Analysis of Deep Learning based Emotion Charting Techniques for Parkinson's Patients using Physiological Signal Analysis

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Declaration

I hereby certify that I have developed this thesis titled as **"Analysis of Deep Learning based Emotion Charting Techniques for Parkinson's Patients using Physiological Signal Analysis"** entirely on the basis of my personal efforts under the sincere guidance of my supervisor Dr. Sajid Gul Khawaja. All of the sources used in this thesis have been cited and contents of this thesis have not been plagiarized. No portion of the work presented in this thesis has been submitted in support of any application for any other degree of qualification to this or any other university or institute of learning.

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Language Correctness Certificate

This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical and spelling mistakes. Thesis is also according to the format given by the university.

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Copyright Statement

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Abstract

In psychology, the term "emotion recognition" describes the process of attributing emotional states based on the observation of nonverbal visual and aural clues. Perfect emotional exchanges between humans and computers can enhance communication. Emotional interactions are advantageous for various applications because they have a significant impact on cognitive functions of the human brain, such as learning, memory, perception, and problem-solving. It may also be applicable to contemporary healthcare, particularly in dealings with Parkinson's disease sufferers. The second most prevalent neurodegenerative condition, Parkinson's Disease (PD), impairs the ability to recognize and express emotions. Different emotion recognition systems are appropriate for various uses depending on the application domain. Nowadays, the concept of emotion recognition is extremely widespread. With the aid of IoT, physiological signals offer a suitable method to identify human emotion. There are several ways that emotions can be expressed, including through speech, behavior changes, facial expressions, and physiological markers. Physical signs provide a clearer understanding of emotion categorization. In order to construct a cutting-edge deep learning architecture for emotion charting for Parkinson's disease, the associated parameters derived from the physiological signals, i.e. EEG, during emotion identification are investigated and evaluated in this study. Using this technique, one can readily forecast the victim's emotional state when conducting an investigation or monitoring the health of Parkinson's disease patients. In this thesis, we have proposed a deep learning based framework which can classify emotions of a PD patient using their EEG signatures. The results indicate that the framework can be improved to accurately classify emotions.

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Chapter 1

Introduction

Brain is central part of human body which controls emotion ,memory, breathing, touch, and all process that regulates the body, when human body suffers from some disease, body also go through from certain emotions like depression, anxiety, happiness and many more. Emotions are controlled by neuro-physiological changes, mainly related to the sentiments, conduct reactions and level of joy and disappointment. Emotions are also defined as positive or negative experience associated to specific patterns of physiological activities. It plays an important role in decision making, effective communication and in extraction of useful information from messages in both speech and images. Mostly the emotion recognition methods are biased because an individual can easily hide their actual emotions or emotional states. Many limitations appear in emotion recognition models due to limited number of facial expression and fake emotions. People with disease cannot express their emotional states correctly. Physiological signals give a better insight of emotion charting. Therefor we consider physiological signals (EEG,ECG and GSR) from dataset of Parkinson's disease and developed an emotion charting system.

1.1 Motivation

Over the past two decades research on human emotion has increase which includes many fields like medicine, psychology, history, computer science and sociology of emotion. Current areas of exploration includes the development of materials that stimulate and elicit emotion. Due to advancement in human computer interaction many applications become operational around the globe leading to multiple solutions for problems which is enhancing the quality of life. Emotion charting enables us to understand human behavior and develop improved systems that can manipulate data on human emotions.

Accurate classification of emotions can reduce the manual effort required by researchers, medical and scientific community. Emotion charting is one of the components of HCI, it helps to keep record and history of individuals with disease and helpful for their recovery. Our motivation for this research is to work mainly on charting feelings of a person that is suffering from Parkinson's disease using physiological signals.

1.2 Problem Statement

Brain is the central part of human body which controls memory, feeling, contact, breathing and each cycle that directs our body, when a person suffers from some disease, body also go through from certain emotional changes like depression, anxiety, happiness and many more. Emotion charting of Parkinson's disease patients using physiological signals can contribute in development of many applications enhancing the quality of life and adding ease in the lives of PD patients

We intend to develop model using deep learning techniques that precisely classify emotional states of PD patients.

1.3 Aims and Objectives

Major objectives of the research are as follow:

- Devise Deep Learning based framework for classification emotion of PD patients using EEG signals.
- To facilitate people so they can make their true emotional assessment this can be further utilized in variety of ways.

1.4 Structure of Thesis

Organization of remaining work of thesis is given below as:

- Chapter 2 covers the details about Parkinson's disease.
- Chapter 3 gives review of the literature and the significant work done by researchers in past few years for classification of emotions using Deep learning techniques.
- Chapter 4 covers the proposed methodology in detail. In this chapter, we will discuss the pre-processing and data preparation steps along with the finalized DNN model.
- Chapter 5 includes all the experimental results accompanied by relevant figures.
- Chapter 6 concludes the thesis and reveals future scope of this research.

Chapter 2

Background

In this chapter a brief introduction of Parkinson 's disease, causes, the induced symptoms, the rating scales according to the stage and the progression of the disease, the clinical diagnosis, the medications and their side effects on body is given. Also we have discusses the prevention and treatment. Hence, this chapter is an outline of the condition and the motivations to look for new plans to help clinicians in the conclusion and appraisal.

2.1 Parkinson's Disease

Parkinson's disease (PD) is now a days seen as the second most typical neurodegenerative issue that is affecting over 6 million people. Disregarding the way that there are intriguing meds that can assemble the survivability of the disorder, there are no mending treatments. The prevalence of PD and debilitation changed life years continue to extend reliably, provoking a creating weight on patients, their families, society and the economy. Dopaminergic medications can basically tone down the development of PD when applied during the starting stages. Regardless, these drugs every now and again become less suitable with the disorder development. Early finding of PD is crucial for ensured mediations so the patients can remain free for the longest time span possible. Sadly, break down are regularly late, due to factors like an overall absence of sensory system experts gifted in early PD finding. PC upheld suggestive (CAD) gadgets, considering automated thinking methods, that can perform motorized investigation of PD, are obtaining thought from clinical consideration administrations [1].

Parkinson's disease is a brain disorder. It is also known as neurodegenerative disorder that is present in later stage of life. It damage parts of brain progressively over many years. In this disease person has difficulty in walking, coordination and balance. By the time PD gets worse and person also faces difficulty in talking. Parkinson's prompts shaking specific pieces of body, sluggish development and firmness in muscles. Its symptoms start gradually and by the time it gets worse.

The traditional qualities side effects of PD are tremor at rest, muscular rigidity, developmental bradykinesia gradualness, akinesia a defer in the beginning of advancements with long reaction times, and postural solidness. The most well-known prescription endorsed to treat patients with PD is Levodopa L (dopa), since the lack of dopaminergic neurons in the substantia nigra in the mind is connected with the presence of the motor symptoms in PD. The et iology of PD is additionally connected with age and openness to free radicals and external toxins, as well as gene mutations [2].

2.2 Causes

The primary driver of this sickness is loss of specific nerve cells in part of cerebrum known as substantia nigra. These nerve cells produce important chemical of brain "dopamine". When the nerve cells die, the production of dopamine chemical also reduces and it causes movement issues in body. Reduction in dopamine results in several symptoms of Parkinson's disease.

Till now scientists can't figure out what exactly causes dopamine to die. Some experts think that genetics and environmental factors are responsible for this disease. Number of genetics factors has been shown that an increase chance of getting PD but exactly who is going to suffer is not clear.

Men and women both suffer from this disease but in a study it is shown that male gets 50In Parkinson's illness, neurons continuously break or bite the dust. PD side effects are because of misfortune of neuron producing dopamine. Dopamine level cause any changes in brain activity, decrease in dopamine level leads to impaired movement and other symptoms of PD.

There are several factors that can cause Parkinson's disease, few are as following:

- **Genes:** Research shows that specific gene mutations can cause Parkinson's. However these are not normal besides in that frame of mind with numerous relatives impacted by PD. In any case, certain gene variations seem to expand the gamble of PD yet with a somewhat little gamble of PD for every one of these hereditary markers.

- **Environmental triggers:** Openness to specific ecological elements or poisons might expand the risk of PD, yet the risk is tiny.

2.3 Risk factors

Following are a few Risk factors for Parkinson's disease:

- **Age:** Youths only here and there experience Parkinson's. It normally begins in focus or late life, and the gamble increases with age. People, generally speaking, encourage the disease around age at least 60 laid out.

- **Heredity:** Having an immediate connection with Parkinson's disease fabricates the potential outcomes that you'll cultivate the contamination. Anyway, your risks are still little aside from assuming you have various relatives in your family with Parkinson's ailment.

- **Gender:** Male can develop Parkinson's more likely than are female.
- **Exposure to toxins:** Advancing receptiveness to pesticides and herbicides may imperceptibly grow your gamble of Parkinson's.

2.4 Symptoms

Parkinson's disease symptoms are divided into two categories

- Motor impairments
- Non-Motor impairments

2.4.1 Motor Impairments

Motor weakness is the fractional or full loss of capability of a body part, by and large appendage or appendages. This prompts the muscle shortcoming, unfortunate endurance, absence of muscle control, or all out loss of motion. Motor hindrance oftentimes show up in neurological circumstances such a cerebral loss of motion, Parkinson's illness, stroke and various sclerosis.

Actual incapacity is related with the motor debilitation and incorporates muscle shortcoming and exhaustion, impeded sensation and unfortunate equilibrium, muscle contracture and spasticity - which should be all utilitarian in the event that we are to bear the standard scope of routine exercises.

Common Motor Symptoms that Require Management

- Tremor is an early side effect of Parkinson's illness likewise a conspicuous one however not generally present and is definitely not a fundamental element for finding.

- Gradualness (bradykinesia) is a center component of Parkinson's sickness (PD).
- Inflexibility is viewed as the third noticeable component on assessment.
- A blend of gradualness (bradykinesia) and unbending nature prompts a few different side effects of PD, micrographia.
- Walk unsettling influence is the fourth unmistakable side effect of PD, this is ordinarily late indication. Walk jumble is definitely not an early component of PD however is every now and again depicted as it is not difficult to perceive and secures the conclusion in later stages [3] . Flexed act, diminished arm swing, ataxia, festination, walk a-petits-pas, camptocormia, retropulsion and turning en coalition are well known terms to portray the step in PD.

Individuals with Parkinson's much of the time experience expanded step impedances as the sickness advances and side effects become more extreme [4]. Debilitations incorporate; [5]

- Hypokinesia (diminished step length with diminished speed)
- Diminished coordination
- Festination (Decreased step length with expanded rhythm)
- Freezing of stride (the failure to deliver compelling strides at the inception of walk or the total suspension of venturing during step)
- Trouble with double entrusting during step

These step debilitation have expanded risk and falling rate. The likelihood of falling increments which likewise increment the gamble of hip crack and wounds that additionally influence a singular's autonomy and capacity to communicate with others. Apprehension about falling has mental influences that might prompt self-confinement and wretchedness [6].

2.4.2 Non-motor Impairments

Non- motor impairment symptoms are a key component of Parkinson's disease (PD). A range of Non-motor symptoms, includes sleep pattern dysfunction, impairment in sense of smell and dysautonimia are considered to be present from the 'pre-motor' stage to the last palliative stage.

Normal motor side effects in both of these groups are tremor and bradykinesia; though, the non-motor side effects every now and again experienced in these groups were cramps, constipation and unnecessary daytime drowsiness (EDS).

Non-Motor Symptoms Can Be More Detrimental

- Disturbance in sleep pattern
- Difficulty in swallowing
- Low blood pressure
- Saliva Drooling or excessive production
- No control on bladder
- Facial Masking: All the time looking mad, sad, or not interested

2.5 Symptoms

The 3 fundamental side effects of Parkinson's illness influence actual development

- Termor
- Bardykinesia
- Rigidity

These fundamental side effects are once in a while alluded to by specialists as Parkinsonism as there can be causes other than Parkinson's sickness.

2.5.1 Other Symptoms

Parkinson's illness can likewise cause a scope of other physical and mental side effects.

Physical Symptoms Given are the symptoms:

- Balance issue: these can make somebody with the condition bound to have a fall and harm themselves
- Ansomia: loss of feeling of smell at times happens quite a while before different side effects create
- Nerve torment: can create upsetting uproars, like consuming, chilliness or deadness
- Issues with peeing -, for example, getting up oftentimes during the night to pee or accidentally peeing(urinary incontinence)
- Blockage
- Wooziness, obscured vision or swooning while moving from a sitting or lying position to a standing position-by an unexpected drop in pulse
- Hyperhidrosis: over the top perspiring
- Dysphagia: gulping challenges - this can prompt unhealthiness and parchedness
- Slobbering: unreasonable creation of spit
- A sleeping disorder: issues resting - this can bring about exorbitant languor during the day

Cognitive and Psychiatric Symptoms

- Gloom

- Tension
- Gentle mental weakness memory issues and issues with exercises that need arranging and association
- Dementia - this incorporates more serious issues, character changes, visual mind flights (seeing things that doesn't exist) and hallucinations (trusting)things that are false

2.6 Stages of Parkinson's disease

Parkinson's disease have following five stages:

- Initial stage, have just gentle side effects and can approach your day to day existence without any problem.
- Symptoms, for example, quakes and solidness start to decline. May foster unfortunate stance or experience difficulty strolling.
- In this stage, development will start to dial back and lose balance. Side effects can frustrate the capacity to perform everyday undertakings, for example, getting dressed or cooking.
- Symptoms gets extreme and cause huge issues with everyday living. Right now, incapable to live alone in light of the fact that one can't get done with everyday responsibilities all alone.
- Walking or standing could be unimaginable. Individuals at this stage are bound to a wheelchair or bed and require a medical caretaker to deal with them at home.

2.7 Realities of Living with Parkinson's

This illness is eccentric, living with the agonizing side effects can be depleting both physical and mental, thus making any arrangements is undeniably challenging.

Day to day errands require a ton of energy for Parkinson's infection patients to finish or are removed through and through. For instance, a sound individual can head to the supermarket, return home and do clothing, cook supper for their family, have opportunity and willpower to unwind by the day's end. An individual with Parkinson's should focus on each undertaking and will be unable to drive by any means.

As the infection advances, many individuals are compelled to surrender their freedom and independence with regards to dealing with themselves. While, with the right medicines, can diminish illness movement and stay free to the extent that this would be possible.

2.8 Treatment of Parkinson 's Disease

There is considered to have no cure for Parkinson's disease but following treatments can relieve some symptoms. These treatments include:

- Physiotherapy (Supportive therapies)
- Medical procedure for certain individuals
- Medication

Prevention From above discuss we come to know that the reason for Parkinson's is obscure and no demonstrated ways of forestalling the sickness.

- Standard activity i.e high-impact excercise could lessen the gamble of Parkinson's illness.

- Individuals who polish off caffeine (which is tracked down in espresso, tea and cola) get Parkinson's illness less frequently than the people who don't drink it. Green tea is likewise connected with a diminished gamble of fostering Parkinson's sickness. It is as yet not known how caffeine admission is connected. Right now there isn't sufficient proof to propose drinking jazzed refreshments to safeguard against Parkinson's.

Chapter 3

Literature Review

Recently, Electroencephalography (EEG) got significant consideration from scientists, since it can give a straightforward, modest, compact, and simplicity to-utilize answer for recognizing feelings. EEG-based feeling acknowledgment task with customary and profound learning procedures widely announced in different explores, this part likewise portrays the most significant examinations in view of Parkinson's sickness.

3.1 Emotion Charting

Feeling classification framework has various applications in numerous fields. Feelings are on a very basic level related with mental way of behaving, direction, and practical wellbeing issues. It makes an effect on simply deciding, expectations in business, medical care and scholastics. Arising genuinely smart applications are fundamentally pertinent in item customization, feeling guideline, and mental wellbeing observing. Computerized feeling handling is either founded on outer deliberate articulations or natural compulsory physiological reactions. Looks, signals, and manner of speaking are a couple of instances of outward articulations in view of willful activities that can undoubtedly be faked or concealed. Physiological reaction to a particular inclination is characteristic for the human body, like heartbeat and electroencephalogram (EEG), which won't be quickly faked or concealed.

One of most significant goals of human-machine connection is the manner by which to make the way of behaving of machine more like human's, particularly in the field of machine feeling articulation. To accomplish this objective, [7] tackles the issues in the human-machine collaboration in three viewpoints: separated feeling, feeling contrast goal, and undercover feeling acknowledgment. In the proposed strategy, the EEG (Electroencephalogram) signal is utilized to introduce the articulation mode of individual inclination and character, and a similitude estimation technique is intended to gauge the distinction between EEG signals. Also, bunch division approach is created to accomplish the differential result in feeling move model. Subsequently, the point of this exploration is to foster a customized arrangement of machine feeling articulation, and to fabricate the powerful close to home communication model among human and machine in a shrewd intuitive climate. The outcomes on the DEAP dataset confirm practicality of the gathering division strategy and the separated inclination move model. The capacity to perceive feeling is one of the signs of feeling insight. Ref [8] proposed to perceive feeling utilizing physiological signs acquired from different subjects. IAPS (International Affective Picture System) pictures were utilized to evoke target feelings. Five physiological signs: Blood volume beat (BVP), Electromyography (EMG), Skin Conductance (SC), Skin Temperature (SKT) and Respiration (RESP) were chosen to extricate 30 highlights for acknowledgment. Two example classification strategies, Fisher discriminant and SVM technique are utilized and looked at for profound state classification. The exploratory outcomes demonstrate that the proposed strategy gives truly steady and effective close to home classification execution as 92% north of six profound states [8].

3.2 Parkinson's Disease

Parkinson's disease is a progressive neurodegenerative condition marked by Lewy bodies seen throughout the brain and the death of dopaminergic neurons. By producing the chemical dopamine, which is essential for regulating voluntary movement sequences, the dopaminergic neuron plays a crucial role in motor coordination and movement regulation. Although the majority of instances of PD have unknown aetiology, complex interactions between genetic and environmental variables are thought to be involved.

After Alzheimer's disease, PD is the second most prevalent neurodegenerative ailment. It affects 1% of people over 60 and reaches about 5% by the time they are 85. The prevalence is increasing as the population ages. The Parkinson Disease Foundation estimates that there are roughly 10 million persons with PD in the world, with one million living in the USA, 1.2 million in Europe, and two expected in China by 2030. In the UK, one in 500 people suffers from this condition, and it is predicted that over the next 50 years, that figure will triple [9]. There isn't a proven disease-modifying treatment yet. The presence of bradykinesia (slowness of movement), rigidity, tremor, and postural instability is used to diagnose PD. 20% of patients don't experience tremor development. It's critical to get an early diagnosis of PD in order to give patients access to the right care and prognosis information. It can be difficult to make an early diagnosis that is correct. Clinical evaluation is used by doctors to diagnose Parkinson's disease (PD), evaluating information primarily gleaned from patient examination and history-taking. Despite the fact that there are currently no tests that are completely sensitive or specific for Parkinson's, brain imaging may occasionally be requested to aid support the clinical diagnosis. About 10–25% of PD diagnoses are incorrect [10], and it takes an average of 2.9 years to reach 90% accuracy [11]. Earhat and Williams' study [12] examined the impact of physical activity (treadmill use). According to the author's analysis of the results of a controlled experiment, persons having mild to moderate Parkinson's disease can use treadmills without risk. However, patients need to be aware of the required safety precautions and should complete this session under the guidance of professionals. Additionally, the research indicates that using a treadmill to exercise can enhance walking distance, stride length, and gait speed (motor skills).

Parkinson's disease (PD) sufferers have difficulty recognising face expression expressions, especially negative ones. They have no control over their facial expressions; the phrase "facial masking" is used to describe them. The brain basis of facial emotion recognition (FER) in healthy and sick people is assessed using neuroimaging techniques, primarily focusing on functional alterations. In a sizable sample of Parkinson's disease patients, this study [13] examined the grey matter and white matter correlates of facial emotion detection. Magnetic resonance imaging and the Ekman 60 test for facial expression identification were administered to 39 people with Parkinson's disease (PD) and 23 healthy volunteers. According to earlier research, PD patients dramatically underperformed when it came to identifying sadness, rage, and disgust. This demonstrates the patients' poor ability to appropriately identify facial expressions.

A wide range of symptoms, including abnormal movements, are associated with Parkinson's disease (PD). Since the signs and symptoms of PD, especially in the early stages, often resemble those of other medical conditions or the physiological changes associated with normal ageing, making an accurate diagnosis of the condition can be difficult. CNN, a form of Deep Neural Network Architecture, was used in [14] to diagnose Parkinson's disease and distinguish PD patients from healthy controls. Using drawing exercises, the researchers identified patient movement deviation. 93.5% accuracy was attained using CNN on the drawing's images. Parkinson's disease (PD) is often diagnosed based on clinical signs, such as the description of a range of movement symptoms, and medical observations. Model [14] has the possibility of being developed into an automated single-task offline real-time diagnostic tool that can be quickly implemented in a clinical context.

Traditional approaches to diagnosis are centred on motor symptoms, which can occasionally be missed by the human eye and result in diagnostic inaccuracy and misclassification. Additionally, non-motor symptoms are minor and might be brought on by any other illness, which contributes to early-stage PD misdiagnosis. Machine learning techniques are utilised to distinguish PD from healthy controls in order to eliminate human error. The databases IEEE Xplore and PubMed provide a thorough literature evaluation of investigations on PD. According to study [15], using machine learning techniques and new biomarkers can help clinicians make a thorough and knowledgeable diagnosis of PD.

Hypomimia, a symptom of Parkinson's disease that adversely affects social interaction and facial expressiveness, significantly lowers the quality of life for both patients and their loved ones. Patients typically have non-motor symptoms (impairments in emotional processing), which are thought to be related to worsened interpersonal difficulties. PD still show inconsistent results when recognising facial emotions, and its cause is unknown. Improve therapeutic practise and boost fundamental understanding, particularly in respect to potential embodied emotion impairment in PD, according to study from [16]. Focus on the recognition of facial emotions, the function of basal ganglia-based circuits in emotion, and the significance of embodied simulation theory in the use of facial imitation.

The ability to perceive emotion has been found to be impaired in people with Parkinson's disease (PD), however the results have indeed been mixed. The effects of sensory input, task type, and particular emotion are yet unknown, and this deficit in PD is related to depression and more general cognitive deficits. A study that examined the impact of numerous potential modifiers of emotion identification abilities in PD and gave a valid assessment of the size of the alleged deficiency was published in

[17]. As this deficit does not seem to be related to anxiety or visuo - spatial deficits, further research into the potential contribution of working memory restrictions is warranted. [17] explains the possible effects of these findings on PD patients' ability to communicate.

A patient's daily life is impacted by Parkinson's disease (PD). Numerous studies have suggested that a sensor- and machine-learning-based system that monitors patients in real environments can provide a thorough analysis of the course of PD and allow for continuous evaluation of the condition. A multi - modal deep learning method for distinguishing between PD patients and healthy individuals was suggested in [18]. To train variational autoencoder (VAE) models, the suggested architecture, called MCPD-Net, has two data modalities: vision and accelerometer sensors in a home setting. These VAEs, which are modality-specific, forecast that a classification module would receive combined adequate representations of human movements. We reduce the disparity between the latent regions that correspond to the two data modalities during our end-to-end training. Because of this, our technique can handle modalities that are missing during inference. When a modality is absent during inference, our method still outperformed other ways by an average gain in F1-score of 0.17, highlighting the value of training on many modalities [18]. There aren't any curative treatments; rather, symptomatic ones can improve the disease's prognosis. A rising burden is placed on patients, their family, society, and the economy as PD prevalence and impairment continue to rise rapidly. Medication slows the progress of PD and is beneficial in the early stages of the disease, but as the disease advances, many treatments lose their efficacy. Unfortunately, PD is detected in its latter phases since there aren't enough neurologists trained in initial PD diagnosis. Patients are most independent in the early stages. Healthcare services are becoming more interested in computer-aided diagnostic (CAD) solutions that use artificial intelligence techniques to perform automated PD diagnosis. According to [19] review, 63 research published between January 2011 and July 2021 presented deep learning algorithms for an automated PD diagnosis utilising several types of modalities, including mobility symptoms(gait, handwriting, speech and EMG) and brain analyses (SPECT, PET, MRI, and EEG) . To improve the utility, application, and impact of such systems to improve early identification of PD globally, conduct additional research on deep learning in automated PD detection.

3.3 Traditional Techniques

The EEG for emotion was processed using a variety of conventional feature extraction techniques. Traditional methods employed classifiers such as the Fast Fourier Transform (FFT), Short-time Fourier Transform (STFT), Discrete Wavelet Transform (DWT), statistical features, Power Spectral Density (PSD), and combinations of these attributes with SVM Classifier and Linear Discriminant analysis. The accuracy is also affected by the amount of emotions; in many cases, the accuracy increased or reduced in accordance with the number of emotional responses. There are two methods for categorizing emotions in literature: the one classifies the six basic emotions (sad, joyful, angry, fear, surprise, and disgust) as a subset, while the second categorizes simply the valance and arousal classes. These conventional methods perform poorly across many different emotion classes and vast swaths of the population [20].

3.4 Deep learning based Techniques

Due to the large population and variety of inclination classes, deep learning techniques were familiar in feeling characterisation with study on the low performance compared to conventional strategies. According to research, using neural networks instead of conventional component extraction techniques with classifiers like K-Nearest Neighbors (KNN) and SVM produces better results or more advanced execution. However, these studies progress from the less complex deep brain networks

(DNN), convolutional brain networks (CNN), and recurrent brain networks (RNN), to a combination of these known as CRNN with different convolutional layer thicknesses and features. However, we are still having trouble using the right DL model to precisely and effectively arrange EEG signals.

Three convolutional layers are used in [21] to improve the SincNet-based classifier. Three deep neural network (DNN) layers are also proposed, and they are used to test the accuracy and potency of the classification using strong EEG signals. The similar results between our suggested SincNet-R model and the original SincNet model and other traditional classifiers like CNN, LSTM, and SVM demonstrate that our proposed model has higher characterisation exactness and better calculation strength. In this study, 62-channel EEG signals were used and practically verified on the SEED dataset.

Ref [22] Four components (Entropy, Energy-Entropy, Spectral Entropy, and Spectral Energy-Entropy) and two classifiers were used to analyse the layout of EEG-based feeling recognition in Parkinson's disease (Probabilistic Neural Network and K-Nearest Neighbors Algorithm) It is clear from the analysis that the suggested energy-entropy mix highlight incorporating PNN and KNN in time space consistently outperforms the benchmark (above 80.07% to 90.74%) for all emotions. As a movement of the focused sensory system, electroencephalogram (EEG) data are used to reflect the Parkinson's disease patient's concealed, true emotions. This study [23] focuses on using AI computations to arrange EEG deep states in PD patients. For emotions, the basic six emotions are used and contrasted with sound controls. In this work, two classifiers—k-closest neighbour (kNN) and support vector machine (SVM)—were presented and investigated in a comparable manner, as well as two methods for extracting highlights—HOS and power range. Using EEG signals in a client-free manner, AI becomes one of the effective methods for PD patients to induce deep states. The great majority of the early investigations focused on PD diagnosis using behaviour measurements. Although not much research is being done, the centre is currently moving toward the distinct proof using EEG.

In [24], 14 channel EEG is used, and EEG data was separated via preprocessing. The Extreme Learning Machine (ELM) classifier with two different kinds of bit capacities is used to organise the sentiments of PD and NC. Repeat Quantification Analysis (RQA) is used to separate the two biggest highlights (Maximum Line Length, Maximum Vertical Line Length) from Recurrence Plot (RP). Trial results show that RQA highlights are remarkably effective at differentiating the feelings in PD when compared to other techniques, and ELM provides the highest mean exactness when compared to other works in writing. Arranging the feelings using various AI calculations and deep learning strategies may be effective for presentations. Speaking with others is also used for Parkinson's illness.The patient's speech has a distinct vocal pattern that is used by researchers to create an exchange learning approach and provide Misture-of-Experts to determine what the PD pathology entails for the problem determination [25]. (MoE). The horrifying components in this model were divided and processed in a slope-supporting choice tree model. Discourse obstruction was used as a benchmark for assessing how uncomfortable the patient, how severe the sickness, and how serious the unhappiness feelings are. Facial recognition and identification have always been used to express gratitude. Three simple steps were used to perceive any feeling. With the use of a camera, we first recognise faces, then the input is evaluated in light of many factors and data using convolutional neural networks, and finally the observed appearance is confirmed to separate human emotion into its constituent parts (happy, angry, sad, surprise, joy and disgust). This system of facial recognition has been put to use in many different contexts. Facial recognition has also been done continually, and the physiological changes are identified by the influence of internal feeling [26].

Parkinson's disease (PD) is typically characterised by non-motor symptoms (exhaustion, dementia, uneasiness, discourse and correspondence issues, gloom, etc). Electroencephalography (EEG) now plays a crucial role in actual close-to-home state finding. As previously discussed, a variety of tests (separating, Fourier changes, wavelet changes, and non-straight techniques) have been suggested for the identification of localised weakness in PD. Nevertheless, these methods are constrained in terms of accuracy and call for the determination of the premise. For the characterization of emotions in PD and conventional controls, tunable Q wavelet change (TQWT) is presented in [27]. (NC). A k-closest neighbour, probabilistic brain network, irregular forests, selection tree, and outrageous learning machine are grouped with six highlights (happy, furious, sad, surprise, delight, and disgust) selected by factual investigation. Three execution metrics are obtained, with a probabilistic brain network achieving the highest mean accuracy, sensitivity, and specificity of 96.16%, 97.59%, and 88.51% for NC and 93.88%, 96.33%, and 81.67% for PD. The intended method in [27] can be used as a standard tool for assessing near-home impedance in clinics. In any event, this technique is limited by the number of tests, the boundaries, and its focus solely on AI computations. By applying deep learning techniques and a larger number of boundaries, the framework's proficiency can be increased. Our primary goal is to gather knowledge and comprehension regarding the handling or application of physiological indicators during execution evaluation. In [27], two example acknowledgment techniques—SVM approach and Fisher straight discriminant—as well as five physiological signs—blood volume beat (BVP), electromyography (EMG), skin conductance (SC), skin temperature (SKT), and respiration (RESP)—have all been tested. 90% of responses were acknowledged, although SVM produces better results than fisher. The purpose of these investigations is to develop a workable PC-assisted tool that will aid medical professionals and researchers in better understanding Parkinson's disease so they can make objective and precise judgments about the clinical course of the condition. A deep learning method has been published in Ref [28] that makes use of a recently developed CNN design to exploit the Wavelet space of resting-state EEG for Healthy Control (HC) , PD (Without medication), and PD (taking drugs). The goal of this method is to distinguish between PD and HC and also to identify the different EEG features between PD participants receiving beneficial medications and those receiving little to no medication. Additionally, we have demonstrated the use of this technique to a three-class problem where deep learning can successfully differentiate between typical patients, PD (OFF med), and PD (On med). Parkinson's disease is initially treated with dopaminergic medications, which slowed the disease's progression but became less effective as the disease advanced. However, early analysis is critical due to the global shortage of nervous system professionals skilled in PD early detection. In order to automate the analysis of PD and garner attention from medical care administrations, research is being conducted in the area of computer-aided analytical instruments. For this reason, deep learning models are the focus. CNN excels at this, and the modalities used for brain imaging include SPECT, PET, MRI, and EEG, as well as motion physical symptoms like walk, handwriting, discourse, and EMG. To reduce the burden of this degenerative disorder and ensure that affected persons can maintain their independence for as long as is practical, PD requires early diagnosis and intervention [19]. [29] offers the 1D-CRNN-ELM design, which combines an Extreme Learning Machine (ELM) and a one-layered Convolutional Recurrent Neural Network (1D-CRNN), both of which have already been discussed in writing. In this system, the EEG is processed beforehand, a prepared CRNN is used as an element extractor, an ELM serves as a classifier, and a second prepared CRNN is used to learn about emotions. With six crucial inclination classes, this cycle provides accuracy of 97.75% for AMIGOS, 83.20% for PD, and 86.00% for HC. A prepared design that has been calibrated using the SEED-IV dataset's four feelings achieves 92.5

In Table 3.1, as of late utilized deep learning engineering are summed up .that were utilized for EEG based feeling grouping. A more straightforward network Deep

Belief Network (DBN) is proposed by Ref. [30] in which broke down EEG recurrence groups and cathodes for SEED dataset that demonstrated close connection of beta and gamma groups with feeling elicitation. With restrictive arbitrary field a superior DBN Deep Belief Network is utilized for freely accessible dataset of AMIGOS for paired grouping of valence (high valence or low valence) and excitement (high excitement or low excitement) [31]. In another review multimodal feeling acknowledgment structure was introduced, which consolidates cerebrum waves and eye developments. This blend was gives further developed acknowledgment exactness. This examination shows that model combination with multimodal deep brain networks can fundamentally improve the exhibition contrasted and a solitary methodology. [32]. Convolutional brain networks are ended up being extremely valuable in characterization undertakings in view of their strong capacities to accomplish cutting edge results. As we probably are aware info element can segregate various classes whenever created unequivocally. Some relative examination were performed and demonstrated that convolutional layers in brain networks is huge for extricating the main highlights and further developed special visualizations [33].

[34] Applied the deep learning approach (Deep convolutional brain network DCNN) on electrocardiogram (EEG) and galvanic skin reaction (GSR) signals. In this paper the feeling identification is finished by the relationship of these signs with the information of excitement and valence of this dataset (AMIGOS). Comparatively in [35] 2D-CNN design was utilized for EEG signals due to its fourteen-channel portrayal giving a similar execution reaction as in [34] . In a review [36] highlights from EEG signals were changed over into topological pictures for example geological and holographic portrayal and two layers of 2D CNN design was carried out involving these pictures as info. Likewise SVM was utilized as a classifier. This gives a thought of utilizing pre-prepared designs utilized for pictures and correspondingly 3D convolutional pieces likewise should have been investigated.

Table 3.1: State of the art techniques for classification of emotion with different datasets

Method	**EEG Channel**	**Dataset**	**Feature**	**Classifier**	**Emotion Classes**	**Accuracy**
DNN	6	SEED-IV	Restricted Boltzmann machine	Bimodal Deep Auto Encoder	4	85.11%
DCCA	62	SEED-IV	Deep Canonical Correlation analysis	SVM	4	87.50%
3D-CNN	14	AMIGOS	3D CNN	PC	4	95.86%
BLSTM +Attention	14	AMIGOS	BLSTM +Attention	DNN	2	72.80%
2D CNN	14	AMIGOS	2D CNN	SVM	2	90.54%
1D CRNN-ELM	14	PD	CRNN	ELM	6	83.20%

Table 3.2: State of the art techniques for classification of emotions of patients with Parkinson's

Method	**EEG Channel**	**Dataset**	**Feature**	**Classifier**	**Emotion Classes**	**Accuracy**
BPC	14	PD	Bispectral functional connectivity index	SVM	6	51.66%
Bispectrum	14	PD	High order Statistical	SVM	6	77.43%
TQWT	14	PD	Wavelet transform, Entropy	PNN	6	93.88%
RQA	14	PD	High order Statistical	ELM	6	84.50%
1DCRNN ELM	14	PD	CRNN	ELM	6	83.20%

In cutting edge, checking of the mental profile of mental problem patients (parkinson's) is concentrated as a specific case on the grounds that these patients can't display their profound states appropriately. Table 3.2 includes a summary of the work done for the EEG-based emotional hierarchy.

Chapter 4

Proposed Methodology

This thesis provides an investigation of physiological signal analysis-based emotion charting strategies for Parkinson's patients. In this chapter the methodology used to analyze the deep learning based emotion charting is explained in detail. The proposed methodology consists of two main phases i.e. feature extraction and deep learning based emotion classification. The physiological signals were first preprocessed, after pre-processing the signals are used as features. Then, to classify Parkinson's disease patients' emotional states, deep neural network is employed.

4.1 Dataset

We employed a dataset of Parkinson's patients for our study, which can be divided into two sets: one for the 20 patients with the condition (9 men and 11 women) and another for the 20 healthy control participants (10 males and 10 females). Parkinson's disease individuals suffer from PD on average for 5.7 years and 58.7 years, respectively. All subjects' EEG data were collected while receiving multimodal stimuli (im- ages, sounds, and videos). The International Affective Picture System (IAPS) database, International Affective Digitized Sounds (IADS), and numerous movies are the sources for multimodal stimuli. Each of the 40 subjects (20 PD and 20

HC) undergoes six sessions, with six emotion categories in each session, for a total of 36 sessions per subject. With session intervals ranging from 49 to 70 seconds, a total of 720 sessions for PD and 720 sessions for HC have been completed. For PD, a minimum interval of 50 seconds was recorded, and for HC, a minimum of 49 seconds. The first 5 seconds of the EEG data were utilised as a baseline for standardisation, and the remaining 45 seconds were divided into 45 segments using the minimum interval's length (44 segments for HC). A total of 45 seconds divided by 720 sessions equals 32,400 samples for PD and 44 seconds divided by 720 sessions equals 31,680 samples for HC are used for further processing. Each session of EEG data is tagged with a specific emotion category established by each participant using a self-assessment questionnaire because each second of data contains 128 samples of EEG signals from 14 channels.

4.2 Pre-Processing

The following steps from [29] are used to perform the pre - processing on the EEG signals from the dataset of Parkinson's disease patients:

- Baseline Removal
- z-score Normalization

4.2.1 Baseline Removal

Baseline signals is the electrical activity of brain with no external stimulus. In [37] a method was proposed to remove the baseline signal which will result in extraction of the desired EEG signal that will give the increased recognition performance on the emotional stimuli. In first five seconds EEG signal gives the neutral response which makes first five seconds as baseline. Then according to the given methodology we divided the baseline into one sec or per second segments for all channels of EEG separately.

The formula to compute the average of all the segments (for our case five segments average) that gives a mean baseline signal of 1-second is given in equation 4.1.

$$meanBL = \frac{1}{\sigma} \sum BL_s \tag{4.1}$$

To remove all the baseline from the complete EEG data signals each signal is divided into 1-second sample and is subtracted from the mean computed from above equation. The resultant signal is an EEG signal with no baseline or baseline removed segments.

4.2.2 z-Score Normalization

Z-score normalization refers to the process of normalizing every value (signal in our case) in dataset such that the mean for all values is 0 and the standard deviation is 1. Formula used for z-score normalization is given in equation 4.2.

$$x_{new} = \frac{x - \mu}{\sigma} \tag{4.2}$$

where

- x: original value
- μ: mean of data
- σ: standard deviation of data

To standardize our EEG signals we used Z-score normalization, the signal after baseline removal is our original value while mean is 0 and standard deviation is 1. Formula given in equation 4.3 is used in our methodology. This normalization of input data will speed up the learning of neural networks.

$$z = \frac{meanBL - \mu}{\sigma} \tag{4.3}$$

4.3 Deep Learning Network

Deep learning permits computational models of many handling layers to understand and address information with varying degrees of thought impersonating how the cerebrum sees and comprehends multimodal data, in this way verifiably catching complex designs of large-scale information. Deep learning is a rich group of techniques, enveloping brain organizations, progressive probabilistic models, and an assortment of solo and managed highlight learning calculations. The new flood of interest in deep learning strategies is because of the way that they have been displayed to beat past cutting edge procedures in a few undertakings, as well as the overflow of complicated information from various sources (e.g., visual, sound, clinical, social, and sensor). [38]

Deep learning techniques accomplish the best presentation in a few spaces (e.g., picture handling, facial acknowledgment) and have a laid out place in protein expectation, having been really applied to buildup contact forecast and turmoil expectation Deep learning (conviction) organizations (DNs) are like a two-layer counterfeit brain organization yet vary in the quantity of secret layers and the preparation method. [39]

The multi-layer network models used in DNNs have advanced that can manage intricate, nonlinear and unstructured information, for example, sound, video, picture and text by changing them into a progressive design of elements with numerous degrees of abstraction .

A DNN's geography, often known as its design, is depicted by the way its multiple layers are linked and arranged. A CNN is a powerful feed-forward DNN that performs this task by naturally extracting highlights from raw input using only the surrounding network of the hubs structured in neighboring layers. A typical CNN geography is made up of a combination of a few convolutional layers that can distinguish highlights from input data in light of nearby hidden spatial examples while taking learning highlights with a higher level of reflection into account. The three phases that make up each layer are convolution, initiation capability (non-linear change), and pooling (nonlinear down-inspecting). By stacking these layers, the organization can dynamically distinguish examples that are more distinctive, reducing the number of associations the organization has. The separated elements are then converted to a single-layered vector using a smoothing layer, and finally, the CNN combines these convolutional layers and traditional thick layers to produce the classifier's output.

Medical diagnosis using Deep Learning Clinical imaging is one broad area of clinical finding where DL has been successfully used. Because of their exceptional ability to utilize image data, CNNs and their modifications have been widely used in this sector for picture-related challenges.

4.3.1 GoogLeNet

One of the major advancements in the field of neural networks, particularly for CNNs, was the Inception Network. Beginning is available in three different versions: 1, 2, and 3. As suggested by the name "Google Net," the primary version was developed by a team at Google and joined the market in 2014. The Inception network's initial iteration is referred to as Google Net.

Over-fitting occurs when an organization works with many highly knowledgeable individuals. To identify the problems, the inventors suggested the Google Net engineering in their research paper [40]. This proposed engineering has channels of different diameters that can operate at the same level, which expands the organization rather than deepening it. The image in figure 4.1 depicts a Naive Inception Module.

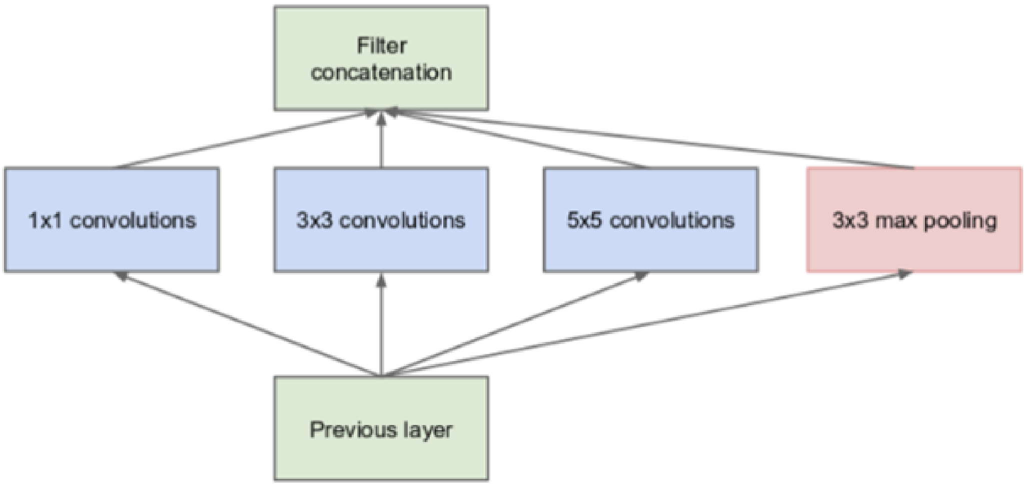

Figure 4.1: Building blocks of GoogLeNet

The Google Net Network has a depth of 22 levels and includes 27 pooling layers. There are a total of 9 beginning modules stacked vertically. The global normal pooling layer is linked to the commencement modules' closures. The complete Google Net architecture is shown in the figure 4.2.

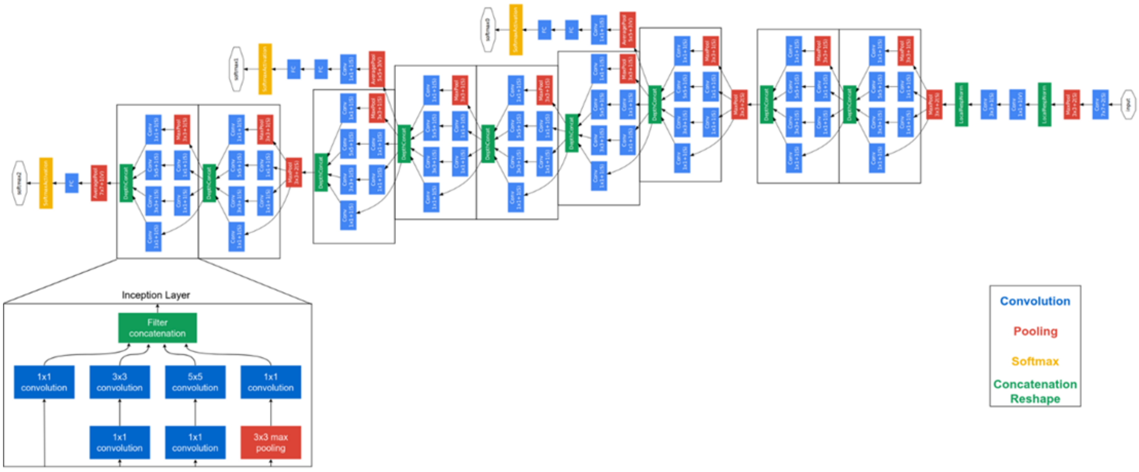

Figure 4.2: The stem in the architecture with the fewest initial convolutions is the Orange Box. The auxiliary classes are indicated by purple boxes. (Image Credits: An Easy Guide to the Inception Network Versions.)

The figure 4.3 explains the specific architecture and settings.

type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

Figure 4.3: Details of GoogLeNet's architecture

4.3.2 SqueezeNET

Squeeze Net is a smaller organization that was intended to take the place of Alex Net. Although it operates three times faster than Alex Net, it has over 50 times less bounds. In 2016, analysts [41] from Deep Scale, Stanford University, and the University of California, Berkeley recommended this engineering. The following are the main principles of Squeeze Net:

- Swap out your 3-by-3 filters for 1-by-1 ones.
- Reduce the number of input channels to 3 3 filters.
- Down sample the network late so that the convolution layers have a large activation map.

The "squeeze" and "expand" layers are part of the Squeeze Net design. Only one squeeze for one convolutional layer. These are handled in a layer that extends and combines 1 1 and 3 3 convolution squeezing. This is seen in figure 4.4.

A squeeze layer and an expand layer combined are referred to as a "fire module" by

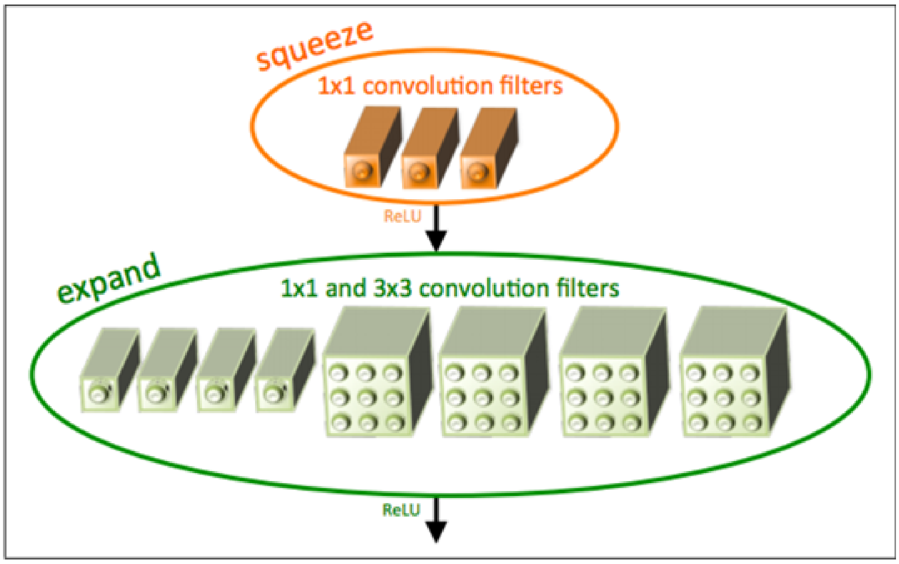

Figure 4.4: Fire Module

the paper's authors. An independent convolutional layer is the first place an input image is transmitted. As according Strategy One above, this is followed by 8 "fire modules" with the names "fire2-9. Figure 4.5 shows an illustration of the resulting Squeeze Net.

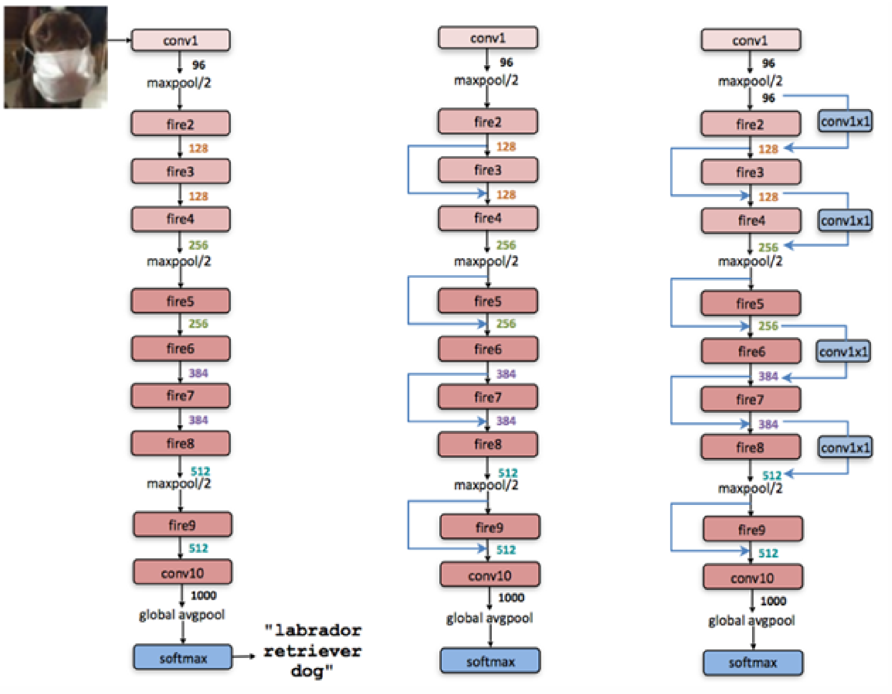

Figure 4.5: SqueezeNET architecture vs AlexNet

Squeeze Net, Squeeze Net with a straightforward bypass, and Squeeze Net with a sophisticated bypass, in that order. By using "simple bypass," Strategy Two increases the number of filters per fire module. Layers conv1, fire4, fire8, and conv10 come before Squeeze Net, which does max-pooling with a stride of 2. The "complicated bypass" that Squeeze Net has as a result of Strategy Three's placement of pooling very late in the network (the rightmost architecture in the image above).

A comparison of Squeeze Net and the original Alex Net is shown in the figure 4.6.

CNN architecture	Compression Approach	Data Type	Original → Compressed Model Size	Reduction in Model Size vs. AlexNet	Top-1 ImageNet Accuracy	Top-5 ImageNet Accuracy
AlexNet	None (baseline)	32 bit	240MB	1x	57.2%	80.3%
AlexNet	SVD [5]	32 bit	240MB → 48MB	5x	56.0%	79.4%
AlexNet	Network Pruning [11]	32 bit	240MB → 27MB	9x	57.2%	80.3%
AlexNet	Deep Compression [10]	5-8 bit	240MB → 6.9MB	35x	57.2%	80.3%
SqueezeNet (ours)	None	32 bit	4.8MB	**50x**	57.5%	80.3%
SqueezeNet (ours)	Deep Compression	8 bit	4.8MB → 0.66MB	**363x**	57.5%	80.3%
SqueezeNet (ours)	Deep Compression	6 bit	4.8MB → 0.47MB	**510x**	57.5%	80.3%

Figure 4.6: SqueezeNET architecture vs AlexNet

As we can see, the weights for Alex Net's compressed model were 240MB and had an accuracy of 80.3%. A Deep Compressed Squeeze Net uses 0.47MB of memory while performing at the same level. Details of further network parameters are provided below:

- Inside the fire module, the ReLU activation is performed between each squeeze and expand layer.
- After the fire9 module, dropout layers are included with a 0.5 probability to lessen overfitting.
- The network does not use any completely connected layers. The Network In Netowork (NIN) framework suggested by was the design inspiration for this decision (Lin et al, 2013).
- The learning rate used to train Squeeze Net is 0.04, and it decreases linearly during the course of training.

- The network employed an Adam Optimizer, and the training batch size was 32.

Due to its compact size, Squeeze Net makes deployment simpler. This network was initially used in Caffe, but it has since acquired popularity and been deployed on a wide range of platforms.

4.4 Proposed Framework

We intend to develop a framework using deep learning techniques that precisely classify emotional states of PD patients. To devise an algorithm for classification we proposed a neural network that have convolutional layers and it can be said to be a convolutional neural network. We have proposed a smaller network that was designed to classify the emotions of Parkinson's disease patient's emotions using the EEG signals. The following are the main concepts of the proposed framework:

- use 1×7 dimension for all filters
- the number of filters per layer decrease as the network feed forward
- Using 2D Network for our 1D input

Our proposed framework has one feature extraction head that gives the extracted features to classify than after extraction of 1D feature from signals, used fully connected layer and then output. The proposed framework 1D-CNN is given inn figure 4.7:

Our Proposed network is 3 layers deep with following changes in filter number while kept the filter size constant:

- First layer: The no. of filters used is 64
- Second layer: For second layer the number of filter is reduced to half which is 32

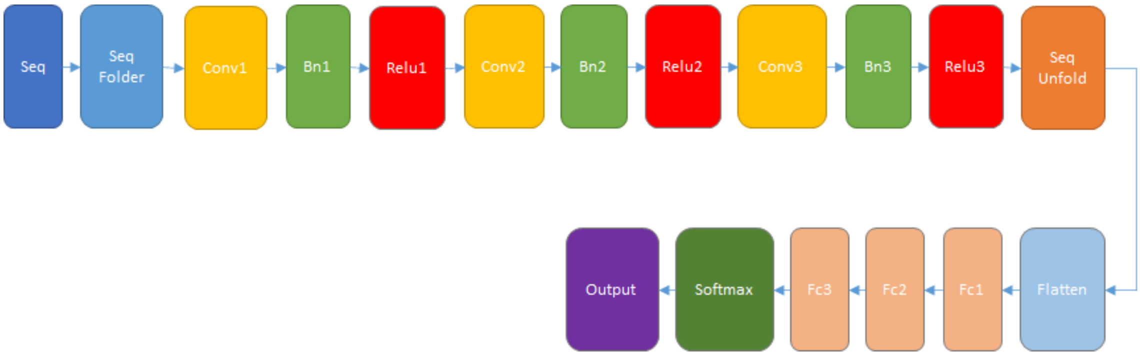

Figure 4.7: Proposed Deep Learning Model

- Third layer: The number of filters used in this layer are 16 filters

Details of further network parameters are provided below:

- The proposed framework receives 1D input.
- Batch normalization, ReLU, and convolutional algorithms make up each 2D network.
- The network employs fully connected layers.
- The neural network's output layer uses the softmax function as its activation function.

Our proposed framework gives classified emotions for Parkinson's disease patients.

Chapter 5

Experimentation and Results

This chapter discusses the experimentation protocol of networks that were analyzed and proposed framework with variation in dataset.

5.1 Experimental Setup

5.1.1 Dataset Description

For our Experiment we have used EEG signals of Parkinson's disease patients after pre-processing. Dataset is characterized into two categories (1) is 20 PD patients that have 9 males and 11 females (2) Healthy control subjects that includes 10 from each gender males and females. These subjects of PD patients have been suffering from PD for the past 5.75 years. Multimodal stimuli, such as images, sounds, and movies, were employed to recode the EEG data. The International Affective Picture System database, International Affective Digitized Sounds, and numerous movies served as the source for the multimodal stimuli. Each participant is put through six sessions, each of which includes one of the six emotion categories (angry, disgust, fear, happy, sad, and surprise), for a total of 720 sessions for each dataset. The time between sessions was 49 and 70 sec (minimum interval for PD was 50 seconds and

49 seconds for healthy controls).

Dataset used for experiment We are using dataset after preprocessing for our experimentation. Each data is split into 1 second's segment whereas each segment is 128 samples. EEG is 14 channel, by 14 channel we means 14 dimensions. For our networks we have kept the split 70-30 for training and testing dataset. With these all description we have used following three type of data variation for experiment:

- Original signals as images
- Scalograms of preprocessed signals
- Spectrograms of Preprocessed signals

And for these above three data variation we analyzed results of two networks (1) Google Net and (2) Squeeze Net which makes total of 6 experimental cases.

5.2 Performance Metrics

To examining the efficiency of our proposed algorithms, key performance index can be obtained using the true classification and misclassifications in a confusion matrix 5.1, as described in given Table, as an example for a simple binary classification. The elements in diagonal show the correct classification for a specific class, class A in this case and are termed as a True Positive and when the remaining classes which are not of interest are also correctly identified as class B. The two terms namely False Positive and False Negative indicate 'false alarm' and 'missed identification, respectively.

Table 5.1: Sample Confusion Matrix

True/Predicted	**A**	**B**
A	True Positive	False Negative
B	False Positive	True Negative

5.2.1 Accuracy

Classification accuracy is calculated as the sum of all correct predictions divided by all predictions. It is calculated using the expression 5.1. Accuracy is a poor performance metric for classification that is unbalanced.

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{5.1}$$

5.2.2 Specificity

The degree of genuine negatives that the model can reliably identify is measured by specificity. This implies that there will be an additional degree of true negatives that were mistakenly thought to be positive and could be referred to as false positives. This amount may also be referred to as a True Negative Rate (TNR). Specificity (true negative rate) and false positive rate would always be 1, respectively. Low specificity suggests that the model is mislabeling many negative results as positive, whereas high specificity suggests that the model is correctly differentiating the great majority of the negative outcomes. It is calculated using expression given in 5.2.

$$Specificity = \frac{TN}{(FP + TN)} \tag{5.2}$$

5.2.3 Sensitivity

Sensitivity is a measure of how effectively a machine learning algorithm can distinguish between good and bad examples. The real positive rate (True positive rate) or recall are other names for it. Sensitivity is used to evaluate model performance since it enables us to see how many successful cases the model was able to correctly identify. Sensitivity (true positive rate) and deceptive negative rate would both be 1. The model performs better at correctly differentiating positive situations the greater the true positive rate. It is calculated using expression given in 5.3.

$$Sensitivity = \frac{TP}{(FN + TP)} \tag{5.3}$$

5.2.4 Precision

A statistic that counts the amount of accurate positive predictions is known as precision. It is employed to determine minority class accuracy. The ratio of successfully anticipated positive values to all accurately predicted positive values is known as precision. It is calculated using expression given in 5.4.

$$Precision = \frac{TP}{(FP + TP)} \tag{5.4}$$

5.2.5 F2 Measure

The F2-measure is the Fbeta-measure with a beta value of 2.0. It lessens the importance of accuracy while increasing the importance of sensitivity. The F2-measure gives more thought to reducing false negatives than decreasing false positives if increasing precision restricts false positives and maximizing recall minimizes false negatives. It is calculated using expression given in 5.5.

$$F2Measure = \frac{5 * Precision * Sensitivity}{(4 * Precison + Sensitivity)} \tag{5.5}$$

5.2.6 Misclassification Rate

Misclassification rate tells us about the incorrectly predicted percentages of observations by a classification model. Its range of values is 0 to 1, where: 0 represents no inaccurate predictions; 1 represents all incorrect guesses. Misclassification Rate = Number of Values Wrongly Predicted / Number of Predictions. A classification model is better equipped to predict the outcomes of the reaction variable when the misclassification rate is lower. It is calculated using expression given in 5.6.

$$MisclassificationRate = \frac{FP + FN}{(TP + FP + TN + FN)} \tag{5.6}$$

5.3 Experimental Results

Experimentation for classification of PD patient's Emotions is carried out using various modalities including:

- Scalograms of the EEG Signal
- Spectrograms of the EEG Signal
- EEG Signals converted into 2D images
- Proposed Deepl Learning Model

5.3.1 Results using Scalograms as Feature Map

After preprocessing we generated Scalograms of the pre-processed signals that gave us the 2D representation of our EEG signals. Figure 5.1 shows the representation of our signals as scalograms.

GoogLeNet

Scalogram was used as input to the Google Net, figure 5.2 shows the trend for training accuracy and loss. It is clear from the training graph that this network fails to learn or train itself on the given data as their is no change in training accuracy and loss.

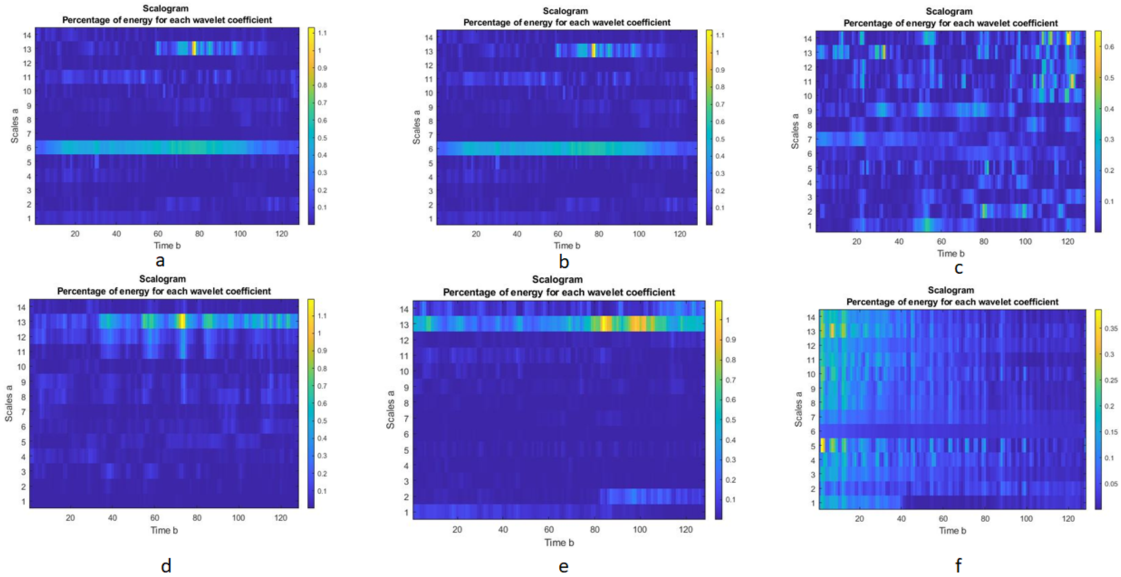

Figure 5.1: Scalograms of emotions (a)-(f), Angry-Surprise.

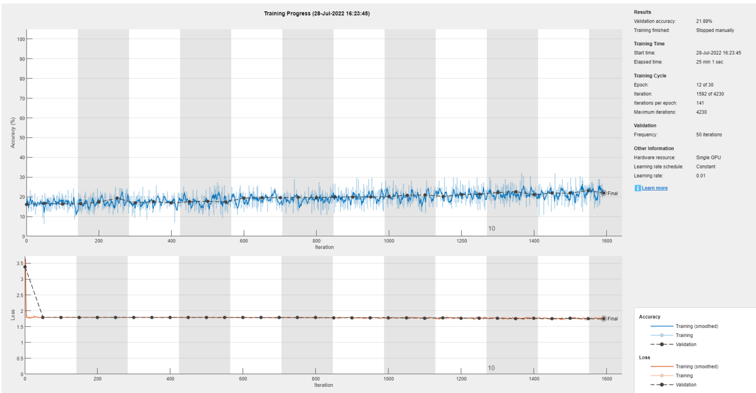

Figure 5.2: Training Accuracy and Loss using GoogLeNet

SqueezeNET

In the next phase, Scalogram was used as input to the Squeeze Net and training graph of this network give no change in training with no variation which shows that the model didn't trained the Scalogram with no results as shown in figure 5.3. This is the same tend as for the Google Net.

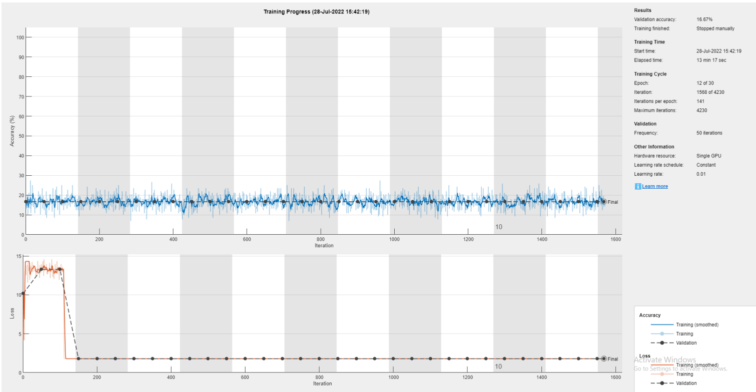

Figure 5.3: Training Accuracy and Loss using SqueezeNET

5.3.2 Results using Spectrograms as Feature Map

After preprocessing we generated Spectrogram of the pre-processed signals that gave us the 2D representation of our EEG signals. Figure 5.4 shows the representation of our signals as Spectrograms.

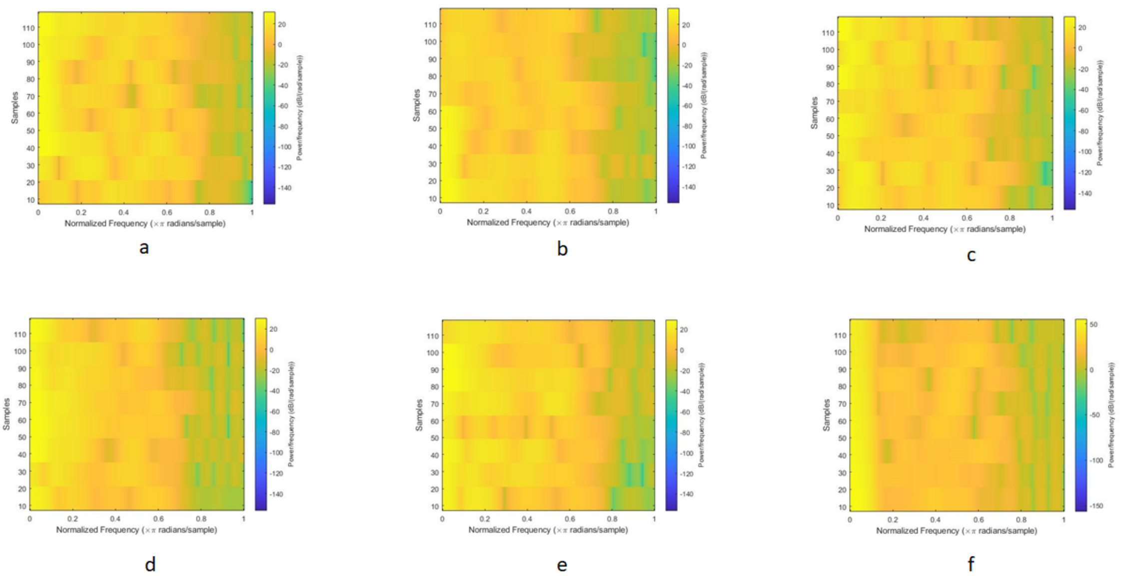

Figure 5.4: Spectrograms of emotions (a)-(f), Angry-Surprise.

From the above representation of Spectrogram and Scalogram we can analyze that the representation of the signals as Spectrogram and Scalogram is similar they do not give much information about the signals.

GoogLeNet

Given is the Results of the training experiment for Google Net for Spectrogram that shows similar trend as for the Scalogram with no results and training output. And loss is also not converging as shown in figure 5.5.

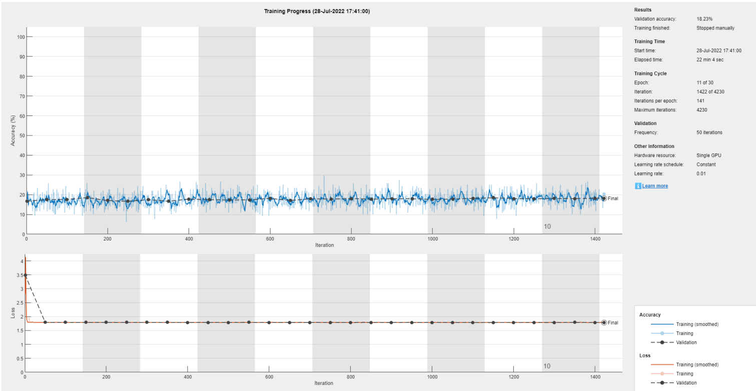

Figure 5.5: Training Accuracy and Loss using SqueezeNET

SqueezeNET

After the above experiment we used Spectrogram feature as input for Squeeze Net and the results shows that the experiment didn't give as training output. The trends can be seen in figure 5.6.

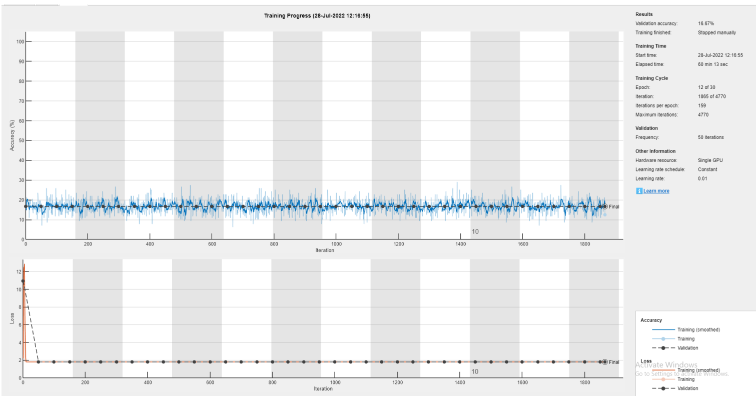

Figure 5.6: Training Accuracy and Loss using SqueezeNET

5.3.3 2D Images Generated from Signals

For this experiment we used the 2D representation of the signals as images to get the training results of the two Networks but the training trend didn't changed and the two chosen network give no results. The trends can be seen in figure 5.7 and 5.8 using GoogLeNet and SqueezeNET.

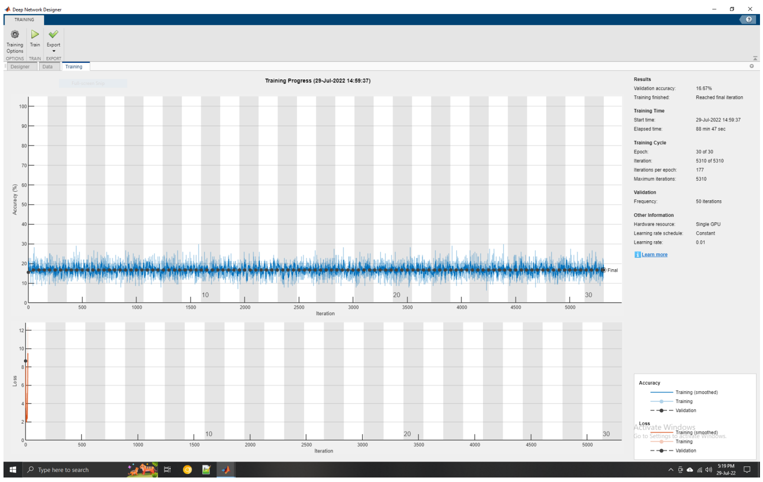

Figure 5.7: Training Accuracy and Loss using SqueezeNET

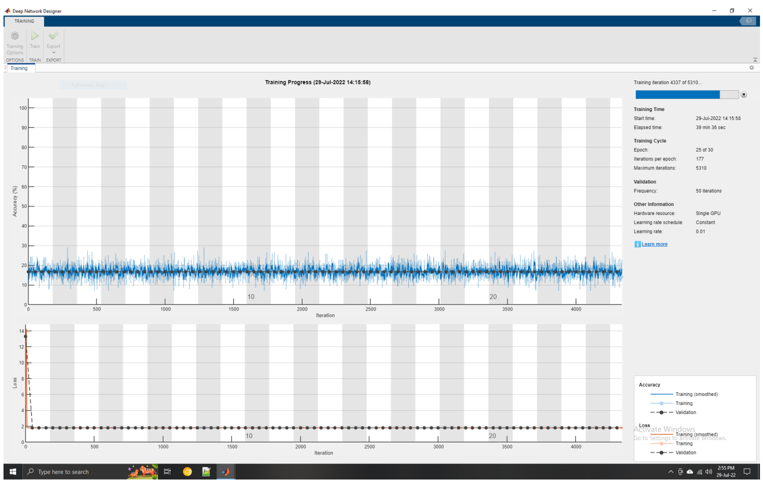

Figure 5.8: Training Accuracy and Loss using SqueezeNET

5.3.4 Proposed Model

We have done two experiments one for the 20 epochs and again did the training for 50 epochs. Results for the proposed model are given below we have already performed 6 experiment with 6 different cases and after that we proposed our method that didn't give much encouraging results but the network started training and our main purpose of this research was to analyze different methods for classification of emotions of Parkinson's disease patients. The traning accuracy and loss trends for the proposed architecture while keeping 20 epochs can be seen in figure 5.9

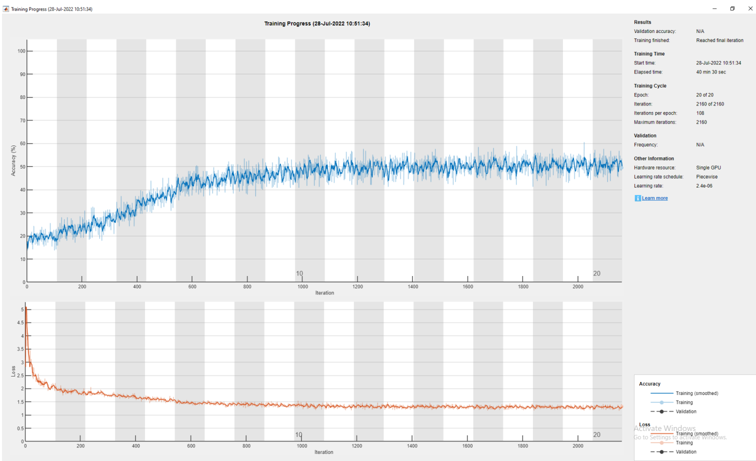

Figure 5.9: Training Accuracy and Loss using Proposed Model for 20 Epochs

While testing the proposed trainied network an accuracy of 50.14% was achieved while the confusion matrix is shown in table 5.2.

Table 5.2: Confusion matrix for 20 epochs

	Angry	**Disgust**	**Fear**	**Happy**	**Sad**	**Surprise**
Angry	566	113	85	111	115	135
Disgust	100	584	79	114	127	84
Fear	110	112	461	147	129	101
Happy	105	128	91	599	93	100
Sad	89	111	94	113	560	76
Surprise	97	121	84	157	110	511

The performance matrices for the proposed model keeping epochs as 20 are stated in table 5.3.

In order to check whether further training the proposed model can yeild better results we increased the epochs to 50. Even with the increase the trend for training accuracy and loss remained similar which can be seen in figure 5.10.

Table 5.3: Performance Matrix for 20 Epochs

Sensitivity	**Specificity**	**Precision**	**F2-Measure**	**Misclassification Rate**
0.5	0.84	0.53	0.52	0.16
0.52	0.82	0.48	0.5	0.17
0.43	0.87	0.52	0.47	0.16
0.54	0.8	0.48	0.51	0.18
0.54	0.82	0.49	0.51	0.16
0.48	0.85	0.51	0.49	0.16

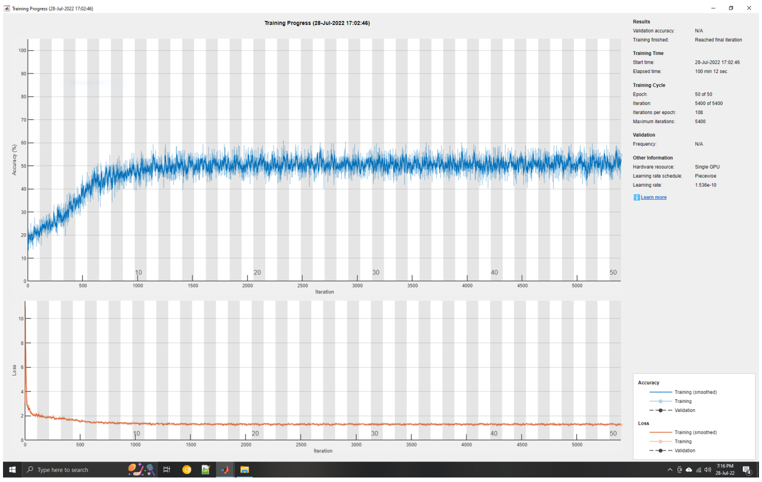

Figure 5.10: Training Accuracy and Loss using Proposed Model for 50 Epochs

While testing the proposed trainied network an accuracy of 51.13% which shows a meger change from 50.14%. Finally the confusion matrix for the testing phase is shown in table 5.4.

Table 5.4: Confusion matrix for 50 epochs

	Angry	**Disgust**	**Fear**	**Happy**	**Sad**	**Surprise**
Angry	536	102	79	113	115	115
Disgust	95	519	88	147	126	103
Fear	98	116	464	153	155	105
Happy	70	89	87	613	108	99
Sad	71	93	101	118	646	85
Surprise	108	105	94	135	94	535

The performance matrices for the proposed model keeping epochs as 50 are stated in table 5.5.

Table 5.5: Performance Matrix for 50 Epochs

Sensitivity	**Specificity**	**Precision**	**F2-Measure**	**Misclassification Rate**
0.51	0.86	0.55	0.53	0.15
0.48	0.85	0.51	0.49	0.16
0.43	0.86	0.51	0.46	0.17
0.58	0.8	0.48	0.52	0.17
0.58	0.82	0.52	0.55	0.16
0.5	0.85	0.51	0.51	0.16

Chapter 6

Conclusion and Future Work

Emotion Classification of PD patients is an important challenge as the disease is progressing and we need to have system with less manual effort. So to do that many researchers are now a days performing research and experiment for the improvement of already proposed methods and devising new methods for the help in medical field for practitioners. We analyzed already proposed methods for the dataset used in [30] which is not publically available. For our experimentation we used Physiological signals more specifically EEG signals for the emotion charting analysis of PD patients. First we performed experiment on three different variation of 2D data that includes: images of preprocessed data, Scalograms and Spectrograms of preprocessed signals. And for networks analysis we choose Google Net and Squeeze Net because of the difference in there architecture. As Google Net is a very deep neural network with 22 layers on the other hand Squeeze Net is 50x smaller and faster than Alex net. This vast difference in the architecture made us choose these two networks. For experimnetattaion the above setup gives us a total of 6 experimental cases to get our analysis done. For the two already trained and tested networks we didn't manage to get our data trained as form the above results we can see that the training have no variation or we can say that the network didn't trained. Then after the 6 experiment with no satisfactory results we proposed a new framework that is 1D CNN which is 3 layered and each layer have filter size of 1 x 7 and the number of filter for layer 1, 2 and 3 is 64, 32 and 16 respectively. Then used a flatten layer and softmax was used as activation function before output then output. The input of this proposed framework was 1D signal of EEG after preprocessing and this signal was used as input for the 2D network of conv, BN and ReLU as one layer. We used Softmax at output because it's a multiclass classification problem where class membership is required on more than two class labels. So the results after the implementation of our Framework were not much impressive but at least the proposed method showed some variation in training. For first experiment we trained till 20 epochs which gives accuracy of 50% approximately then we performed the experiment for 50 epochs and this shows that the increase in epochs will not change the accuracy much. So we stopped here as our purpose of this whole research was analysis not improving accuracy. In our study we have tested different models and proposed a novel deep learning framework that classifies the PD patient's emotions.

For future directions we suggest to use the emotion charting method for other cognitive disease like Alzheimer's disease, stroke, traumatic brain injury or developmental disabilities. This is not a binary class problem, it's a multiclass problem and there is room for improvement. The accuracy can be improved by using combination of different deep learning methods. The scope of this study can be extended to 3D deep learning methods.

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