scalp electrode is itself one of the causes of noise induction. The identification and removal of objects is the biggest ongoing problem for engineers these days. A rapidly expanding and developing sector is BCI technology for application in the diagnosis and recovery of brain diseases. When combined with BCI technology, When it comes to proper diagnosis, diverse variations of feature extraction and classification approaches for machine learning show increasing precision. These eeg-based BCI paradigms were tested in the current analysis in compliance with the application classification for the diagnosis of brain disease. Machine learning strategies such as CNN, SVM, GMM, etc. were reviewed within the diagnosis classification.

EEG signals are of a highly subjective, non-Gaussian, non-correlated, random type and are known as chaotic signals. In order to create a framework that can be run in real environments, a lot of development needs to be done, according to the study. Multiple linear and nonlinear signal processing strategies were discussed, including Time domain, frequency, time-frequency, as well as frequency domain methods for space-time.

Using non-linear methods helps to clarify the complex physiological activities that take place in the brain, such as chaotic actions and abrupt changes. Conclude, this review shows that when combined with various combinations of machine learning techniques, the use of BCI technology for brain disease care is a promising area that shows increased precision in both classification and differentiation of clinical purpose while implemented to prediction.

V. REFERENCES

[1] Shiliang Sun and Jin Zhou," A Review of Adaptive Feature Extraction and Classification Methods for EEG-Based BrainComputer Interfaces," in IEEE Joint Conference (IJCNN) on Neural Networks International, pp. 1746 – 1753, 2014.

[2] Marler, John R., Pamela Winters Jones, and Marian Emr. Setting new directions for stroke care: proceedings of a national symposium on rapid identification and treatment of acute stroke. No. 97. The Institute, 1997.

[3] Alpaydin, E. (2004). Introduction to Machine Learning[PowerPoint slides].Retrieved from https://camino.instructure.com/courses/44637/files/folder/Slides?preview=2485276

[4] Pari Jahankhani, Vassilis Kodogiannis and Kenneth Revett," EEG Signal Classification Using Wavelet Feature Extraction and Neural Networks," IEEE John Vincent Atanasoff JVA International Symposium on Modern Computing, pp. 120 –124, Oct. 2006.

[5] Akkus, Z., Galimzianova, A., Hoogi, A. et al. J Digit Imaging (2017) 30: 449. https://doi.org/10.1007/s10278-017-9983-4

[6] S. Bauer, L.-P. Nolte, and M. Reyes, "Fully automatic segmentation of brain tumor images using support vector machine classification in combination with hierarchical conditional random field regularization, in Medical Image Computing and Computer-Assisted Intervention" , pp. 354361-MICCAI, Springer, 2011.

[7] Amjed S. Al-Fahoum and Ausilah A. Al-Fraihat, "Methods of EEG Signal Features Extraction Using Linear Analysis in Frequency and Time-Frequency Domains," ISRN Neuroscience, Hindawi Publishing Corporation, Article ID 730218, 2014.

[8] D. Puthankattil Subha, Paul K. Joseph, Rajendra Acharya U, Choo Min Lim," EEG Signal Analysis: A Survey," Springer Science vol.34, pp.195–212, 2007.

[9] N.A. Md Norani, W. Mansor, L.Y. Khuan," A Review of Signal Processing in Brain Computer Interface System," IEEE EMBS Conference on Biomedical Engineering & Sciences, pp. 443 – 449, Nov. 30 2010-Dec. 2 2010.

[10] Gupta, Sayantan, and Sukanya Roy. "Medav filter—filter for removal of image noise with the combination of median and average filters." Recent Trends in Signal and Image Processing. Springer, Singapore, 2019. 11-19.

[11] Roy, Sukanya, et al. "Brain Anomaly Prediction Using Modified Clustering (MC)." 2019 6th International Conference on Computing for Sustainable Global Development (INDIACom). IEEE, 2019.

[12] Hoffmann, U., Vesin, J. M., Ebrahimi, T., & Diserens, K. (2008). An efficient P300-based brain–computer interface for disabled subjects. Journal of Neuroscience methods, 167(1), 115-125.

[13] Wolpaw, J. R., Birbaumer, N., McFarland, D. J., Pfurtscheller, G., & Vaughan, T. M. (2002). Brain–computer interfaces for communication and control. Clinical neurophysiology, 113(6), 767-791

[14] JR. Panda, P.S. Khobragade, P.D. Jambhule, S. N.Jengthe, P.R.Pal, T.K. Gandhi," Classification of EEG Signal Using Wavelet Transform and Support Vector Machine for Epileptic Seizure Diction",IEEE International Conference on Systems in Medicine and Biology, pp. 16-18, December 2010.

[15] Alexandros T. Tzallas, Markos G. Tsipouras and Dimitrios I. Fotiadis," The Use of TimeFrequency Distributions for Epileptic Seizure Detection in EEG Recordings," IEEE Annual International Conference EMBS Cité Internationale, August 2007

[16] Suwannarat, A., Pan-ngum, S., & Israsena, P. (2018). Comparison of EEG measurement of upper limb movement in motor imagery training system. Biomedical engineering online, 17(1), 103.

[17] Cheng, D., Liu, Y., & Zhang, L. (2018, April). Exploring Motor Imagery Eeg Patterns for Stroke Patients with Deep Neural Networks. In 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 2561-2565). IEEE. https://ieeexplore.ieee.org/document/8461525

[18] Keirn, Z.A.; Aunon, J.I. A new mode of communication between man and his surroundings. IEEE Trans. Biomed. Eng. 1990, 37, 1209– 1214.

[19] Roy, Sukanya, et al. "Predictive Analysis & Classification of Diseases in Organs using Modified-C Clustering Technique." 2020 7th International Conference on Computing for Sustainable Global Development (INDIACom). IEEE, 2020.

[20] Roy, Sukanya, et al. "Identification of medical disorders in eye and biometric authentication analysis with iris retina scan using machine learning." Biotechnology and Biological Sciences. CRC Press, 2019. 29-33.

Study of Various Classification Approaches including Deep Learning in Heart Disease Prediction

Subhalaxmi Chakraborty, Department of Computer Science, University of Engineering & Management, Kolkata, India
Prayosi Paul, Department of Computer Science, University of Engineering & Management, Kolkata, India
Aditi Ghosh, Department of Computer Science, University of Engineering & Management, Kolkata, India
Suparna Bhattacharjee, Department of Computer Science, University of Engineering & Management, Kolkata, India
Soumadeep Sarkar, Department of Computer Science, University of Engineering & Management, Kolkata, India

***Abstract*—**During the last couple of decades, apart from other diseases, heart disease has proved to be a major cause of human death. This refers to a wide variety of heart conditions which include diseased vessels, structural problems and blood clots. This paper is aimed to make an effective prediction about the vulnerability to heart disease of a person depending on the given health parameters at a very early stage & to reduce premature death, with an improved accuracy and reliability compared to other traditional models. Our proposed prediction model has proved to be reliable in this connection and has yielded a maximum accuracy of 99.0% using Random Forest, Support vector machine and Decision trees and K-nearest neighbour algorithms. Using Cross Validation, we have also prepared the model (with the highest accuracy level of 98.6%) to work efficiently, taking the correct pattern of the dataset. Further, the proposed model has outperformed other traditional models in terms of accuracy using some other algorithms (Hybrid Ensemble model, Extreme Gradient Boosting with Random Forest and Stochastic Gradient Descent with accuracies of 94.2%, 87%, 78% respectively). Moreover, TensorFlow has also been used in order to get reliable prediction of heart disease with an approximate accuracy of 83.44%. The novelty of our proposed model lies in showcasing better results compared to those obtained by the traditional models and this model can easily be applied in medical science to provide better diagnosis.

Keywords—Heart disease, Random Forest, Support vector machine, Decision trees, KNN, TensorFlow.

I. INTRODUCTION

Heart disease is a lethal cause that is responsible for sudden death. People all over the world are suffering from cardiovascular diseases. Every year approximately 17.9 million people die from cardiovascular disease according to World Health Organization [1]. Today, everyone is familiar with these two common terms: heart attack and stroke. Heart disease encloses a vast variety of symptoms and causes which are categorized into different terms like Coronary Artery Disease (CAD), Cardiomyopathy, Atherosclerosis [2] with some common symptoms like chest pain, shortness of breath, nausea. During the last couple of decades with the growth of modern technologies, medical surgeries and treatments also reached a high level of success. Approximately, in India, out of every 100 people 23 die from heart disease [3]. According to the European Society of Cardiology, 26 million people of heart disease were diagnosed and every year near about 3.6 million people suffered from heart disease [4]. From literature [5], it is observed that the scarcity and absence of skilled and experienced medical experts and doctors in some countries is also a great problem. In such scenario heart disease prediction using machine learning has created a new approach to reduce the premature death. Machine learning algorithm models can forecast the onset of disease and has played significant role in data processing and investigation. Accuracy of any model depends on the working perfection of the algorithm. Machine Learning has several standard algorithm techniques which includes Random Forest, Decision Tree, SVM, K Nearest Neighbour, Logistic Regression.

Using Machine Learning Algorithms, Kohli et al. [6] have worked on prediction of heart disease using linear regression which has given the accuracy of 87.1%. Palaniappan et al. [7] have presented an Intelligent Heart Disease Prediction System (IHDPS) using data mining techniques such as Neural Networks (NN), Naive Bayes (NB), Decision Tree (DT) and concluded that NB model gives the best correct prediction among the others which is 86.12%, NN model gives 85.68% and DT model achieved 80.4% correct prediction.

Gudhade et al. [8] has realized a decision support system based on MLP neural network and Support Vector Machine (SVM) architecture for the classification of heart disease. Using the SVM approach it has been concluded with an accuracy of 80.41% by them. They have used the Artificial Neural Network which classifies their data with 97.5% accuracy into 5 categories.

Cheng et al. [9] have worked to build an architecture to evaluate Carotid Artery Stenting prognosis by using Artificial Neural Network and they showed that the performance of ANN model with an accuracy of 82.5% in testing set and 80.76% accuracy in overall patients. For identifying heart disease, Das et al. [10] have presented a procedure which have used a SAS base software 9.1.3 and in the centre of the proposed system there is a Neural network (NN) ensemble method. They worked for this methodology by taking data from Cleveland heart disease database and have acquired a classification accuracy of

89.01%. In this paper the standard algorithms of machine learning and their implementation on heart disease detection dataset is described along with their individual significance. The motive of this paper was to create such a model which will be able to give the most accurate result using the standard algorithms along with hybrid ensemble, cross validation, gradient descent, XGBRF and CNN using TensorFlow [11]. This model is aimed at detecting a person's sensitivity to heart disease using Machine Learning Algorithms from different aspects along with Hybrid Ensemble Model, Extreme Gradient Boosting with Random Forest and Stochastic Gradient Descent. Here the dataset of heart disease obtained from Kaggle is used to address the binary classification problem of heart disease based on parameters namely age, pulse rate, cholesterol, blood pressure, blood sugar and many more parameters are there. The models had predicted the result based on the train and test data which is divided in a 70-30 ratio.

II. PROBLEM DESCRIPTION

The dataset contains factors which have an intense effect on the condition of human heart. In this paper, the parameters considered in order to compute the major risk percentage according to CAD [12] are: age, sex, blood pressure, heart rate, diabetics, cholesterol. Moreover, some extra features are also added in the dataset like: Chest pain (Cp), Fasting blood sugar (fbs), Rest ecg, Maximum heart rate achieved (thalach), Exercise induced angina (exang), ST depression induced by exercise relative to rest (oldpeak), the slope of the peak exercise ST segment (slope), Target. Fig. 1 represents the correlation between the various attributes. The flowchart of the proposed model is represented by Fig. 2.

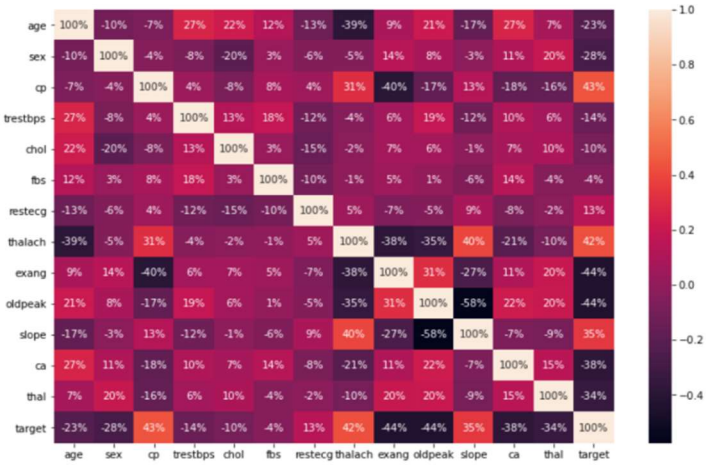

Fig. 1: Heatmap representation of correlations between attributes

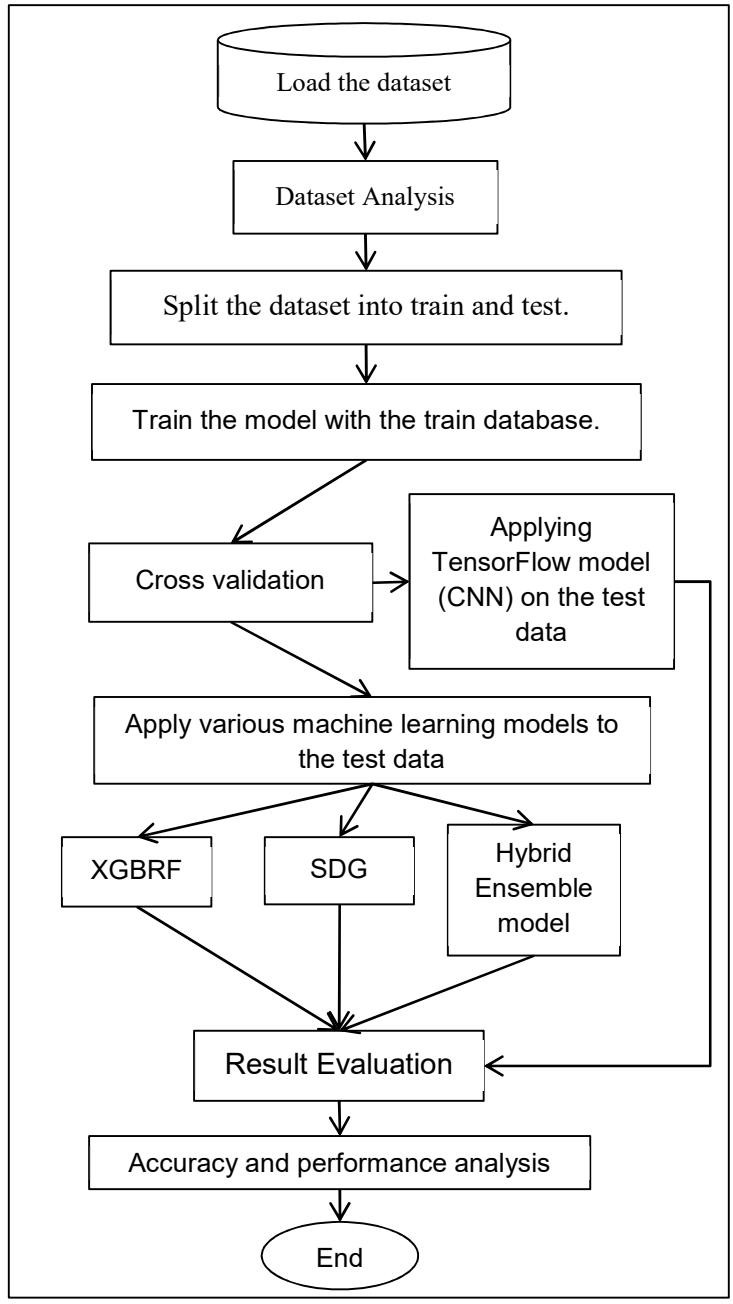

Fig. 2: Flowchart of the proposed model.

III. OVERVIEW OF THE CLASSIFICATION METHODS AND THEIR IMPLEMENTATION:

Stochastic Gradient Descent

Stochastic Gradient Descent is a well-known optimization approach for finding the model parameters that tie in with the best fit between predicted and actual outputs. In machine learning's application field, the usage of stochastic gradient descent is increasing day by day. It favours to optimize

different problems in deep learning and also can be considered as a faster alternative for training support vector machines.

For training deep learning model, sometimes we consider the objective function as a sum of a finite number of functions:

$$f(x) = \frac{1}{n}\sum_{i=1}^{n} f_i(x) \quad \cdots\cdots\cdots (i)$$

where n is the size of training dataset, i is training data instance index, $f_i(x)$ is a loss function based on the training data instance indexed by i. Graphical representation of stochastic gradient descent is represented by Fig. 3.

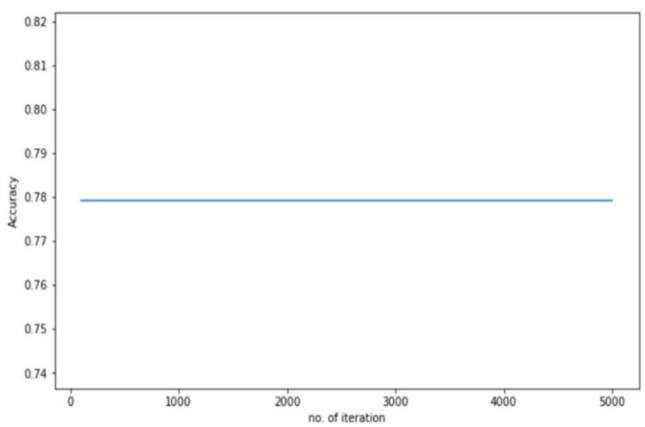

Fig. 3: Graphical representation of Stochastic Gradient Descent

Random Forest

This classifier is used to construct several decision trees during the training of that model. After that being an "Ensemble technique", it combines all the predictions gained from all the trees and makes the final one. In this case, the importance of the attribute is based on the decrease of node impurity calculated by the probability of reaching that node where probability = (no. of samples reach the node/total number of samples) [13].

The importance for each feature is calculated in Scikit-Learn as

$$fi_i = \frac{\sum_{j:node\ j\ splits\ on\ feature\ i} ni_j}{\sum_{k \in all\ nodes} ni_k} \quad \text{------- (ii)}$$

where,
fi sub(i) = the importance of feature i,
ni sub(j) = the importance of node j

It can be normalized as:

$$normfi_i = \frac{fi_i}{\sum_{j \in all\ features} fi_j} \quad \text{------- (iii)}$$

Now the final feature importance:

$$RFfi_i = \frac{\sum_{j \in all\ trees} normfi_{ij}}{T} \quad \text{---------- (iv)}$$

where RFfi sub(i)= the importance of feature i calculated from all trees in the Random Forest model, normfi sub(ij)= the normalized feature importance for i in tree j, T =total number of trees.

K Nearest Neighbour

The main objective of KNN classifier is to predict the class of a given data point by identifying the class of the nearest observation. The scale of the variables matters for the prediction. As any variable present on large proportion will have a greater impact on the distance between the observations, and hence on the KNN classifier, than variables that are on a small proportion [14]. In this procedure "K=1" is taken first to get the prediction. In order to observe if a better result is possible, an error rate versus K value plotted. The K value for least error is considered for best result. This is the plotted graph in this research paper which gives the best K value as 1. Here, Fig. 4 refers to the error representation of KNN.

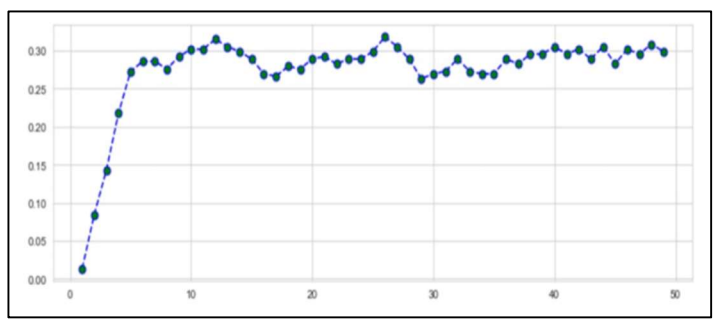

Fig. 4. Graphical representation of error calculation of KNN

Support Vector Machine

It is one of the supervised learning algorithms which is used to create the best decision boundary segregating n-dimensional space into different classes and the best decision boundary is called "Hyperplane". So, it chooses extreme points ("Support Vectors") to make the hyperplane [15]. Here, we have made changes on some parameters, such as-setting "C" value in increasing order to make the hyperplane much smoother, setting "Gamma" value in decreasing order to make hyperplane tuning and setting "kernel" as "rbf", we have tried to find out the best hyperplane for our model.

Naive Bayes

It is also one of the most efficient Supervised learning algorithms which is basically based on "Bayes Theorem". Naive Bayes classifier needs a small training data to determine the parameters needed for classification and it assumes that the value of a particular feature is independent of the value of any other features [16]. So, while working with continuous data, an assumption often taken is that the continuous data corelated with each class are distributed according to a normal (or Gaussian) distribution. This feature will be:

$$P(x_i|y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} exp\left(-\frac{(x_i-\mu_y)^2}{2\sigma_y^2}\right) \quad \text{------- (v)}$$

Gaussian Naive Bayes supports continuous valued features and models each as conforming to a Gaussian (normal) distribution.

Logistic Regression

In linear regression some estimated probability may be negative in order to balance and make it close to zero. For a binary classification such a negative result does not make any sense. Here the logistic regression is introduced and it uses a logistic function [14].

$$p(X) = \frac{e^{\beta_0+\beta_1 X}}{1+e^{\beta_0+\beta_1 X}} \quad \text{------- (vi)}$$

Here p(X) is the probability of a dataset named default. This expression ensures that the output will always lie between 0 and 1 for all values of X where X is the set of predictors. It is noticed that for low balances the prediction is close to, but not less than zero. Likewise, for high balances prediction is close to, but not more than one. The logistic function will always produce a sigmoid curve shown in figure 5, and not depended on the value of X, a sensible prediction is achieved. The curve is as follow-

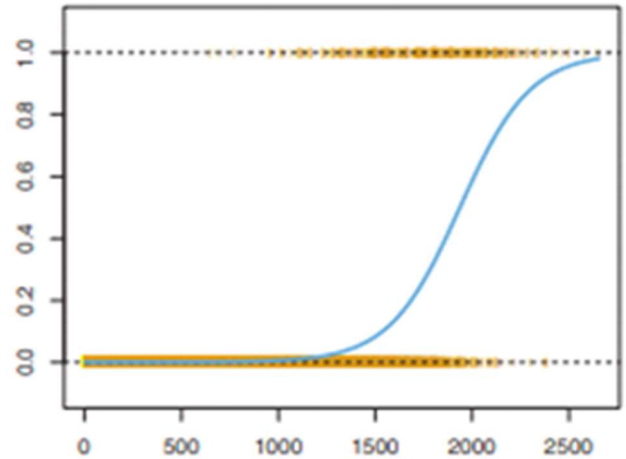

Fig. 5: Sigmoid curve of Logistic Regression

Decision Tree

Using decision trees, it is predicted that each observation belongs to the most commonly occurring class of training observations in the area to which it belongs. To analyse the results of a tree, it is better to show interest not only in the class prediction corresponding to a particular terminal node region, but also in the class proportions among the training observations under that region [13].

The associated term is entropy which is generally used to evaluate the quality of a particular split. Entropy can be represented by the following expression:

$$D = -\sum_{k=1}^{K} \hat{p}_{mk} \log \hat{p}_{mk} \quad \text{--- (vii)}$$

Here, $\hat{p}_{mk}$ represents the proportion of training observations in the mth region that are from the kth class.

Cross Validation

Cross validation is an important technique which is used to assure whether our model is getting the correct pattern of the dataset without getting too much noise. In this process, the model is trained using a specific part of the dataset and then trained using the complementary subset of the data-set. Here, we have used "K-Fold Cross validation", in which method the dataset is divided into "k" number of subsets & then training is performed on all the subsets leaving one (k-1) subset for the evaluation of the trained model. Thus, the iteration is done "k"(taken k=10) times with a different subset reserved for

testing purposes each time. It is simpler to examine the detailed results of the testing process.

```
Accuracy: 0.9860529986052998
Sensitivity: 0.9804469273743017
Specificity: 0.9916434540389972
```

Fig. 6: Graphical Representation of Accuracy, Sensitivity and Specificity after Cross Validation

Extreme Gradient Boosting with Random Forest

Extreme Gradient Boosting is used to introduce the techniques to speed up the training of the model and to make better result overall performance of the model. Here, we have configured this with an ensemble tree algorithm (Random Forest) where a random portion of the input variables in the tree at each split point is considered. This guarantees that each tree included in the ensemble is effective, but different in random ways. We have done this as follows:

```
[[114  26]
 [ 15 153]]

[46] print(classification_report(y_test,p1))

              precision    recall  f1-score   support

           0       0.88      0.81      0.85       140
           1       0.85      0.91      0.88       168

    accuracy                           0.87       308
   macro avg       0.87      0.86      0.86       308
weighted avg       0.87      0.87      0.87       308
```

Hybrid Ensemble

The objective is to improve the performance results of machine learning problems for multiclass classification problems using this algorithm by using several classifiers in an ensemble. In this paper this approach has been used to get a more appropriate accuracy [14].

In this method more than two separate models are created with the same dataset. A new ensemble model is created based on voting and aggregation of the results of their performance helps in the ultimate evaluation of this model. Here in this paper six methods are used in order to get the ensemble model. Those are logistic regression, naïve bayes, random forest, decision tree, k nearest neighbour and SVM.

```
              precision    recall  f1-score   support

           0       0.95      0.92      0.93       140
           1       0.94      0.96      0.95       168

    accuracy                           0.94       308
   macro avg       0.94      0.94      0.94       308
weighted avg       0.94      0.94      0.94       308
```

TABLE-I: Experimental Evaluation and Corresponding Result along with the Comparative Discussion [17].

Model	Accuracy	Sensitivity	Specificity	FP rate
RF	0.986	0.980	0.992	0.0178
DT	0.975	0.975	0.975	0.2020
NB	0.809	0.844	0.774	0.1130
SVM	0.972	0.958	0.986	0.2941
KNN	0.971	0.958	0.983	0.2023
LR	0.844	0.866	0.822	0.0595
HEM	0.931	0.958	0.921	0.0416

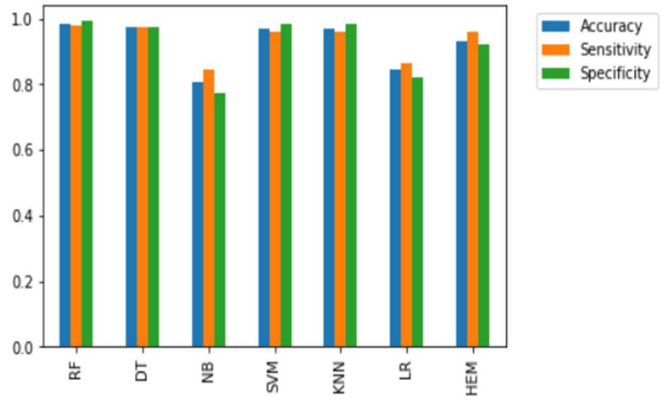

Fig. 6: Graphical Representation of Accuracy, Sensitivity and Specificity after Cross Validation of various models mentioned in TABLE-I.

TABLE-II: Experimental Evaluation and Corresponding Result along with the Comparative Discussion

Model	Accuracy	Sensitivity	Specificity
GD	0.779	0.714	0.857
HEM	0.942	0.958	0.921
XGBRF	0.867	0.911	0.814

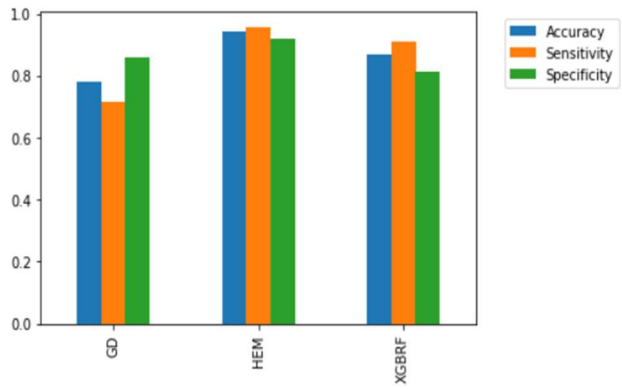

Fig. 7: Graphical Representation of Accuracy, Sensitivity and Specificity for GD, HEM and XGBRF mentioned in TABLE-II.

Using TensorFlow (CNN Or Convolutional Neural Network)

Being the heart of deep learning, a neural network contains multiple perceptron layers where perceptron is the basic building block of network. To build a network of perceptrons, we can connect layers of perceptrons, using a multi-layer perceptron model. Every neural network contains three portions and those are: 1) input layer, 2) output layer, 3) hidden layer. CNN is the version of a neural network where the concept of multilayer perceptron is used. It is more often used in solving classification problems and analysing visual data. This CNN model consists of three layers and those are: 1) convolutional layer, 2) pooling layer, 3) fully-connected layer. It is considered as more advantageous than others as the pre-processing required in a CNN is much less compared to other classification algorithms. While in primitive methods filters are needed to give manually, with enough training, CNN have the ability to learn these characteristics. The role of the CNN is to bring down the data into a suitable form which is easy to process, without losing crucial attributes which are necessary for getting a good prediction result. Here, model accuracy and model loss are represented by Fig. 8 and Fig. 9 respectively. It is observed that as the number of epochs is increasing from 0 to 100, the model accuracy is increasing and the model loss is decreasing gradually.

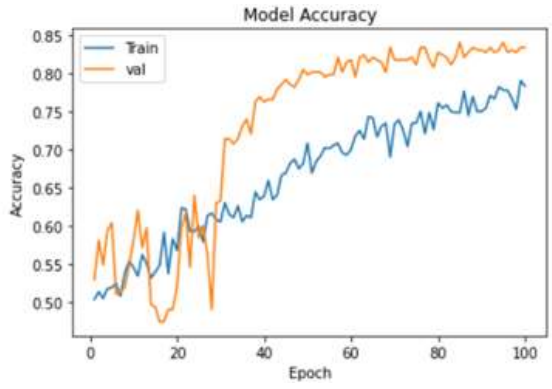

Fig. 8: Graphical representation of Model Accuracy

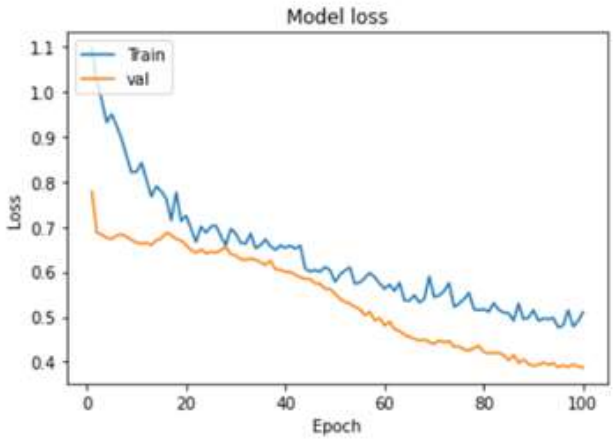

Fig. 9: Graphical representation of Model loss

IV. CONCLUSION AND FUTURE WORK

In order to process the unorganized raw data related to heart disease the Machine Learning approach is used and a better accuracy has been gained. In this research paper the main objective is to provide a new and novel discernment towards heart disease. To accomplish this challenging objective along with various classic machine learning algorithms (RF, XGBRF, SGD, KNN, DT, SVM, HEM, LR, etc.), CNN is also used and which is implemented using Tensor flow. Due to its reliability & accuracy this model can be adopted as the basic treatment aid to detect heart disease at a very early stage which can drastically control the mortality rate. Machine learning is a growing field of various invented technologies as well as opportunities. The idea of innovation is not bound under any limit so further extension of this paper is attainable. New feature selection technique as well as data processing methods can be included and better accuracy can be gained.

REFERENCES

[1] "Cardiovascular diseases (CVDs)", World Health Organisation (WHO), https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds), Accessed 30th July, 2021.

[2] "Heart disease", Mayo Clinic, https://www.mayoclinic.org/diseases-conditions/heart-disease/symptoms-causes/syc-20353118, Accessed 25th June, 2021

[3] S. Shylaja, & Muralidharan S. 2R., "Hybrid SVM-ANN Classifier is used for Heart Disease Prediction System", International Journal of Engineering Development and Research, vol. 7, no. 3, pp. 365-372, 2019.

[4] J. Lopez-Sendon, "The heart failure epidemic," Medicographia, vol. 33, no. 4, pp. 363–369, 2011.

[5] S. Ghwanmeh, A. Mohammad, and A. Al-Ibrahim, "Innovative artificial neural networks-based decision support system for heart disease diagnosis," J. Intell. Learn. Syst. Appl., vol. 5, no. 3, 2013.

[6] Pahulpreet Singh Kohli and Shriya Arora, "Application of Machine Learning in Diseases Prediction," 4th International Conference on Computing Communication and Automation (ICCCA), 2018.

[7] S. Palaniappan and R. Awang, "Intelligent heart disease prediction system using data mining techniques," in IEEE/ACS International Conference on Computer Systems and Applications. IEEE, pp. 108–115, 2008.

[8] M. Gudadhe, K. Wankhade, and S. Dongre, "Decision Support System for Heart Disease based on Support Vector Machine and Artificial Neural Network," Computer and Communication Technology (ICCCT), International Conference, pp. 741–745, 2010.

[9] C.-A. Cheng and H.-W. Chiu, "An Artificial Neural Network Model for the Evaluation of Carotid Artery Stenting Prognosis Using a National-Wide Database," Proc. 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 2566–2569, 2017.

[10] R. Das, I. Turkoglu, and A. Sengur, "Effective diagnosis of heart disease through neural networks ensembles," Expert Syst. Appl., vol. 36, no. 4, pp. 7675–7680, May 2009.

[11] Jian Ping Li, Amin Ul Haq, Salah Ud Din, Jalaluddin Khan, Asif Khan, and Abdus Saboor, "Heart Disease Identification Method Using Machine Learning Classification in E-Healthcare," IEEE Access, Vol. 8, 2020.

[12] National Health Council,' Heart Health Screenings', 2021. [Online] Available: https://www.heart.org/en/health-topics/consumer-healthcare/what-is-cardiovascular-disease/heart-health-screenings

[13] Scott Hartshorn, "Machine Learning With Random Forests And Decision Trees: A Visual Guide For Beginners Kindle Edition", 2016.

[14] Gareth James, Daniela Witten, Trevor Hastie, Robert Tibshirani, "An Introduction to Statistical Learning with Applications in R", 2017.

[15] Nello Cristianini, "An Introduction to Support Vector Machines and Other Kernel-based Learning Methods Illustrated Edition, Kindle Edition", 2000.

[16] Shadab Adam Pattekari and Asma Parveen, "Prediction System for Heart Disease Using Naive Bayes," International Journal of Advanced Computer and Mathematical Sciences, Vol. 3, Issue 3, 2012, pp. 290-294, 2012.

[17] A. U. Haq, J. P. Li, J. Khan, M. H. Memon, S. Nazir, S. Ahmad, G. A. Khan, and A. Ali, "Intelligent machine learning approach for effective recognition of diabetes in E-healthcare using clinical data," Sensors, vol. 20, no. 9, p. 2649, May 2020.

MULTICAST TRAFFIC GROOMING IN ELASTIC OPTICAL NETWORK UNDER DYNAMIC SCENARIO

Panchali Datta Choudhury
University of Engineering and Management
****Email: panchali.dattachoudhury@uem.edu.in***

Abstract: Elastic optical networks allow elastic allocation and de-allocation of optical resources to optimize network resources and reduce traffic demand blocking probability for dynamic traffic demands. The routing of dynamic traffic demands is a challenging task since the traffic demands are not predefined, they arrive and leave randomly. The approach presented here is a grooming, routing and spectrum allocation technique for multicast traffic demands in elastic optical networks for dynamic type of traffic demands. The simulation results show reduced blocking probability compared to existing approach.

Keywords: dynamic, flexible-grid, optical grooming

I. INTRODUCTION

Elastic optical network (EON) has mini grid architecture which allows elastic bandwidth allocation for different traffic demands.

There are broadly two types of traffic demands one-to-one (or unicast) and one-to-many (or multicast). Applications of multicast type of traffic are live streaming conferences, Internet television, etc. These type of communication is supported by the broadcast and select mechanism of bandwidth variable transponders (BVT), and the unwanted signals are filtered out using the bandwidth variable optical cross connect (BV-OXC). A multicast-tree is implemented for data transmissions Multicast routing and spectrum allocation in EONs have been well studied in the past [1-3].

Optical grooming of traffic is grouping same type of traffic demands and switching them as a whole.

In EON, spectrum-slicing does not occur early in BVT and grooming reduces wastage of network resources. Groomed traffic demands do not require guard slots in between them. Same source optical grooming is selected over different source optical grooming since orthogonality feature cannot be sustained between optical paths for different source grooming [4].

If two multicast traffic demand have same source and similar set of destinations then they can be transmitted using same light-tree, and adding any guard bands between groomed traffic demands is not necessary, just two guard band slots are added at the beginning and at the end of the allocated spectrum.

In this paper, a grooming, routing and spectrum assignment approach is applied to dynamic (arrive and leave randomly) multicast (one-to-many) traffic. The target of this work is to reduce blocking of traffic demands.

II. RELATED WORK

In dynamic scenario, traffic comes and leaves after certain time duration. In case of dynamic traffic grooming, an incoming traffic demand is matched with any existing traffic demand to find whether they have same source and similar destinations.

The authors in [5] propose traffic grooming policies based on a multi-layer auxiliary graph model and a spectrum reservation scheme incorporated into these policies. The results show the different trade-off present among different traffic grooming policies.

In [6], the authors propose a dynamic source aggregation approach in which the sub-wavelength traffic demands having same source are grouped together and transmitted through a single transmitter. The authors present the benefits of aggregating traffic demands and its impact on spectrum utilization and transmitter saving.

In [7], the authors propose a dynamic traffic grooming approach that uses an auxiliary graph model. They use sliceable bandwidth variable transponder enabled EONs and address electrical and optical grooming for dynamic traffic. Different traffic grooming policies are adopted by adjusting edge weights of the auxiliary graph model. The authors present two spectrum reservation schemes. These schemes efficiently use the capacity of transponders. The authors provide a comparative study of the presented policies and trade-off among these policies.

III. PROPOSED APPROACH

The problem of grooming in dynamic traffic demands along with provisioning the demands and allocating required spectrum to the demands are discussed in this section. Dynamic traffic demands arrives randomly and stays active for their holding time, so while comparing an incoming traffic demand with an existing traffic demand, it needs to check the status of the traffic demands. A traffic demand with status as active is compared with the incoming traffic demand, and if they have same source and some common links in their respective trees, then they can be groomed together. If the spectrum assignment constraints are satisfied then slots are assigned to the traffic demands by applying First-Fit policy. The proposed heuristic for solving grooming problem for the dynamic multicast traffic demands is presented in algorithm 1.

Algorithm 1: Dynamic Multicast Traffic Grooming Routing and Spectrum Assignment (DGRSA) in EON

Input: The physical network topology G (V, E) and one-to-many traffic demand (s, {D}, b)
Output: A solution for the dynamic multicast traffic grooming problem

1. Generate a traffic demand
2. Calculate a multicast tree for incoming traffic demand (using union of shortest paths found by Dijkstra's algo)
3. **if** *an incoming traffic demand and an existing active traffic demand has similar source and same destination set* **then**
4. select the existing traffic demand for grooming
5. **end**
6. check spectrum continuity and contiguity constraint for establishing traffic demands
7. **if** *all the constraints are satisfied* **then**
8. the traffic demands are groomed together (no guard band required between them)
9. assign spectrum using First-Fit spectrum assignment scheme
10. **end**
11. **if** *grooming is not possible* **then**
12. establish the incoming traffic demand by adding guard bands
13. spectrum is assigned using First-Fit spectrum assignment scheme
14. **end**
15. **if** *traffic demand cannot be established at all* **then**
16. drop the traffic demand
17. **end**
18. De-allocate all the allocated slots after its holding duration is completed

V. RESULT DISCUSSION

The performance of the proposed heuristic for dynamic grooming approach is evaluated on two popular network topologies the fourteen nodes NSF network and twenty eight nodes US-Backbone network. The network topologies for NSFNET and US-BACKBONE are shown in the Figure 1 and Figure 2 respectively.

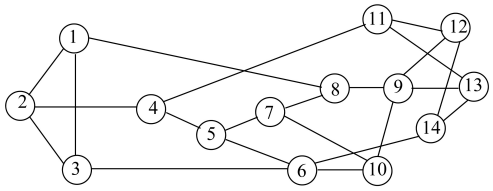

Figure 1: The NSF network topology

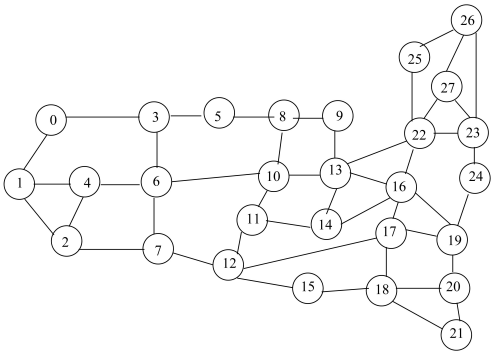

Figure 2: The US-BACKBONE network topology

The performance evaluation of EON provisioning with dynamic multicast traffic demands is shown in Figure 3 and Figure 4. It is observed that the dynamic traffic grooming algorithm (DG-MRSA) has less probability of blocking compared to its non grooming counterpart.
The reason for such results lies in the fact that grooming traffic demands reduces the spectrum usage since groomed traffic demands do not need guard band slots to e inserted in between them. Less spectrum usage means more slots are available for future traffic demands and so blocking reducing.

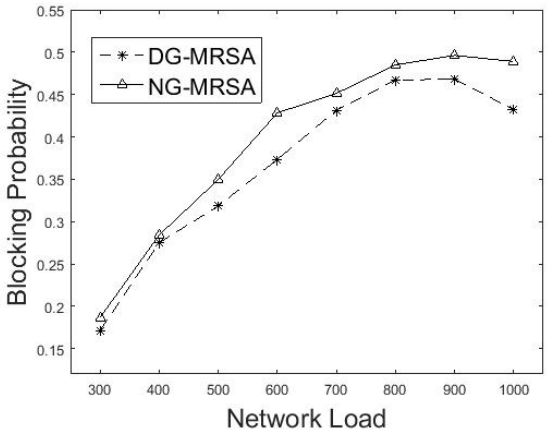

Figure 3: The relationship between blocking probability and network load in NSFNET network.

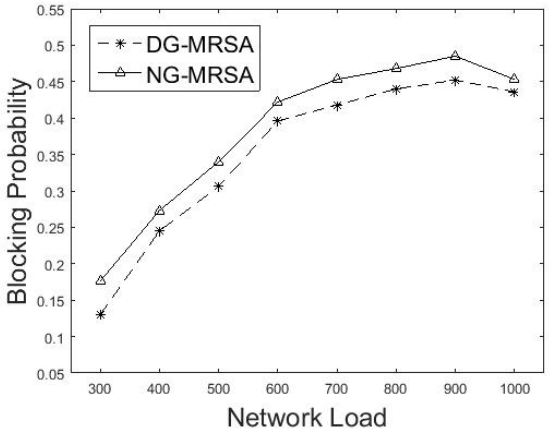

Figure 4 : The relationship between blocking probability and network load in US-BACKBONE network.

VI. CONCLUSION

Dynamic traffic demands are not known a-priori, they arrive and leave randomly. The approach presented here is a grooming, routing and spectrum allocation technique for multicast traffic demands in elastic optical networks for dynamic type of traffic demands. The simulation results show reduced blocking probability compared to its non-grooming counterpart.

REFERENCES

[1] Li, S., Lu, W., Liu, X., Zhu, Z.: Fragmentation-aware service provisioning for advance reservation multicast in sd-eons. Optics express 23(20) (2015) 25804–25813

[2] Fan, Z., Li, Y., Shen, G., Chan, C.C.K.: Dynamic resource allocation for all-optical multicast based on sub-tree scheme in elastic optical networks. In: Optical Fiber Communication Conference, Optical Society of America (2016) W2A–50.

[3] Moharrami, M., Fallahpour, A., Beyranvand, H., Salehi, .A.: Resource allocation and multicast routing in elastic optical networks. IEEE Transactions on Communications65(5) (2017) 2101–2113.

[4] Zhang, G., De Leenheer, M., Mukherjee, B.: Optical traffic grooming in ofdm-based elastic optical networks [invited]. Journal of Optical Communications and Networking4(11) (2012) B17–B2.

[5] Zhang, S., Martel, C., Mukherjee, B.: Dynamic traffic grooming in elastic optical networks. IEEE Journal on selected areas in communications 31(1) (2012) 4–12.

[6] Khodashenas, P.S., Comellas, J., Spadaro, S., Perell´o, J.: Dynamic source aggregation of sub wavelength connections in elastic optical networks. Photonic Network Communications 26(2-3) (2013) 131–139.

[7] Zhang,J.,Ji,Y.,Song,M.,Zhao,Y.,Yu,X.,Zhang,J.,Mukherjee,B.: Dynamic traffic grooming in sliceable bandwidth-variable transponder-enabled elastic optical networks. Journal of Lightwave Technology33(1) (2015) 183–191.

IoT based smart system to detect mental health emergencies: A proposed model

Swatick Mullick
Electronics and Communication Engineering
University of Engineering and Management, Kolkata
West Bengal, India
swatickmullick117@gmail.com

Akash Kumar Singh
Electronics and Communication Engineering
University of Engineering and Management, Kolkata
West Bengal, India
singhakashkumar453@gmail.com

Achyut Kumar Shaw
Electronics and Communication Engineering
University of Engineering and Management, Kolkata
West Bengal, India
achyut122000@gmail.com

Vicky Viswakarma
Electronics and Communication Engineering
University of Engineering and Management, Kolkata
West Bengal, India
vicky25011998@gmail.com

Mimansha Kishan
Electronics and Communication Engineering
University of Engineering and Management, Kolkata
West Bengal, India
mimmokishan22@gmail.com

Debanjana Ghosh
Assistant Professor, Electronics and Communication Engineering
University of Engineering and Management, Kolkata
West Bengal, India
dghosh2992@gmail.com

***Abstract*— Health is one of the major point of concern that every individual is worried about. There are different aspects of health. Slight variations in any of the aspects can be unpleasant at any point of time. Amidst this pandemic there has been quite a many incidents of dramatic loss of lives due to severe issues in mental health. It's obvious that there might be certain level of stress during our daily lives. If the levels of this stress factor maximizes then it would bring many unfavorable health problems such as anxiety, sadness, depression and other physical health problems too. So our main aim is to develop an efficient system which can be quite favorable to large no of patients in early detection of any mental health issues. This project gets hold of most of the constraints that lead to stress, anxiety, and several other mental health problems. We have proposed the design of an efficient mental health monitoring system which will be able to measure stress levels based on sensing various physical parameters, such as heart rate, Spo2, body temperature and pressure. It also involves a GPS sensor to locate and rescue a patient in case of emergencies like panic attack.**

Keywords*— *Internet of Things, Mental Health, sensor, panic attack, SpO2.

I. Introduction

Mental health problem is one of the fast growing health problem which is common across the globe. Mental health problems due to anxiety, stress are at a stake worldwide. The WORLD HEATH ORGANIZATION considers depression as one of the global crisis. It includes change in our emotional, psychological, social well-being. According to WHO: Mental Health is a state of well-being in which an individual realizes his or her own abilities, can cope with normal stresses of life, can work productively, and is able to make a contribution to his or her community. The mental health is a point of concern at every stages of life right from childhood to adolescence. Modern city life cultures do not enables a person to focus much on their healthy lifestyle which in turn can be a dominating factor in deteriorating a person's mental health also. IoT and embedded systems are the blooming technologies which have a great role in different research domains including Telemedicine.

Internet of things are the systems of physical devices that are embedded with sensors, software and other technologies for the purpose of connecting and exchanging data with other compatible devices and systems through internet. IoT in health care is found to be beneficial because of it's smarter way of remotely monitoring a patient. With increasing use of smart wearable sensors and smart phones, there already exists a lot more applications to remotely monitor patients of diabetes, heart disease etc. The body sensor network technology is one of the important technology in IoT which is used in studying heath care systems. It uses a combination of very low power and wireless nodes of a sensor that are used to analyse various human body parameters and the environment which is surrounding the patient.

It is quite harder to detect a person's actual emotion but there are lots of body sensors such as heart rate sensors, SpO2 sensors, body temperature sensors and many more which can be used in collecting data of various body parameters and can be used in analysing various types of mental health issues.

Rest of the paper is structured as follows. Section II is about the study of existing works. Section III gives the overview of the components used in the model. Section IV describes the main working principle. Section V and VI explains about the results and the problems faced during the simulation. Section VII contains the future proposals on this topic. Section VIII is about the brief conclusion.

II. Literature Survey

Modern health care uses various types of smart systems in the form of wearable devices for monitoring. In case of the mental health of a person, collecting real time patient data is quite necessary followed by processing and analysing of the collected data. Advancements in the field of IoT and electronic sensors help to achieve the competency to build these types of systems.

Authors in [1] used heart rate sensors, temperature sensor and respiratory sensors to determine the level of stress by using the signal response of these sensors. In [2] mainly two types of sensors; heart rate sensor and brain wave sensor were used to identify various brain waves and analyses the stress levels which also includes attention and meditation levels. Authors in [3] worked on the importance of body temperature, blood oxygen saturation, as well as blood pressure. Since mental state of a person is also dependent on various types of stress hormones which affect respiratory and cardiovascular systems and related with skin temperature which are related to sleep, hence it depends on heat loss of the body to the environment and a fall in core body temperature. Authors of

this paper identified the key phases of mental state of a patient by collecting different parameters followed by data analysis, model training and evaluation. Some researches also worked on employing mechanical sensors such as vibration sensors, accelerometers and gyroscope which are generally used to monitor regular activities such as walking, exercise which also plays an integral role in maintaining the mental state of a person. Authors in [4] employed both IoT and machine learning which at first collects several body parameters details and then uses predictive analysing methodology to predict mental health related issues at a very early stage as possible. It is also capable of automated scheduling of doctors and has an automated suggestion procedure involving necessary actions need to be taken based on those collected data. Another paper [5], used the principle of indoor environmental quality and indoor lightning quality. The authors suggested the importance of proper indoor quality and poor lighting quality in regard to good mental health and an AI based methodology for recognizing daily activities. Principle of Galvanic Skin Response in [6] has been used to identify the emotional state of person at an instant of different age groups. Authors in [7] have used Actigraphy devices which is used to monitor human sleep patterns and sleep disorders which are generally useful for mental conditions, such as bipolar disorder. This paper also described on software and social media sensing by using numerous mobile applications which computed time and frequency spent by an user on each category.

III. System Components

The proposed system contains several sensors to monitor different health parameters in real time.

A. *Heart Rate Sensors:*

Heart rate Sensors is an electronic module specifically designed to measure heart rate in beats per minute. It uses an optical LED light source and a LED light sensor.

B. *Temperature Sensor:*

Body temperature is the degree of heat maintained by the body. Temperature sensors such as LM35 is an integrated circuit sensor that can be used to measure temperature with an electrical output proportional to the temperature (in °C). This sensors can measure from -55°C to 150°C.

C. *Pressure Sensor:*

Pressure is being measured using a sensor namely BMP180. It consists of a piezo resistive sensor.

D. *GPS Module:*

GPS stands for Global Positioning System which is a satellite based system that uses satellite and ground stations to measure and compute its position on Earth and it provides position information anywhere in the world.

E. *Blood Oxygen Saturation Sensor:*

It is an electronics module specifically made to measure blood saturation levels. In this module (Fig. 1) there is a red LED light source and an IR light which are used to send light to the photodiode. The photodiode measures the intensity of transmitted light by red and IR led which is used to calculated blood oxygen saturation.

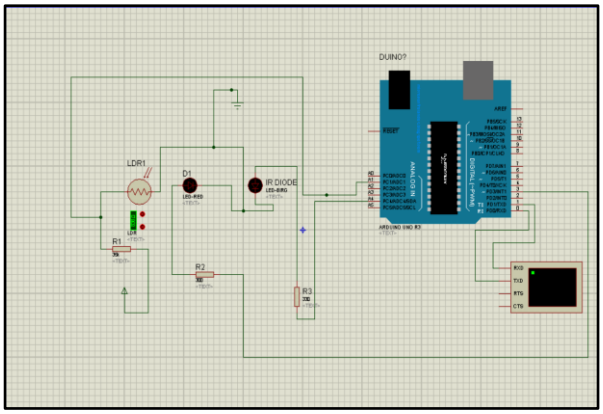

Fig. 1 Circuit diagram for SpO2 detection

The ratio of red and IR signals received by the photodiode with the oxygen saturation value is done to measure blood oxygen saturation levels.

IV. Methodology

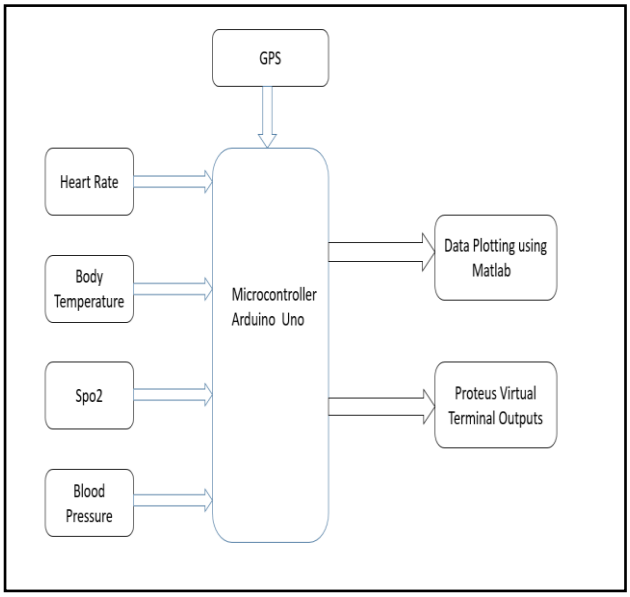

Fig. 2 Block Diagram

The entire process is proposed as below;

Step 1: Various body sensors and environmental sensors are used in the above system which collects various body parameters for monitoring the patient's condition.

Step 2: After the data has been collected from various sensors these data are being processed to a structured dataset.

Step 3: The processed data are plotted in MATLAB to analyse various mental health related emergencies.

Step 4: In the virtual screen it shows the corresponding body health values at a particular instance and based on results the system displays what are the immediate responses that needs to be taken.

Step 5: A GSM module and a GPS module has been used which will be able to notify doctors and other health workers describing the health condition and also the location of that patient in case of emergency.

V. Experimental Result

The entire proposed circuit is simulated and the data produced by each sensors are recorded and plotted respectively.

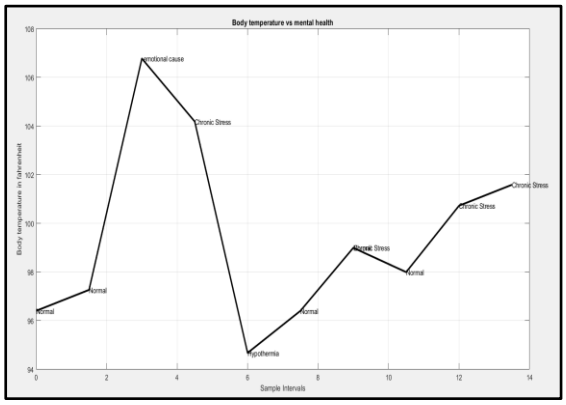

Fig. 3.1 Body temperature vs. Time

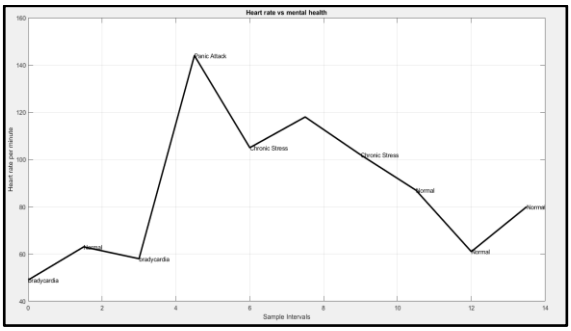

Fig. 3.2 Heart Rate vs. Time

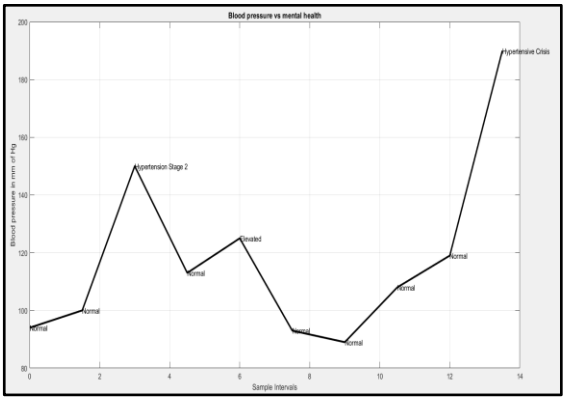

Fig. 3.3 Blood Pressure vs. Time

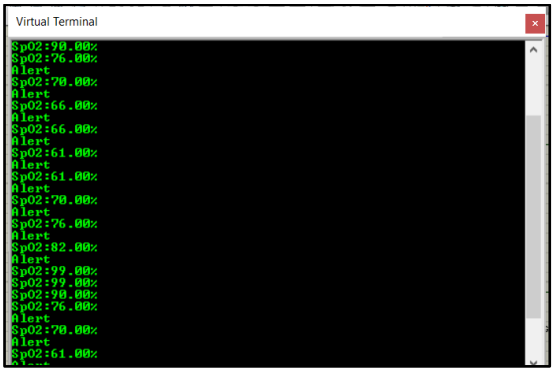

Fig. 3.4 SpO2 Outputs in Virtual Terminal

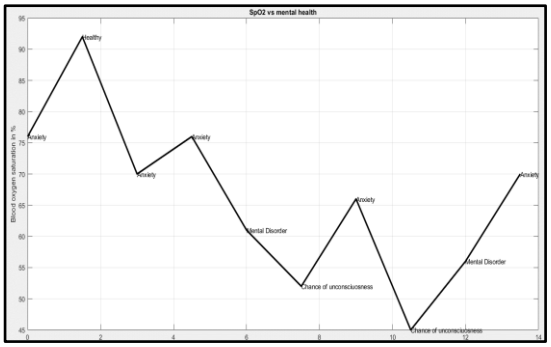

Fig. 3.5 SpO2 vs. Time

Fig. 4 represents the entire circuit of the proposed model. The circuit contains all the necessary sensors and the microcontroller along with the GPS module.

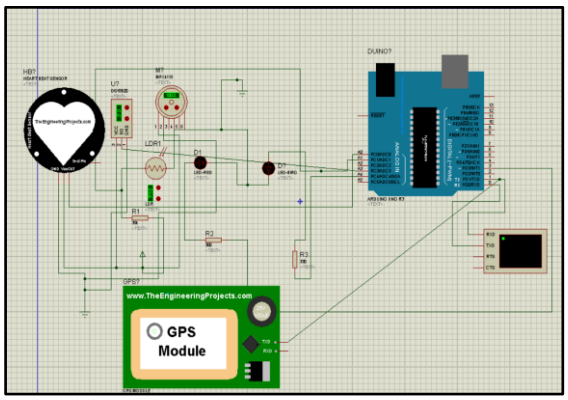

Fig. 4 Circuit diagram of the smart device

VI. Problem Faced

The SpO2 was not available in Proteus library. So it was needed to be designed by maintaining most of the constraints and other parameters. Although the GPS module used can show us latitude and longitude and hence locations but since this is a simulation based project the GPS module is installed with only fixed sets of data.

VII. Future Work

This work will further be implemented using actual hardware kits where all real time data collections can be done. A smart wearable health band can be developed by using the same methodologies. A database needs to be developed containing important medical parameters of a patient. While designing the hardware of this system will be able to send notification to hospitals and doctors as per emergency of a patient.

VIII. Conclusion

Numerous studies and researches were made to choose proper methodologies in determining various mental status of a person based on corresponding signals and their variation. This proposed system will be useful to person in order to manage the emergencies created due to anxiety, stress, depression and hypertension. Hence this system can play an efficient role in order to detect, diagnose and manage the emergencies regarding mental health and in recent future will be a powerful tool to make people more aware of mental health.

REFERENCES

[1] P. Jain, E. Alphonso, A. Miranda, P. Bhojak and S. Jaiswal , "Stress Detection Using Arduino", International Research Journal of Engineering and Technology (IRJET), March 2020.

[2] E. Gayathri, N. Bhavani, G. Ankitha, R. Mounika, Venkateshappa, "Human Stress Level Detection and Monitoring System", International Journal of Software & Hardware Research in Engineering, May 2016.

[3] E. Garcia-Ceja, M. Rieglera, T. Nordgreenc, P. Jakobsenc, K. J. Oedegaardf, Jim Tørresena,"Mental Health Monitoring with Multimodal Sensing and Machine Learning: A Survey", Pervasive and Mobile Computing, December 2018.

[4] C. El Morr , "Virtual Communities, Machine Learning and IoT: Opportunities and Challenges in Mental Health Research", International Journal of Extreme Automation and Connectivity in Healthcare.

[5] M. J. Rodrigues, O. Postolache and F. Cercas , "Physiological and Behavior Monitoring Systems for Smart Healthcare Environments: A Review", Sensors, April 2020.

[6] M. Viqueira Villarejo, B. García Zapirain and A. Méndez Zorrilla, "A Stress Sensor Based on Galvanic Skin Response (GSR) Controlled by ZigBee", Sensors, May 2012.

[7] https://www.sciencedirect.com/topics/nursing-and-health-professions/actigraph

[8] D. Ghosh, P. Mukherjee, "Internet of Things for e-healthcare employing Telemedicine to treat COVID-19", International Journal of Innovative Research in Science, Engineering and Technology (IJIRSET), August 2020.

[9] Shashidhar R, Abhilash S, Sahana V, Alok N A, Roopa M , "Iot Cloud: In Health Monitoring System", INTERNATIONAL JOURNAL OF SCIENTIFIC & TECHNOLOGY RESEARCH, JANUARY 2020.

[10] R. Sahota, P. Kumari, "Low Cost, Wireless Patient Monitoring System with Single Sensor using Arduino and GSM", International Journal for Research in Applied Science & Engineering Technology (IJRASET).

[11] P. Kabilan , P. Sakthivel, S. Karthi , Dr. G. Mahesh Manivanna Kumar , "Smart Wearable IoT based Heatlh Monitoring Sustem (HMS) using BSN", International Research Journal of Engineering and Technology, February 2019.

[12] P. Biswas, S. Halder, "Remote Health Monitoring Systems using Internet of Things", International Research Journal of Engineering and Technology, May 2020.

Sentiment Analysis of Human Speech using CNN and DNN

[1]Saumya Roy ,University of Enginneering and Management
Kolkata, India
s4aumyaroy@gmail.com

[2]Sayak Ghoshal University of Enginneering and Management
Kolkata, India
s.ghoshal226@gmail.com

[3*]Rituparna Basak University of Enginneering and Management
Kolkata, India
*rituparna.basak02@gmail.com

Abstract: Communication is the exchange of thoughts, ideas and feelings through emotion. In this paper we have proposed a method where human speech is converted into digital input. The digitized sound is fed into the proposed models and the voice of every person is classified into discrete emotional characteristics by its intensity, pitch, timbre, speech rate and pauses. In the proposed method, authors have applied multi scale area attention in a deep 2D-CNN connected to dense DNN to obtain emotional characteristics with wide range of granularities and therefore the classifier can predict a wide range of emotions on a broad scale classification.

Keywords— Sentiment Analysis, Audio Analysis, Deep Learning, Neural Networks, Emotion Detection, Deep Neural Network(DNN), Convolutional Neural Network(CNN).

I.INTRODUCTION

Speech is considered to be the most valuable and widely used means of communication. Speech Emotion Recognition (SER) has wide application perspectives on psychological assessment, robotics etc. For example, a doctor treating a patient suffering from depression can keep a track of his patient's development and design a recovery plan according to the emotions hidden in the patient's speech. Over the past few years, there has been a consequential development in the field of analyzing the emotions of speech with Deep Learning, but there are still deficiencies in the research of SER, such as insufficient model accuracy, shortage of useful dataset, and lack of computing resources. In SER, emotion may depict distinct energy patterns in spectrograms with varied granularity of areas. However, typical attention models in SER are usually optimized on a fixed scale, which may limit the model's capability to deal with diverse areas and granularities.

In SER, change in energy patterns in spectrograms results in different types of emotions. Typically, an attention neural network[1] classifier of speech emotion recognition is usually optimized on a fixed attention granularity. A drawback of an attention neural network classifier of SER is that it is usually optimized on a fixed attention granularity. In the proposed method this constraint is removed by applying multi scale area attention in a Deep CNN as well as Dense DNN to obtain emotional characteristics with a wide range of granularities and therefore the classifier can predict a wide range of emotions on a broad scale classification. For example, sentiments such as annoyance, joy have different levels of intensity, so instead of just categorizing the presence or absence of the emotion, level of intensity of the emotion can be identified as well. Hence comparative study using both the models is conducted.

Models that have been used for SER previously suffer a problem of sample scarcity. A novel approach is used to deal

with data sparsity. For this reason, augmentation of data with addition of stretching, pitch modification and noise insertion. This adds variation to the dataset and it also improves the chances of getting better accuracy. For example, a training data with all anger emotions expressed in higher pitch will now have the same emotion in lower pitch, hence maximizing the chances of identifying anger, when spoken in a lower timbre. Similarly, the sample set might consist of audio of fast speakers and be essentially biased. Stretching helps in removing this bias. Addition of noise to the data is proven to be a useful[2] tool for classifying real time date, since real time data tend to have background noise. To the effectiveness of the proposed method, extensive experiments are carried out on RAVDESS[8], CREMA-D[9], TESS-D[10] dataset.

.

II.Literature Survey

In the paper [1] ,authors have studied a new techniques of utterance-based emotion recognition. The comparison between the efficiency of Support Vector Machines (SVM) and Binary Support Vector Machines (BSVM)[14] techniques are clearly depicted by the authors. The different frame based features like,Acoustic features including energy, MFCC[10][11], Perceptual Linear Predictive[12][13] (PLP), Filter Bank (FBANK)[15], etc. are taken into considerations.

In the paper [2] an improved multimodal approach for sentiment analysis is proposed. The basic goal for this paper is binary classification of sentiments that is either positive or negative. For a better user experience, from the speaker speech emotion, age or gender was recognized. In this paper, the technique of Two-dimensional Convolutional Neural Networks [16] and Deep Neural Networks is used for encoding each segments into a vector of fixed length by integrating the activations of the last hidden layer over time.

In the paper [17] proposes a real-time Speech emotion recognition system based on End-to-end (E2E) learning.From a one second frame of raw speech spectrograms the technique of deep neural network is used to study the emotions. A deep hierarchical framework, pragmatic optimization and data augmentation helps in achieving the desired results. Promising results are reported.

In the paper [3] a well organised procedure has been provided by the author for implementing SER political debates; The emphasis is laid on manufacturing the outcome and then to prepare visualisation of the said results. Two alternative approaches have been considered, a classification-oriented approach and a lexicon-oriented approach. In the former universal and domain oriented sentiment lexicons are used. Two general techniques for implementing domain oriented lexicons-based approach has also been considered. These are (a) direct generation and (b) adaptation. Direct generation focuses on producing exclusive lexicons depending upon the data labels. Adaptation considers a common and inclusive lexicon based approach and adjusting it as per necessity to develop it into a non-generic and exclusive symbol of a particular domain.

The results obtained from the above discussed approaches were considered and compared with the “classification-based” approach. By observing and analysing the attitude of the political speakers in the debates, the sentiment mining approaches were compared. Collective labelled speech data was considered, which were of political significance which was extracted from debating transcripts. The outcome of the comparison helped them realise that using sentiment mining the speakers attitude can be determined conclusively.The proposed Debate Graph Extraction (DGE) framework, in its functioning, effectively extracts the debate graphs from political debate transcripts. They proposed to graphically represent debates with speakers as nodes. In this framework, the speakers are represented as nodes, with nodes having specific labels and links between nodes. These links depend upon the exchange of speeches. The labels on the nodes depended upon the sentiment of the speakers. The attitude of the speaker was then used to classify a link as supporting or non-supporting. If the outcome of both speakers was same, i.e. both positive or both negative then the link was labelled as supporting or else it was labelled opposing. Visualisation of results were carried out via graphs that represent the essence of the debate, in an abstract manner. Lastly they discuss about how debate graphs can be structurally analyzed using the techniques based on network mathematics and community detection techniques.

In the paper [4] ,they proposed automatic sentiment detection system for natural audio streams. Part of speech tagging and maximum entropy modelling (ME) has been used as the suggested technique to develop a sentiment detection model, that was text-based in nature. The number of model boundaries in ME was reduced drastically by an attuning technique while conserving the classification capability. Using decoded ASR (automatic speech recognition) transcripts and the ME sentiment model, sentiments of YouTube videos were able to be determined. As evaluation, they have gathered motivating classification accuracy. According to the results analysis showed that performance on sentiment analysis on spontaneous speech data is possible in spite of word error rates.

In the paper [6] aims to underline different techniques to detect vocal expressions of different emotional states. Moreover, the features extracted from machine learning methods and speech datasets were analysed with an emphasis on classifiers. Additionally, this paper shows the outline areas where emotion recognition can have an effective application like cognitive sciences , psychology, marketing and healthcare.

III.Problem Statement

The human speech is the most natural way of expressing ourselves. We know emotions play an important role in communication analysis, and the detection of the same is significantly important in today’s digital world of remote communication. In text based classification certain emotions like sarcasm, dual meaning sentences cannot be identified. Tonal Qualities of the voice is required to classify the emotions more accurately. An SER system can be defined as a collection of methodologies that classifies speech signals to detect embedded emotions. The human speech contains many features different to each individuals. If we consider all those

features while training the model, then the model will be biased to the training set which is not desired. So we have considered only the properties common to human voices like loudness, timbre, and quality. Our attempt lies in trying to detect underlying emotions embedded in speech through analysis of the acoustic features of the audio recording.

IV. Dataset

Three instances of audio datasets was used during our analysis, which contains the vocal emotional expressions in sentences spoken in a range of (joy, grief, rage, agitation, annoyance, and calm). Total 1440 and 7,440 clips of 115 actors were collected which had a diverse ethnic background, it was merged with 8882 files. We have worked only with the audio recordings of the audio-visual data. The sentences are spoken by trained Actors belonging to a variety of races and ethnicities (Latino Americans, African American, Asian, Caucasian). The sentences are classified using one of six different emotions (Joy, Grief, Rage, Agitation, Annoyance, and Calm) and four different emotion levels (Low, Medium, High, and Unspecified). The audio file format is WAV. We have preprocessed the dataset to clear noise and to introduce stretching.

V. Proposed Solution

Three classes of features can be mainly identified in a speech. These can be classified as lexical features, the visual features, and the acoustic features. For example: the various expressions of the speaker, the terminology used, and properties like vocal quality, pitch, anxiety, noise, energy, etc.

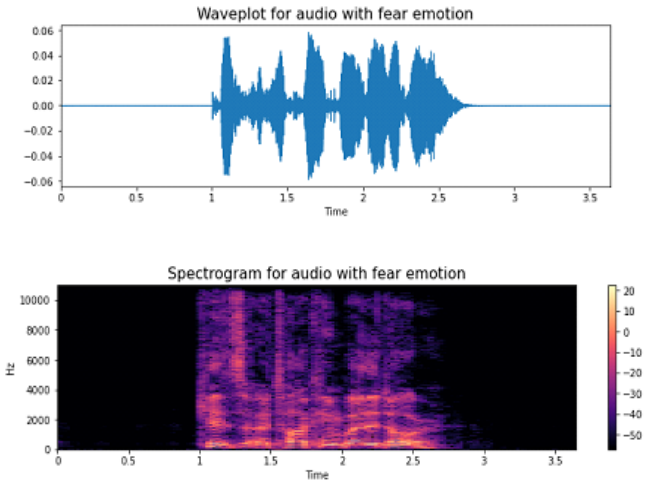

Fig 5.1. The spectrogram for audio with fear emotions.

Analysis of lingual features would require a script of the speech. However, it will require a processing and extraction of text from speech in order to analyze sentiments from real-time audio. Analyzing visual features would require the access to the video of the conversations, and it is not in the scope of this research. Therefore, analysis of the auditory features is done in this work, since analysis of the acoustic features is possible in real-time. Audio from real-time conversations is extracted and analysed in order to accomplice the task

Furthermore, the representation of emotions can be done in two ways:

- Discrete Classification: Emotions were classified into distinct labels like rage, calmness, neutral, cheerfulness and joy etc.
- Dimensional Representation: Representations of emotions with dimensional categories such as Activation Energy (on a low to high scale), Valence (on a negative to positive scale), or and Dominance (on an active to passive scale)

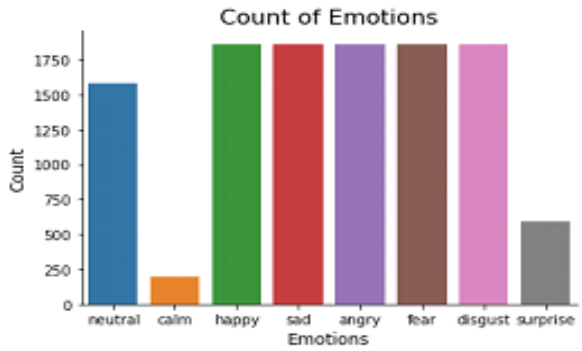

Fig 5.2. The various categories of sentiments our model predict

The two mentioned approaches have their distinct advantages and disadvantages. The dimensional representation approach is an elaborative process but there is a lack of annotated audio data in the dimensional format. The discrete classification is more straightforward and less resource hungry to implement. In discrete classification approach, emotions are classified on a specified scale for the analysis. Emotions are classified using the trained model and predicted as discrete outputs. This approach is easier to implement and understand and as such has greater outreach.

In the proposed method , discrete classification approach is used for analysis. We classify the emotions on a specified scale. The emotions are classified using the trained model and emotions are predicted as discrete outputs. This approach has a greater outreach.

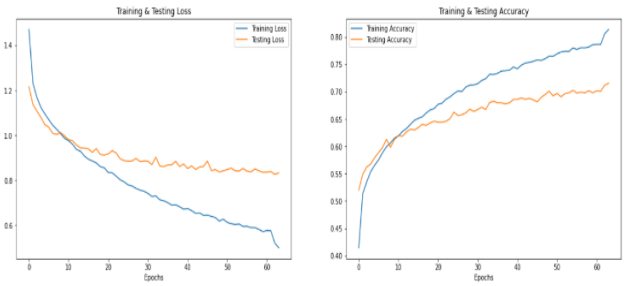

Fig 5.3. (a) Training and Testing loss **(b)** Training and Testing Accuracy of 2D-CNN model 2D- CNN model

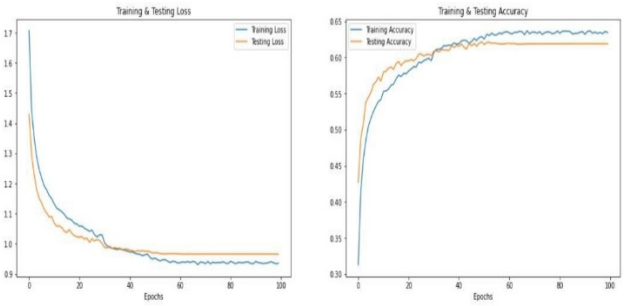

Fig 5.4. (a) Training and Testing loss **(b)** Training and Testing Accuracy of Dense DNN model Dense DNN model

Figure 5.3 shown above plots the output of the training and testing for 2D-CNN model. In the X-axis, the number of epochs is plotted.
In Fig. 5.3(a) training and testing loss of 2D-CNN model is shown and Fig. 5.3(b) training and testing accuracy of 2D-CNN model is shown.
On analysis of the graphs, each epoch in both the graphs tend to merge at a point which is desired. After the point of saturation, there is no significant change in the difference between training and testing loss of the model and also training and testing accuracy of the model which shows the strong integrity of the proposed model.

Figure 5.4 shown above plots the output of the training and testing for the Dense DNN model. In the X-axis, number of epochs is plotted.
In Fig. 5.4(a) training and testing loss of Dense DNN model is shown and Fig. 5.4(b) training and testing accuracy of Dense DNN model is shown. On analysis of the graphs, with each epoch in both the graphs the lines tend to merge at a point. After merging, the lines diverge, which indicates significant variance between the training and the testing loss. With higher number of epochs, the loss decreases since the model refuses to achieve saturation. In case of the accuracy plot , with higher number of epochs, the accuracy increases since the model refuses to achieve saturation.

After careful observation and improvement of our model, we are able to achieve an accuracy of 61.89%. Thus, our model is able to provide some noteworthy results that can have myriad of applications.

VI. Conclusion

In the proposed method, an accuracy of 61.89% is achieved using both DNN and CNN. Thus, our model is able to provide some noteworthy results that can have wide range of applications. Efficient utilization of the audio signals and their tone, pitch and granularity can also help in detection of lies, mimicry as well as mental state of a person. A text-based approach will not provide such pronounced outcomes as they are bound only to linear degree of variation. Furthermore, for exploring broader spectrum analysis and interpretation, such as analysis of interviews, interrogations etc., Multimodal Sentiment Analysis should be taken into considerations.

For future work, we intend to expand and add more features into the proposed framework. Bidirectional LSTM is also a convenient proposition for training over audio datasets MFCC. Addition of embedding framework, as attention frameworks[7] seem to work well for many voice recognition tasks, or residual layers when there is an absence of handful labels, and there is a high possibility of overfitting. Collecting more data in the feature, as TESS and RAVDESS[8] only provide limited samples of user information is also a direction to be explored and analyzed. Due to limited data augmentation of data and variation such as using stretch and adding noise has been done where most of those features would not be impacted. The application of sentiment analysis techniques can be used to predict the demeanor of individuals. Increasing the spectrum in sentiment classes may provide valuable information, which is not captured efficiently earlier. Our efforts should also highlight the tendency of our model to isolate hateful speeches and sexist remarks.

VII. References

[1] Wenpeng Yin, Hinrich Schütze, Bing Xiang, Bowen Zhou; ABCNN: Attention-Based Convolutional Neural Network for Modeling Sentence Pairs. Transactions of the Association for Computational Linguistics 2016; 4 259–272. doi: https://doi.org/10.1162/tacl_a_00097t

[2] Roland Goecke; Gerasimos Potamianos; Chalapathy Neti, "Noisy audio feature enhancement using audio-visual speech data" DOI: 10.1109/ICASSP.2002.5745030

[3] Nattapong Kurpukdee , SawitKasuriya , VatayaChunwijitra ,Chai Wutiwiwatchai and PoonlapLamsrichan ,"A Study of Support Vector Machines for Emotional Speech Recognition", 978-1- 5090-4809-0/17/$31.00 ©2017 IEEE

[4] HarikaAbburi, "Audio and Text based Multimodal Sentiment Analysis using Features Extracted from Selective Regions and Deep Neural Networks", International Institute of Information Technology Hyderabad - 500 032, INDIA June 2017

[5] Zaher Ibrahim Saleh Salah, "Machine Learning and Sentiment Analysis Approaches for the Analysis of Parliamentary Debates", May 2014

[6] Suraj Tripathi, Abhay Kumar, Abhiram Ramesh, Chirag, Singh, Promod Yenigalla, "Deep Learning based Emotion Recignition System Using Peech Features and Transcription"

[7] LakshmishKaushik, AbhijeetSangwan, John H. L. Hansen," Sentiment Extraction From Natural Audio Streams", 978-1- 4799-0356-6/13/$31.00 ©2013 IEEE

[8] S. Lugović, I. Dunđer and M. Horvat,"Techniques and Applications of Emotion Recognition in Speech", MIPRO 2016, May 30 - June 3, 2016, Opatija, Croat

[9] Omer Tai, Yang Liu, Jimmy Huang, Xiaohui Yu, Bushra Aljbawi., "Neural Attention Frameworks for Explainable Recommendation".

[10] Mingke Xu 1 , Fan Zhang2 , And Wei Zhang "Head Fusion: Improving the Accuracy and Robustness of Speech Emotion Recognition on the IEMOCAP and RAVDESS Dataset" DOI 10.1109/ACCESS.2021.3067460

[11] Houwei Cao, David G. Cooper, Michael K. Keutmann, Ruben C. Gur, Ani Nenkova, Ragini Verma "CREMA-D: Crowd-Sourced Emotional Multimodal Actors Dataset"

[12] Muhammad Zafar Iqbal "MFCC and Machine Learning Based Speech Emotion Recognition Over TESS and IEMOCAP Datasets".

[13] Fang Zheng, Guoliang Zhang & Zhanjiang Song "Comparison of different implementations of MFCC".

[14] Hynek Hermansky "Perceptual linear predictive (PLP) analysis of speech".

[15] Hynek Hermansky, Louis Anthony Cox, Jr "Perceptual Lnear Predictive (Plp) Analysis-Rsynthesis Technique".

[16] Sungmoon Cheong, Sang Hoon Oh, Soo-Young Lee "Support Vector Machines with Binary Tree Architecture for Multi-Class Classification".

[17] Martin Vetterli, Cormac Herley "Wavelets and Filter Banks: Theory and Design".

[18] Jing Chang, Jin Sha "An efficient implementation of 2D convolution in CNN".

[19] H.M. Fayek; M. Lech; L.Cavedon; "Towards real-time Speech Emotion Recognition using deep neural networks" DOI: 10.1109/ICSPCS.2015.7391796.

[20] Ziquan Luo; Hua Xu; Feiyang Chen; "Audio sentiment analysis by heterogeneous signal features learned from utterance-based parallel neural network" DOI: 10.1109/ICSPCS.2015.7391796.