LOCAL BINARY PATTERN FOR EMOTION RECOGNITION USING EEG

A PROJECT REPORT

submitted by

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to

the APJ Abdul Kalam Technological University
in partial fulfillment of the requirements for the award of the Degree

of

Master of Technology
in
Electrical and Electronics Engineering
with specialisation in
Industrial Instrumentation and Control

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DECLARATION

I undersigned hereby declare that the project report entitled "**Local binary pattern for emotion recognition using EEG** ", submitted for partial fulfillment of the requirements for the award of degree of Master of Technology in Electrical and Electronics Engineering with specialisation in Industrial Instrumentation and Control, of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by me under the supervision of *Dr. Muhammed Shanir P P*, Project Guide, Assistant Professor, Department of Electrical and Electronics Engineering.*Prof. Amal A*, Project Co-ordinator, Assistant Professor, Department of Electrical and Electronics Engineering. This submission represents my ideas in my own words and where ideas or words of others have been included. I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree, diploma or similar title of any other University.

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CERTIFICATE

This is to certify that the project report entitled "**Local binary pattern for emotion recognition using EEG** " submitted by **AKHILA G BABU.** , **(Reg. No. TKM21EEII01)** of fourth semester to the APJ Abdul Kalam Technological University in partial fulfillment of the requirements for the award of the Degree of Master of Technology in Electrical and Electronics Engineering with specialisation in Industrial Instrumentation and Control, is a bonafide record of the project work done by her under our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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ABSTRACT

In the context of Human-Machine Interface and Brain computer interface emotion recognition has demonstrated numerous important roles. However, the majority of currently used emotion identification techniques perform poorly in recognising emotions, which prevents their widespread use in practical applications. Although emotion recognition based on electroencephalogram (EEG) has higher priority. Present EEG based emotion recognition system have either lesser performance or higher computation complexity or both. Prevent these problems proposes a Local Binary Pattern (LBP) based emotion recognition system.

LBP is a simple yet effective method for texture analysis and classification. In proposed system a LBP of 9 neighbouring pixels are selected, then corresponding binary number will produced by thresholding its value with the value of the centre pixel. This binary code is converted to decimal value. This procedure is iteratively done along the entire signal. The result of this work is that we can efficiently classify emotions with greater classification accuracy and less mathematical complexity than in previous studies.

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ABBREVIATIONS

BCI	Brain-Computer Interaction
DEAP	Dataset for Emotion Analysis using Physiological Signals
EEG	Electroencephalogram
HMI	Human Machine Interface
KNN	K-Nearest Neighbor
LBP	Local Binary Pattern
NLP	Natural Language Processing
SVM	Support Vector Machine

NOTATIONS

p_i	nearby sample values
P_c	Central value
D	Euclidean distance

Chapter 1

INTRODUCTION

1.1 GENERAL BACKGROUND

Human emotion is a complex mental state or activity that can represent individuals attitudes and perceptions and is essential for interpersonal communication.It is the process of identifying and understanding human emotions based on various cues such as facial expressions, vocal intonations, body language and physiological responses. It involves using technology such as computer algorithms and machine learning to analyze these cues and infer the emotional state of an individual. Human-Machine Interface (HMI) and Brain-Computer Interface (BCI) techniques can be combined with emotion recognition using EEG (electroencephalography) to create systems that enable users to control and interact with technology based on their emotional states. HMI focuses on the design and development of interfaces that facilitate communication and interaction between humans and machines. It is also used to create user interfaces that allow individuals to provide input based on their emotional states, as measured by EEG. BCI refers to the communication pathway established between the brain and an external device or computer system. They also employed to interpret the brain signals related to emotions and facilitate the interaction between the user and the technology. Combining HMI and BCI techniques in emotion recognition using EEG enables users to have direct control over technology based on their emotional states. This can have applications in various domains, including healthcare, virtual reality and gaming, systems, household appliances, food and other industries. In terms of humanization, it is hoped that the robot would be able to think like a human and identify emotional states in order to achieve greater human-computer interaction. The accuracy of emotional

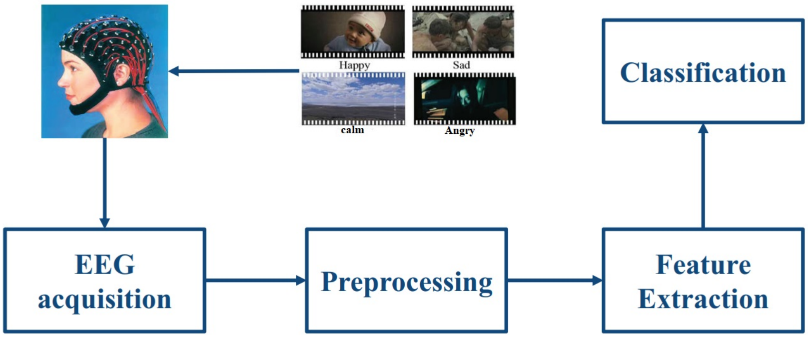

Figure 1.1: General block diagram of EEG based emotion recognition system.

recognition rate is one of the key factor that emotional robots can put into practical application, which is also great significance to its realization.

Above block diagram (figure 1.1)shows the general procedures of EEG based emotion recognition. EEG is a technique used to measure electrical activity in the brain. It can be utilized for emotion recognition by analyzing specific patterns and signals associated with different emotional states. General steps for recognition of emotion using EEG.

- EEG acquisition:It refers to the process of capturing and recording the electrical activity of the brain using an EEG.
- Preprocessing: Clean the EEG data to remove noise, aartifacts, and unwanted signals. This step may involve filtering, baseline correction and referencing.Select the most informative features from the extracted set. This step aims to reduce the dimensionality of the data while retaining the relevant information.
- Feature Extraction: Extract relevant features from the preprocessed EEG data. Select the most informative features from the extracted set. This step aims to reduce the dimensionality of the data while retaining the relevant information.
- Classification:After Feature Extraction these data is fed into the supervise semi supervised and unsupervised classifiers and testing, and finally the classification problem is executed.

The accuracy of EEG-based emotion recognition systems depend on various factors preprocessing feature extraction and classification,mainly its depend on feature extraction.The choice of features extracted from the EEG signals can impact the performance of emotion recognition algorithms. Selecting appropriate features that capture the relevant information related to emotional states is crucial for achieving accurate predictions. For overcoming this problems LBP based emotion recognition is introduced for emotion recognition.

1.2 OBJECTIVES

- To develop an emotion recognition algorithm with lower mathematical complexity and higher performance.
- To perform emotion recognition algorithm to identify best performing channel.
- Implementing the developed algorithm for emotion classification and evaluating the performance of the model.
- To reduce the number of electrodes in EEG with out affecting the recognition accuracy

1.3 SCOPE

Proposes a local binary pattern for emotion recognition using EEG which is help to improve accuracy, which avoids the system complexity.

1.4 ORGANISATION OF THE REPORT

The report is organized in 6 chapters. Chapter 1 titled by introduction includes general block diagram, objective, scope and scheme of project work which focuses on the general details and background of the system. Chapter 2 surveys the literature review done on this work. Chapter 3 titled by Electroencephalogram completely explain the details of EEG. Chapter 4 deals with complete description of the system and chapter 5 and Chapter 6 deals with results analysis and conclusions of the report respectively.

Chapter 2

EEG BASED EMOTION RECOGNTION

2.1 OVERVIEW

Emotions play an adaptive, social, or motivational role in the life of human beings as they produce different characteristics indicative of human behavior . Emotions affect decision making, perception, human interactions, and human intelligence. It also affects the status of humans physiologically . Emotions can be expressed through positive and negative representations, and from them, it can affect human health as well as work efficiency .Understanding emotional signals in everyday becomes an important aspect that influences people's communication through verbal and nonverbal behavior . One such example of emotional signals is expressed through facial expression which is known to be one of the most immediate means of human beings to communicate their emotions and intentions .Currently, the advancement of artificial intelligence and machine learning is being actively developed and researched to adopt to newer applications. Such applications include neuroinformatics field which studies the emotion classification by collecting brainwave signals and classifying them using machine learning algorithms. THis would help improve human-computer interactions to meet human needs.

2.2 THE IMPORTANCE OF EEG FOR USE IN EMOTION CLASSIFICATION

EEG is considered a physiological clue in which electrical activities of the neural cells cluster across the human cerebral cortex. EEG is used to record such activities and is reliable for emotion recognition due to its relatively objective evaluation of emotion compared to non-physiological clues (facial expression, gesture, etc.). Works describing that EEG contains the most comprehensive features such as the power spectral bands can be utilized for basic emotion classifications . There are three structures in the limbic system as shown in Figure 2.1, where the brain heavily implicates emotion and memory from the hypothalamus, amygdala, and hippocampus. The hypothalamus handles the emotional reaction while the amygdala handles external stimuli that process the emotional information from the recognition of situations as well as analysis of potential threats. Studies have suggested that amygdala is the biological basis of emotions that store fear and anxiety . Finally, the hippocampus integrates emotional experience with cognition[1] .

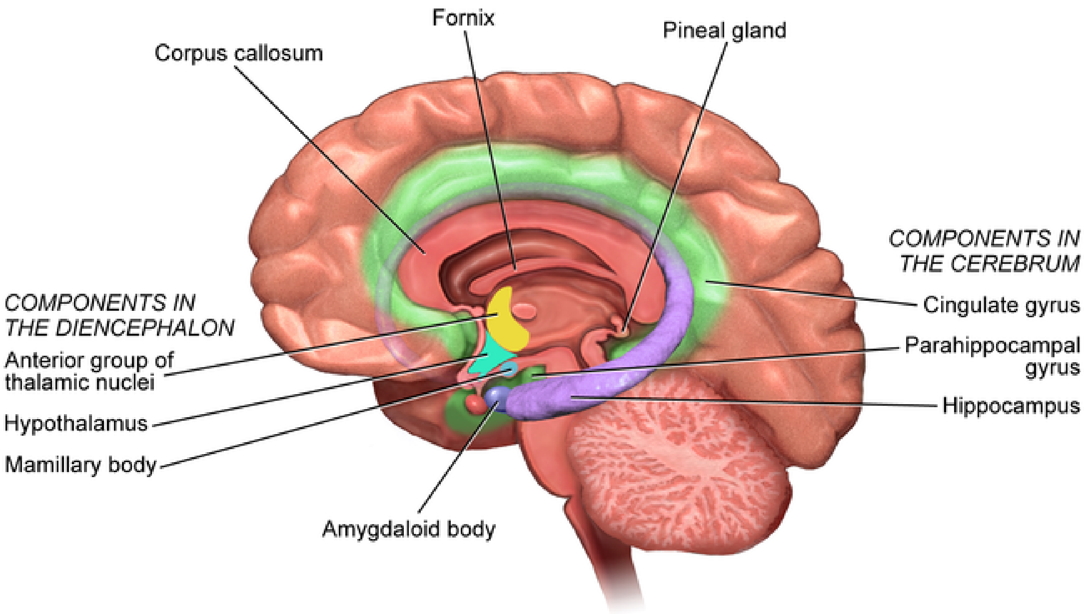

Figure 2.1: The limbic system is the area of the brain involved with emotion

2.3 EEG

An electroencephalogram (EEG) is a non-invasive technique used to record and measure the electrical activity of the brain [2] . EEG measures the electrical potentials generated by the firing of neurons in the brain using electrodes placed on the scalp. Brain cells communicate via electrical impulses and are active all the time, even during asleep .It also measures voltage fluctuations caused by ionic current in the brain's neurons[3].

The essential components of an EEG:

- **Electrodes**: Electrode is used to pick up the electrical activity and their attached wire is connect with the EEG machines.
- **Amplifiers**:It is used for amplifying the signals, these rhythms are only micro volts in amplitude.
- **Writer Units**: It is helps to record the rhythms on paper,moving usually at 30mm/sec

2.3.1 EEG ELECTRODES

EEG consists of 10 – 20 electrode placement system for EEG recording. On the scalp, distances between two electrodes are given as 10% and 20% of the distance between specified points. Nasion and Inion are the two reference points near the ear lobes of the human. Over the head, the distance between nasion and inion are divided into 5 points. The nasion inion distance via the vertex is measured and three electrodes are placed as one in frontal, one in central and one in parietal. They are spaced at 10%, 20%, 20%, 20%, 20%, and 10% of the length. Similarly, the nasion-inion distance is measured along the temporal lobes, and five electrodes are placed: two in the frontal, two in the temporal, and one in the occipital lobes. They are also spaced at 10%, 20%, 20%, and 20% of the length on either side. Finally, six electrodes are fixed on the circle's periphery; two in the frontal, two in the central, and two in the parietal. So, in total, 19 electrodes are placed on the brain scalp, one of which serves as a reference electrode and is located at the ear lobe[4] . This is commonly referred to as the 10–20 EEG system. The billions of cells in the brain produce very small electrical signals that form non-linear patterns called brainwaves. An EEG machine measures the electrical activity in the cerebral cortex and the outer layer of the brain, during an EEG test. EEG sensors are placed on a participant's head, then the electrodes non-invasively detect brainwaves from the subject.

EEG sensors can record up to several thousands of snapshots of the electrical activity generated in the brain within a single second. The recorded brainwaves first sent to amplifiers, then to a computer or the cloud to process the data[5]. The amplified signals, which resemble wavy lines, can be recorded on a computer, mobile device, or on a cloud database.

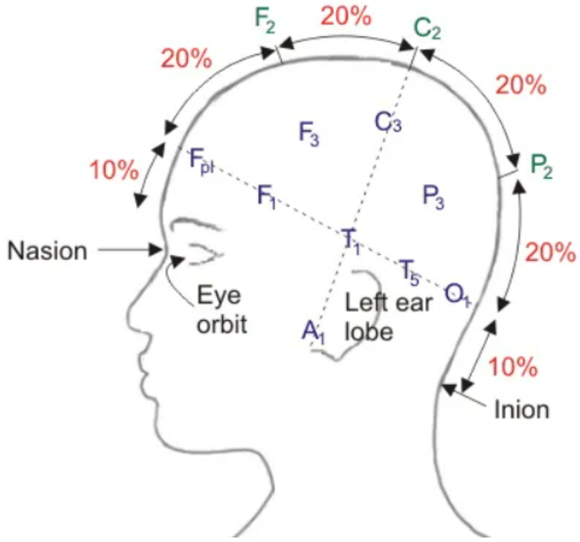

Figure 2.2: EEG Electrode placement

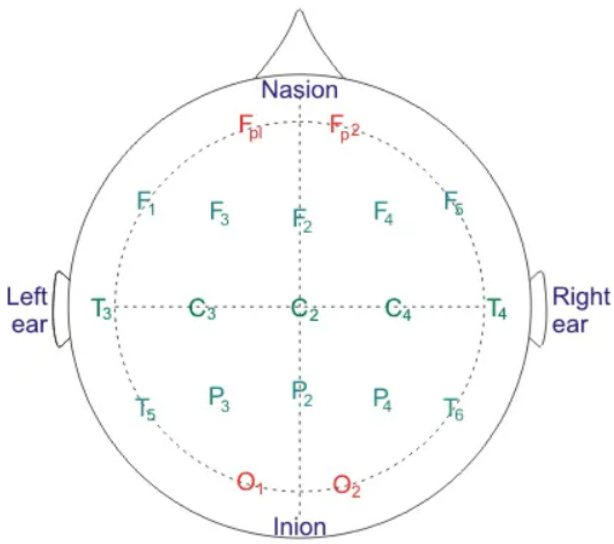

Figure 2.3: EEG electrode placement

2.3.2 FREQUENCY BANDS IN EEG

EEG captures the collective electrical activity of thousands to millions of neurons in the brain. The recorded signals are classified into different frequency bands or brainwave patterns. These include:

- Delta Waves (0.5-4 Hz): Typically observed during deep sleep or in some abnormal brain conditions. It tends to be the highest in amplitude and the slowest waves. It is seen normally in adults in slow-wave sleep. It is also seen normally in babies.

- Theta Waves (4-8 Hz): Theta is seen normally in young children. Associated with drowsiness, relaxation, and certain sleep stages.

- Alpha Waves (8-13 Hz): Predominant during awake and relaxed states, with eyes closed.

- Beta Waves (13-30 Hz): It is seen usually on both sides in symmetrical distribution and is most evident frontally. Beta activity is closely linked to motor behavior and is generally attenuated during active movements. Present during alertness, concentration, and active cognitive processing.

- Gamma Waves (>30 Hz): Associated with complex cognitive processes, sensory perception, and consciousness.

2.3.3 EEG RECORDING PROCESS

EEG recording involves the process of capturing and recording the electrical activity of the brain using electrodes placed on the scalp [6].

Here are the key steps involved in EEG recording:

- Preparation: The participant's scalp needs to be prepared before electrode placement. This typically involves cleaning the scalp to remove any dirt, oils, or residue that may interfere with the electrode skin contact. If necessary, the hair may be lightly abraded or washed to improve conductivity.

- Electrode Placement: EEG electrodes are placed on specific locations on the scalp according to standardized systems like the International 10-20 system or the 10-10 system. The placement ensures consistent and systematic coverage of the scalp for recording brain activity from different regions. The electrodes are secured using adhesive collars, electrode caps, or individual adhesive patches.

- Ground and Reference Electrodes: A ground electrode is placed at a neutral location on the scalp to provide a reference point for the EEG signals. The reference electrode serves as a baseline against which the other electrode voltages are measured. Common choices for the reference electrode include linked mastoids (A1 and A2) or an average reference derived from multiple electrodes.

- Impedance Check: Before recording, it is important to check the impedance of each electrode to ensure good electrode-skin contact. High impedance can lead to poor signal quality and increased noise. Impedance can be checked using specialized impedance meters or built-in impedance checking features in EEG amplifiers.

- Amplification and Digitization: The EEG signals picked up by the electrodes are amplified using an EEG amplifier. The amplifier increases the signal amplitude for better detection and processing. The amplified signals are then digitized, converting the analog electrical signals into digital format for further analysis.

- Sampling Rate and Filter Settings: The EEG signals are sampled at a specific rate, typically ranging from 250 to 1000 samples per second (Hz). The sampling rate determines the temporal resolution of the recorded data. Additionally, filters are applied to remove unwanted frequencies outside the EEG frequency range (e.g., powerline noise, muscle artifacts). Common filters include high-pass, low-pass, and notch filters.

- Recording Duration: The duration of an EEG recording session depends on the specific requirements of the study or clinical application. It can range from a few minutes for specific tasks or events to several hours for sleep studies or continuous monitoring.

- Artifact Monitoring: During the recording, it is important to monitor and minimize artifacts that can interfere with the EEG signals. Common artifacts include eye blinks, eye movements, muscle activity, and environmental noise. Techniques such as eye movement monitoring, muscle artifact detection, and noise reduction methods may be employed to mitigate these artifacts.

- Documentation: It is essential to document relevant information about the recording session, such as the participant's demographics, electrode placement details, filter settings, and any significant events or observations during the recording. This documentation aids in the analysis and interpretation of the recorded data.

  Following the recording, the digitized EEG data can be further processed, analyzed, and interpreted using various techniques, such as filtering, epoching, spectral analysis, event-related potential analysis, or connectivity analysis. These analyses provide insights into brain activity, cognitive processes and neurological conditions[7].

2.4 SUMMARY

In this chapter, explained the details about electroencephalogram reading and recording procedure. Next chapter describe the work related on emotion recognition using non physiological and physiological signals.

Chapter 3

LITERATURE REVIEW

3.1 OVERVIEW

Existing studies in the field of emotion recognition can be divided into four categories: vision-based, text-based and speech-based. Vision-based emotion recognition aims to identify the emotional states of facial expressions from images or video frames. It is a typical pattern recognition process, usually including the stages of face detection and localization, feature extraction and tracking on facial landmark points, machine learning model design and training, among which the facial expression related feature extraction and recognition are more important to determine the recognition performance. Text-based emotion recognition methods extract and recognise subjective emotional representations in text using Natural Language Processing(NLP), text mining and computing linguistics technologies. The characterization of speech signals or corpora of different tonal emotion states, which are used to train the machine learning model and obtain the corresponding emotional states of different voices, is referred to as speech emotion recognition[8] .

In general, these three types of emotion recognition methods are referred to as non-physiological signal-based emotion recognition. Their common advantage is that they are relatively simple to implement; however, they cannot guarantee the reliability of recognition. For example, can conceal their true emotional states by changing their facial expressions, voices, and intonations. Physiological signals have significant advantages over non-physiological signals, such as being harder to disguise, more objective, and providing more information. Earlier studies in this field concentrated on peripheral physiological signals such as skin impedance, respiration, and blood volume pulsation. However, the change rate of these signals is slow, limiting the time resolution. EEG data has become an important data source for emotion recognition due to recent advances in signal acquisition and wearable computing devices because it is generated by central nervous system activities and is directly correlated to emotion production. As a result, EEG has been regarded as the "gold standard" for emotion recognition[9] .

3.2 WORKS CONDUCTED WITH NON-PHYSIOLOGICAL SIGNALS

In non physiological based emotion recognition methods are mainly use features such as facial expressions, body postures and speech. Here are a few examples:

- Text-based Emotion Recognition: This approach involves analyzing written text, such as emails, social media posts, or chat conversations, to infer the emotional state of the author. Natural Language Processing (NLP) techniques can be employed to analyze the linguistic content, sentiment, and contextual cues to understand the underlying emotions.

- Speech-based Emotion Recognition: By analyzing speech patterns, tone, pitch, and other acoustic features, it is possible to infer the emotional state of a speaker. Machine learning algorithms can be trained on large speech datasets to recognize patterns associated with different emotions.

- Facial Analysis: Observing behavioral cues, such as typing speed, scrolling patterns, or browsing habits, can provide insights into the emotional state of an individual. For example, increased typing speed might indicate excitement or frustration, while prolonged pauses could suggest confusion or uncertainty.

- Multimodal Emotion Recognition: This approach combines multiple sources of information, such as facial expressions, speech, body language, and physiological signals, to improve the accuracy of emotion recognition. By integrating data from different modalities, researchers can create more comprehensive models for emotion analysis.

Below table contains the investigated information of some works done with non-physiological signals for the emotion classification.

Table 3.1: Comparison of different works with the facial and speech signals

No.	Author	Signal	Data set	Method
1	Albert C et al.[10]	Facial features	CK+, MMI	Propose an one-shot emotion score method for addressing person-independent facial emotion recognition.
2	Al et al.[11]	Facial features	JAFFE	Adaptive Robust Local Complete Pattern is used for generating feature representation of facial images
3	K Ghanem [12]	Facial features	CK+, MMI	Hidden markov models for modeling occurrence order of facial temporal dynamics
4	S Yang, B Bhanu[13]	Facial features	FERA, CK+	Understanding discrete facial expressions in video using an emotion avatar image using LBP
5	DS Moschona[14]	Speach signals	EmoDB	An affective service based on multi-modal emotion recognition, using speech emotion recognition

It is worth noting that non-physiological type emotion recognition methods might not be as accurate or reliable as physiological indicators since they rely on indirect or inferred cues. Nonetheless, advancements in machine learning and data analysis techniques have made significant progress in this field, allowing for more sophisticated emotion recognition systems.

3.3 WORKS CONDUCTED WITH PHYSIOLOGICAL SIGNALS

A physiological method of emotion recognition involves analyzing and interpreting physiological signals and responses of the human body to identify and understand emotional states. Here are a few common physiological methods used for emotion recognition:

- Electroencephalography (EEG): EEG measures the electrical activity of the brain by placing electrodes on the scalp. Different emotional states can be associated with distinct patterns of brainwave activity, allowing researchers to identify and classify emotions based on these patterns.

- Heart Rate Variability (HRV): HRV is the variation in time intervals between consecutive heartbeats. Emotions can influence the autonomic nervous system, which in turn affects heart rate variability. By analyzing heart rate patterns, it is possible to detect emotional states such as stress, anxiety, or relaxation[15] .

- Galvanic Skin Response (GSR): GSR measures the electrical conductivity of the skin, which is influenced by sweat gland activity. Emotional arousal can cause changes in sweat gland activity, resulting in alterations in skin conductivity. GSR can be used to detect emotional states such as excitement, fear, or anxiety[16] .

- Facial Electromyography (EMG): EMG measures the electrical activity of facial muscles. Different emotions are associated with specific patterns of muscle activation in the face. By monitoring facial muscle movements, it is possible to recognize emotions like happiness, sadness, anger, or surprise[17].

- Functional Magnetic Resonance Imaging (fMRI): fMRI measures brain activity by detecting changes in blood oxygenation levels. It can provide insights into the brain regions involved in emotional processing. By analyzing fMRI data, researchers can identify neural correlates of specific emotions[18].

These methods are often used in combination to achieve more accurate and reliable results in emotion recognition.From this literature we can conclude that emotion recognition from EEG is more reliable because it gives direct measurement of brain activity and high temporal resolution.

3.4 WORKS CONDUCTED WITH EEG SIGNALS

Below table shows Comparison of different works done on electroencephalogram signals.

Table 3.2: Comparison of different works done on electroencephalogram signals

No.	Author	Class	Dataset	Method
1	CA Frantzidis, C Bratsas, CL Papadelis[19]	2	DEAP	A two-step classification procedure is proposed for the discrimination of emotional states between EEG signals evoked by pleasant and unpleasant stimuli.
2	M Murugappan, N Ramachandran, Y Sazali[20]	2	DEAP	The raw EEG signals are preprocessed using Surface Laplacian filtering method and decomposed into 3 different frequency bands using Discrete Wavelet Transform.
3	B Nakisa, MN Rastgoo [21]	4	MAHNOB, DEAP	Evolutionary computation algorithms for feature selection of EEG-based emotion recognition using mobile sensors
4	V Gupta, MD Chopda[22]	4,2	SEED	comprehensively investigate the channel specific nature of EEG signals and to provide an effective method based on flexible analytic wavelet transform for recognition of emotion

No.	Author	Class	Dataset	Method
5	P Ackermann, C Kohlschein[23]	3	DEAP	Evaluate the use of state of the art feature extraction, feature selection and classification algorithms for EEG emotion classification

Different classes such as 2, 3, or 4 different classes were taken into consideration in each work. The majority of the works considered valence and arousal-based emotions. For previous work two-class problem both low valence and high valence, or low arousal and high arousal are selected.But here we selected High valence low valence and low arousal low valence and Vice versa are considered as 2 class classification.. For the four-class problem, a combination of low and high valence and arousal is applied. Major problem observed that all works are based on feature extraction. Different feature extraction increase the complexity of the system.

3.5 SUMMARY

This chapter reviews the research on a number of emotional recognition techniques utilizing non-physiological methods, as well as the suggested method (using EEG signals). I saw that feature extraction, which is the basis for all works, is used to quantify the information. Another important observation is feature extraction highly depends accuracy and complexity of the system. The following chapter covers the procedures and strategies we employed for feature extraction in our research.

Chapter 4

METHODOLOGY

4.1 OVERVIEW

The previous chapter conducted an analysis of work related on emotion recognition using non physiological and physiological signals. This chapter explains the methodology utilized in the work as well as the dataset, emotion categorization, classifiers, and other tools that were employed.

4.2 PROPOSED METHOD

The block diagram of proposed system is shown in Figure 4.1. EEG recording from skull is used as dataset. The dataset has first been preprocessed it may contain some irrelevant noises and channels that do not provide any valuable information, so remove those channels and noises. Following that, trial-specific data is utilized for emotion mapping and obtain the data for each trial's channel. So a channel separation is done and these channels are the mapped to an emotions formulated (4-classes/emotions).After that feature extraction is done by using 1D local binary pattern.Then these data is fed into the classifiers (KNN and SVM classifiers are used in this work) for training and testing, and finally the classification problem is executed.

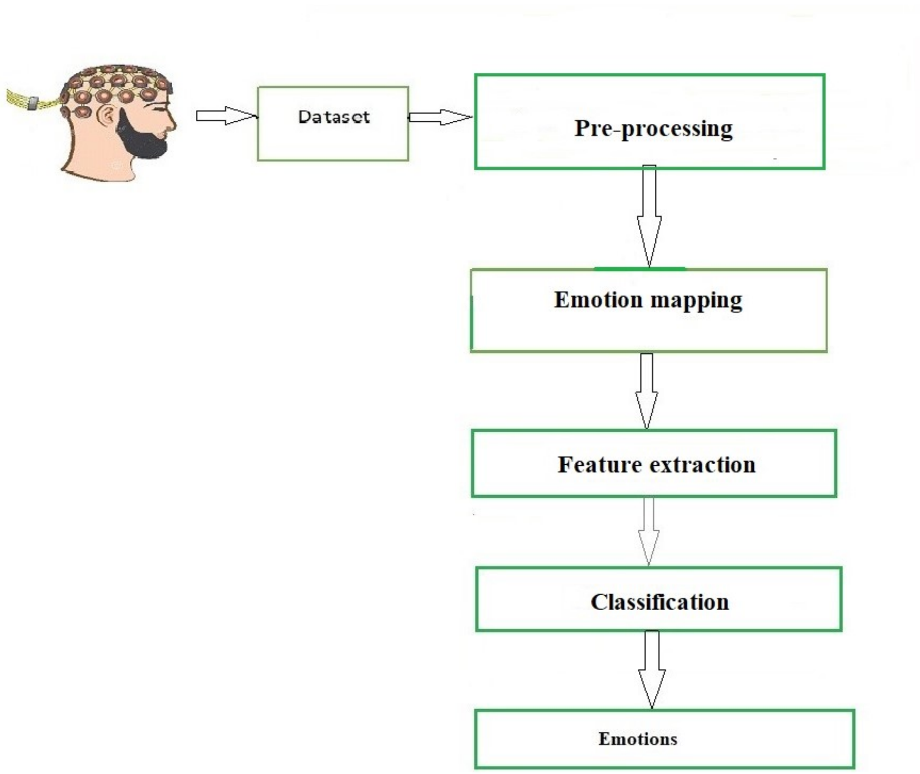

Figure 4.1: General block diagram

4.3 LOCAL BINARY PATTERN

Local Binary Pattern (LBP) is a texture descriptor that is widely used in computer vision and image processing. It was first introduced by Ojala et al. in 1996 as a simple yet effective method for texture analysis and classification. The basic idea behind LBP is to describe the local texture patterns of a signal by comparing the intensity values of its pixels with the intensity value of a center pixel [24] .

It can also be applied in EEG emotion recognition tasks. In the context of EEG emotion recognition, LBP can be used as a feature extraction method to capture the local texture patterns in the EEG signals. The idea is similar to the traditional LBP algorithm applied to images, but instead of comparing pixel intensities, it convert -each value of a signal to its binary patterns by using thresholding condition with respect to center value and its neighborhood values . This approach is repetitiously done along the entire signal. An EEG signal is a 1D time series signal; hence the original LBP for 2D signals cannot be directly applied over such a signal. The 2D LBP was therefore modified for 1D time series signal [25] .

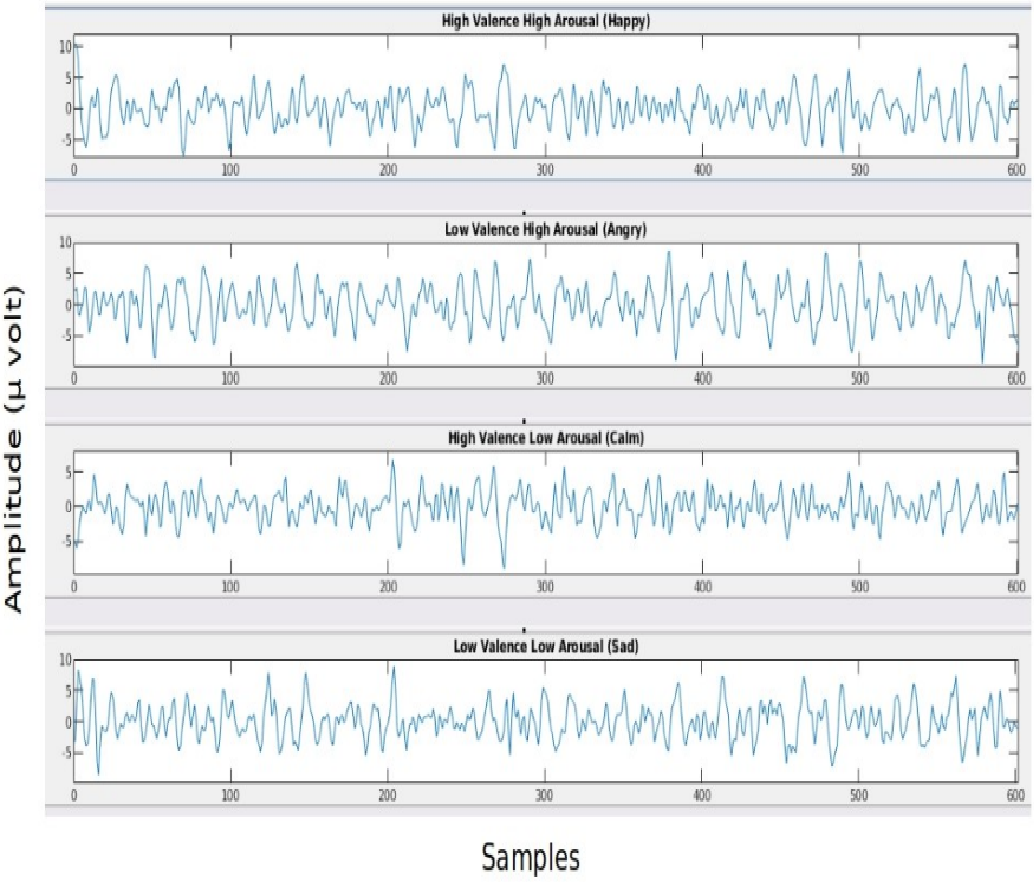

Figure 4.2: Examples of EEG signals taken from four different classes.

The feature extraction steps involved in 1D-LBP is given as.

- Step 1:Apply preprocessing steps to the signal, such as filtering, neighbour selection , to enhance the signal quality and remove noise or artifacts.
- Step 2: For a signal set the center and neighbor points.
- Step 3: The four neighboring samples were taken before P0, P1, P2, P3 and after P4, P5, P6, P7 from each center sample Pc.
- Step 4: Apply thresholding condition
- Step 5:The neighboring values are compared with the center point value.
- Step 6:If the neighboring value is greater than or equal to the center value then it take as takes 1 otherwise it takes 0
- Step 7:A binary LBP code for a neighborhood was formed.
- Step 8:The decimal value of this binary code represents the local structural information around the given Pc

$$P_c = \begin{cases} 1, & \text{for } P_i \geq Pc \\ 0 & \text{for } P_i < Pc \end{cases}$$

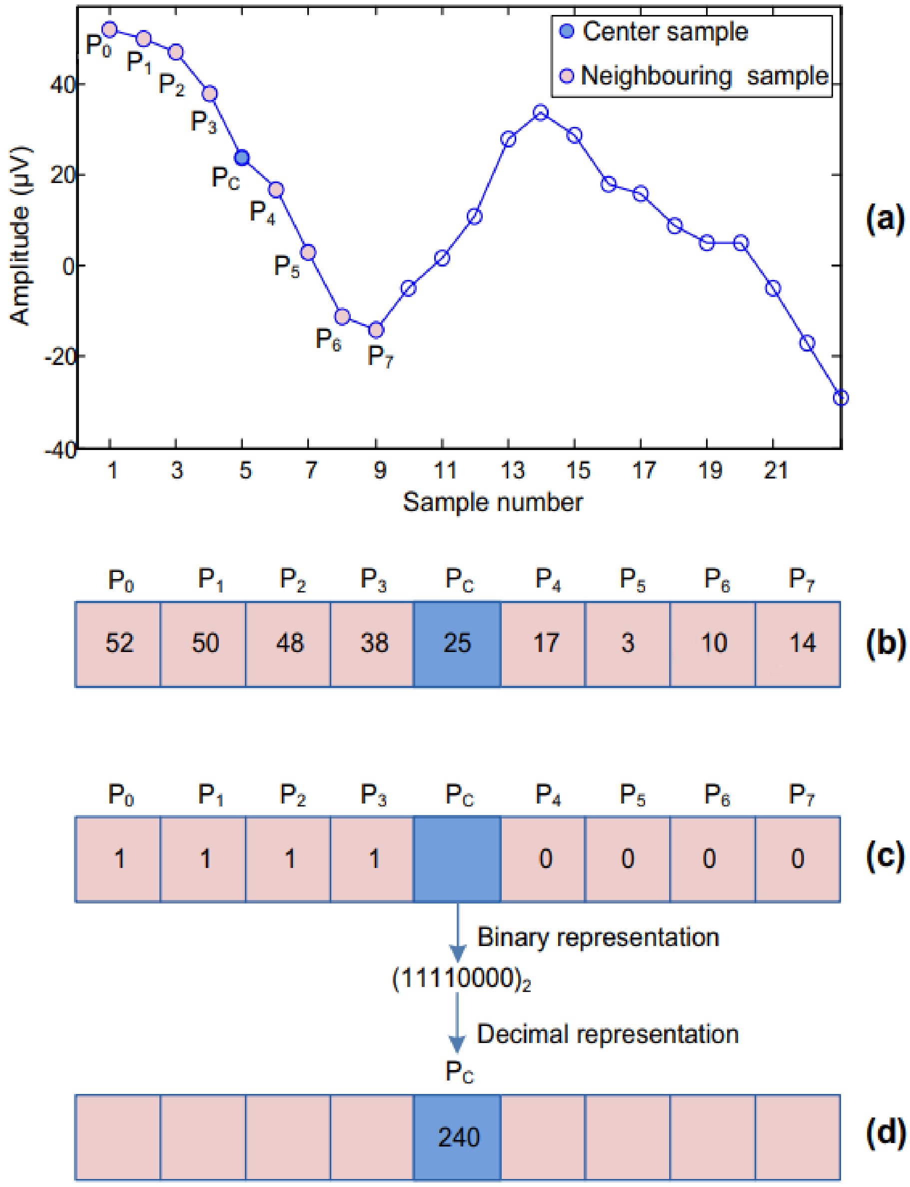

Figure 4.3: Feature extraction with LBP

9 adjacent samples were taken into account as coming before and after the center sample Pc for each sample of the signal (see Figure. 4.3(b)). The four nearby samples were taken from each center sample (Pc) before (P0, P1, P2, P3) and after (P4, P5, P6, P7). The values of all nearby samples P = P0, P1, P2, P3, P4, P5, P6, P7 were compared with the value of the central sample (Pc), just like in Figure. 4.3(c). The eight nearby samples were thresholded against Pc, as shown in equation, to create the binary number . This Pi value is taken as 1 if the bordering Pi value is larger than or equal to the center value, and 0 otherwise. As a result, a neighborhood's binary LBP code was created. This binary code's decimal value corresponds to the local structural data surrounding the specified Pc (see Figure.4.3(d))[26] .

The applied LBP signal includes values for each signal sample that range from 0 to 255. Different patterns are associated with different 1D-LBP values. The frequency at which each of these 256 unique patterns arises in a particular signal. Using the scored or selected features allows for a reduction in the number of patterns in a EEG signal without sacrificing much data. These chosen features also indicated the frequency of signal appearances of unique concealed patterns.We explore certain unique LBP values that exhibit strong morphological characteristics in the EEG signal. The EEG signal's downward and upward going properties can be captured by the LBP value of 240 and 15. LBP value of 240 is obtained if there are 9 consecutive decreasing sample points. It suggests that the four post samples (P5 to P8) are having smaller amplitude than the four prior samples (P1 to P4), which have bigger amplitudes than the center sample (Pc). The LBP value for 15 catches the growing trend in the EEG signal and acts in a manner opposite to that of the LBP value for 240. Additionally, the LBP values of 0 and 255 give us a way to identify the EEG signal from other signals. LBP 0 and 255 represent maxima and minima, respectively, with the center value at the peak or valley of the EEG signal's 9 consecutive sample points. Form 1 to 255 values from LBP converted to 1D LBP by choosing 2transition method. A 1D-LBP pattern is a uniform pattern (LBPu2) if it contains at most two bitwise transitions from 0 to 1 or 1 to 0 at its binary representation when the binary string is considered circular. For example; 11100001 (with 2 transitions) is a uniform pattern, whereas 11110101 (with 4 transitions) is a non-uniform pattern. Thus, the feature dimension was reduced, down to 58 features. The bins of the signal will represent the different local patterns observed in the segment. Concatenate the signals from all segments to create a feature vector that represents the local texture patterns across the entire signal. Use this extracted LBP features as input to a machine learning algorithm, like SVM and KNN to train a model for emotion classification.

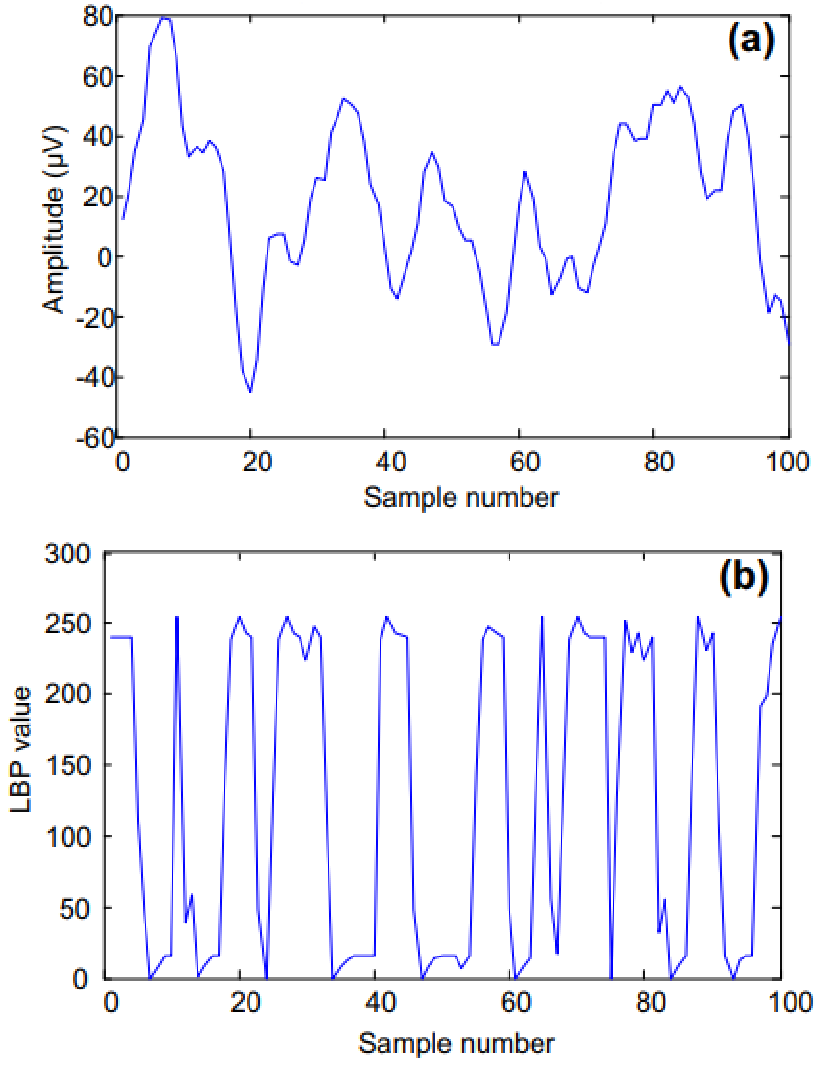

Figure 4.4: (a)A segment of the raw EEG signal (b)LBP applied signal

The model can learn to recognize patterns in the LBP features and classify the emotional state of the person.

4.4 KFOLD CROSS VALIDATION

Kfold Cross-Validation is a statistical method for estimating machine learning model skill. It is often used in applied machine learning to compare and select a model for a specific predictive modeling problem since it is simple to grasp, simple to implement, and produces skill estimates with lower bias than other methods [27] .

- The dataset is randomly partitioned into k equal-sized subsets or folds.
- The model is trained and evaluated k times, with each iteration using a different fold as the test set and the remaining folds as the training set.
- For each iteration, the model is trained on the training set and evaluated on the test set. The evaluation metric(s) of interest, such as accuracy or mean squared error, are recorded.
- The final performance of the model is typically summarized by computing the average and standard deviation of the evaluation metric across all k iterations.

The main advantage of k-fold cross-validation is that it provides a more robust estimate of a model's performance compared to a single train-test split. By repeating the training and evaluation process multiple times on different subsets of the data, it helps to mitigate the impact of the specific data points used for training or testing.

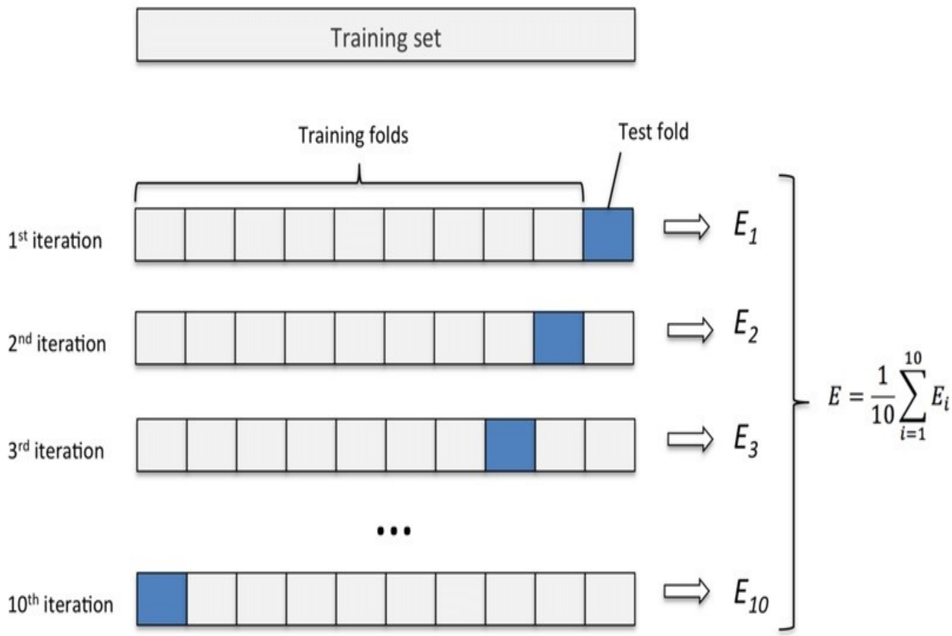

Figure 4.5: KFold cross validation technique

4.5 CLASSIFIERS

4.5.1 K-NEAREST NEIGHBOUR

One of the simplest machine learning algorithms, based on the supervised learning method, is K-NN . The K-NN algorithm makes the assumption that the new case and the existing cases are comparable, and it places the new instance in the category that is most like the existing categories. A new data point is classified using the K-NN algorithm based on similarity after all the existing data has been stored. This means that utilising the K-NN method, fresh data can be quickly and accurately sorted into a suitable category. Although the K-NN approach is most frequently employed for classification problems, it can also be utilised for regression. The K Nearest Neighbor algorithm, which is used for both regression and classification (most frequently), belongs to the domain of supervised learning. It is a flexible approach that may also be used to resample datasets and impute missing values. The K Nearest Neighbor method, as its name suggests, uses K Nearest Neighbors to forecast the class or continuous value for a new data point.

K value determines how many neighboring points have to be considered,depending on the number of points and the distance between them, the method operates by calculating the distance between these points' mathematical values. Figure 4.4 shows the working of KNN

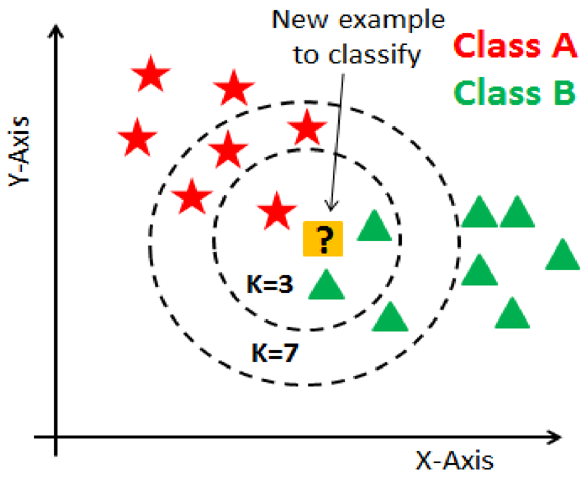

Figure 4.6: KNN classifier

classifier [28] . It determines the chance that each data point will be similar to the test data by first calculating the distance between each data point and the test data. The highest probability points are used for classification. The distance function can be Hamming, Minkowski, or Euclidean. Euclidean is used as a default method. If (x1, y1),(x2, y2) are the coordinates of two points, then the formula for Euclidean distance, D is

$$D=\sqrt[2]{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

The input x is then assigned to the class with the highest probability once the distance D has been calculated by the above equation.The formula for probability is shown in below equation.

$$P(y=j \mid X = x) = \frac{1}{K} \sum_{i \in \mathcal{A}} I\left(y^{(i)} = j\right)$$

4.5.2 SUPPORT VECTOR MACHINE

Support Vector Machines(SVM), which is a popular supervised machine learning algorithm used for classification and regression tasks. SVMs are particularly effective for dealing with complex datasets and can handle both linearly separable and non-linearly separable data.The basic idea behind SVM is to find an optimal hyperplane that best separates the different classes in the input feature space. The hyperplane is defined by a subset of the training data points called

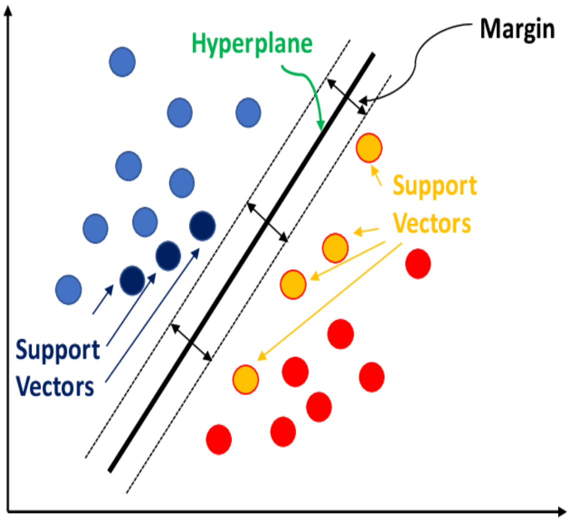

Figure 4.7: SVM classifier

support vectors, which are the closest points to the decision boundary. SVM aims to maximize the margin between the support vectors of different classes, resulting in a robust classifier [29] .

SVMs have been widely used for EEG-based emotion recognition tasks. The goal of EEG-based emotion recognition is to classify or predict the emotional state of an individual based on their EEG signals. SVMs can be effectively employed as classifiers in this context.

4.6 SUMMARY

In this section, theoretical information of traditional LBP ,SVM KNN and Kfold cross validation are explained. Moreover, 1D-LBP based feature extraction method was discussed.

Chapter 5

RESULTS

5.1 DATA DESCRIPTION

The DEAP dataset used in this project. The DEAP dataset consists of 32 subjects, 16 of them are women and the remaining 16 are men.These 32 participants watched a one-minute video, and the EEG readings during that time were captured with the aid of 32 scalp electrodes.During the experiment, participants physiological signals and self-reported emotional ratings were recorded. In a similar manner, each participant is shown 40 videos of one-minute duration. The data is first collected at 512 Hz sampling frequency and then down-sampled to 128 Hz.

The dimension of the data and the sampling rate are mentioned in the Table and the graphical version of the DEAP dataset is mentioned in the Figure 4.3 The dataset consists of the recordings of the physiological signals (EEG and EOG) for a length of 63 sec. It is expected that during the initial viewing of the videos, emotion labelling has not begun. The 3-s duration is therefore regarded as the baseline recording. There are a total number of 8064 samples for this time duration (63 sec x 128 Hz). For the emotion labelling, the participants are asked to write down the levels of valence (1–9), like/dislike (1–9), dominance (1–9), and familiarity (1–5), as well as arousal (1–9). The resulting signals are downsampled at a frequency of 128 Hz, and the artefacts are eliminated using a bandpass filter (4-45 Hz).Each trial is the outcome of all 40 channels that are available in the experiment setup for recording physiological signals. The 8 channels/electrodes are utilised to collect EOG data, while the remaining 32 are inserted into the scalp to collect EEG signals[30]. Therefore, a single individual will undergo a total of 40 trials, and likewise there will be a data of 32 subjects [31].

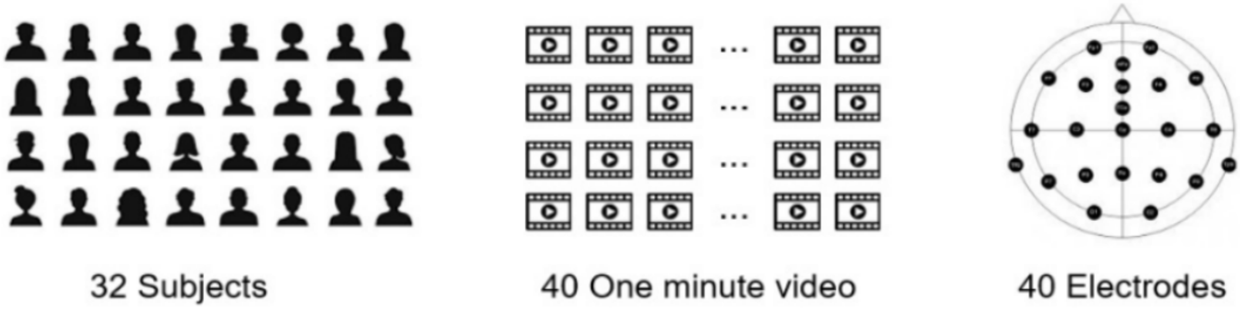

Figure 5.1: DEAP dataset

Table 5.1: Representation of DEAP dataset

Data	$40 \times 40 \times 8064$ video/trials $\times$ channel $\times$ data
Labels	40×4 video/trials $\times$ label (valence, arousal, dominance, liking)
Sampling rate	128 Hz

5.2 PRE-PROCESSING

As mentioned earlier the DEAP dataset contains both EEG and Electrooculogram (EOG) signals, where the 32 electrodes for the experiments records the EEG signals while the remaining records EOG. The nature of the EEG necessitates proper preprocessing and the removal of noise and artefacts. Electrooculogram (EOG) data (eye-generated artifacts) had been eliminated from 14 the DEAP dataset. EEG measurements from 40 trials over 32 channels and 32 subjects make up the utilised data. With the use of the Valence-Arousal model, one can determine how each trial corresponds to a certain emotion. Each trial will last one minute, therefore there will be 32 one-minute EEG measurements total for each session. The data is initially divided into distinct trials (40 trails x 32 subject), which is a total of 1280 trials, with each trial containing readings from 32 channels (32 channels x 40 trials). In a trial, the same emotion is mapped to each channel reading.In total, there are 51200 samples of channel data in the dataset (32 subjects x 40 trials x 40 channels), but only 40960 of those samples include the relevant information needed for this study (32 subjects x 40 trials x 32 channels). For a single subject, it is 1280 channel data samples[32]

5.3 EMOTION MAPPING

Its been mentioned that, after each video trials, the participants are asked to write down the levels of valence (1–9), like/dislike (1–9), dominance (1–9), and familiarity (1–5), as well as arousal (1–9) for their emotional state recognition. From this values, considering the values of valence and arousal only, a certain set of rule is formulated for the classification of emotions.The value is in the range of 1 to 9, where 9 represents the highest value and the 1 represents the lowest value. For eg., consider the value of arousal is 9, then the person is in a state of high excitement or very alert. Like this, 4 emotion classes are formulated with the values of valence and arousal[33]. By considering 5.5 as a threshold value, above which the valence and arousal is considered to be high and below which they are considered to be low. By the combination of the 4 group, four quadrant can be constructed. Each quadrant represents a combination which in-turn represents an emotion. The combinations and emotions considered are:

- high arousal and low valence (angry)
- low arousal and high valence (calm)
- high arousal and high valence (happy)
- low arousal and low valence (sad)

The four quadrants of the valence-arousal space , shown in Figure.4.3 This figure addresses the 4-class classification problem according to the produced emotions in each of these quadrants.High valence low valence and low arousal low valence and Vice versa are considered as 2 class classification.So, the problem definition is Based on the EEG readings obtained from the dataset, categorise different emotion types.

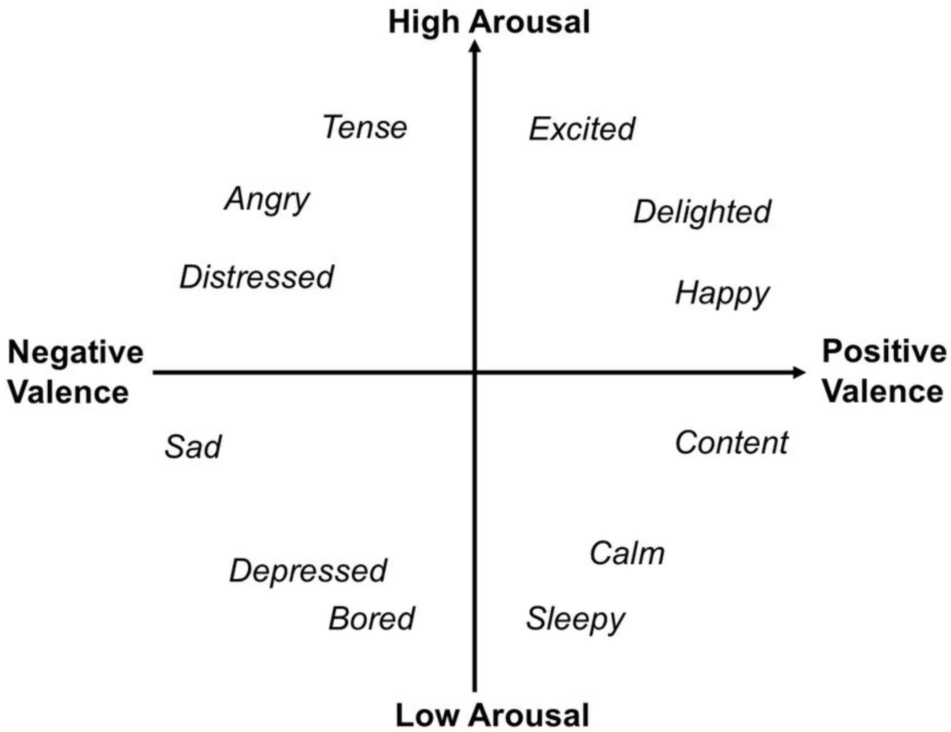

Figure 5.2: Valence-Arousal model

5.4 PERFORMANCE EVALUATION

The efficiency of a classification model is evaluated using a N x N matrix termed a confusion matrix, where N is the total number of target classes. The machine learning model's predicted goal values are compared to the actual goal values in the matrix. This gives us a thorough insight of the errors that our categorization model is committing as well as how effectively it is working. Precision and sensitivity are equally crucial for information retrieval because it requires both. When compared to the negative class, it also prioritizes the positive classes. Precision and sensitivity only use true positives (TP), false positives (FP), and false negatives (FN); true negatives (TN) are not taken into account.

- True positive - Predicted class and actual class both are positive
- True negative – Predicted class and actual class both are negative
- False positive – Predicted positive but actual class is negative
- False negative - Predicted class is negative but actual class is positive.

Figure 5.3 represents a 2x2 confusion matrix showing the TP, TN, FP, FN exclusively for class0. From this various parameters for performance evaluation can be calculated. Precision deter-

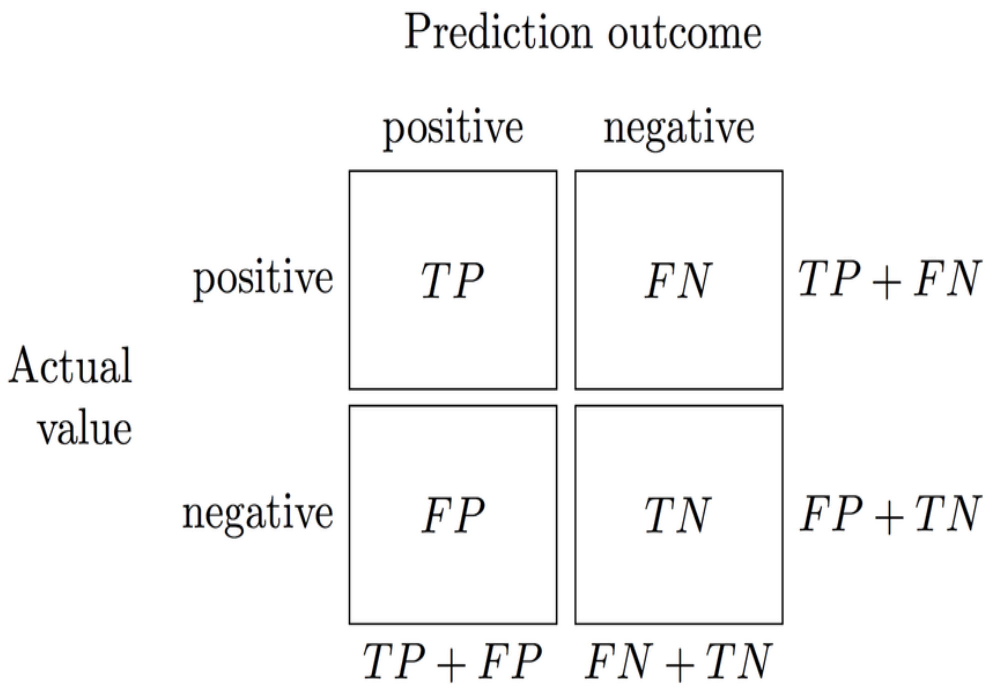

Figure 5.3: A 2X2 Confusion matrix showing the TN, TP, FN, FP

mines the percentage of the truly positive out of all the positive predicted, whereas the sensitivity gives the predicted positive percentage out of all the total positive.Specificity and sensitivity reveal the possibility of false negatives and false positives. The statistical evaluations of accuracy and precision of a test demonstrate its essential reliability. The terms used to describe the origins of variability are not interchangeable. A test method may be precise (reliably reproducible in what it measures) without being accurate (actually measuring what it is intended to measure), or vice versa.The performance of the recommended emotion classification algorithm has been validated using metrics including accuracy, sensitivity, specificity, and precision.The given equations illustrates how these parameters are represented mathematically.

$$\begin{aligned}
\text{Precision } &= \frac{TP}{TP+FP} \\
\text{Accuracy } &= \frac{TP+TN}{TP+FP+TN+FN} \\
\text{Sensitivity } &= \frac{TP}{TP+FN} \\
\text{Specificity } &= \frac{TN}{FP+TN}
\end{aligned}$$

Here we considering 2 class problem Low arousal , Low valence and High arousal , Low valence or Low arousal , High valence and High arousal and High valence

5.5 RESULT OBTAINED FROM KNN AND SVM

After obtaining features from the histogram of LBP, which has a value that can range from 0 to 250, the uniform LBP is calculated using those values. It contains at most two bitwise transitions from 0 to 1 or 1 to 0 at its binary representation when the binary string is considered circular. For example; 11100001 (with 2 transitions) is a uniform pattern, whereas 11110101 (with 4 transitions) is a non-uniform pattern. Thus, the feature dimension was reduced, down to 58 features.The selected numbers are 0, 1, 2, 3, 4, 6, 7, 8, 12, 14, 15, 16, 24, 28, 30, 31, 32, 48, 56, 60, 62, 63, 64, 96, 112, 120, 124, 126, 127, 128, 129, 131, 135, 143, 159, 191, 192, 193, 195, 199, 201, 223, 224, 225, 227, 231, 239, 240, 241, 243, 247, 248, 249, 251, 252, 253, 254, 255. This features are used for classifier, the results of each subject are used to evaluate the model's performance by analyzing the confusion matrix and determining the classes precision, sensitivity, specificity and accuracy.

Here precision determines the proportion of the true positive out of all the positive predicted. While sensitivity provides the projected positive percentage out of all the positive. Specificity and sensitivity reflect the possibility of false negatives and false positives. The statistical evaluations of accuracy and precision of a test demonstrate its essential reliability.

Table 5.2: Result obtained from proposed models

Channel	class	Features	Performane	
1 to32	2	58	SVM	43.2%
			kNN	36.7%
1 to7	2	58	SVM	73.4%
			kNN	60.7%
7 to23	2	58	SVM	73.54%
			kNN	82.12%
$2, 6, 10, 15, 18, 20, 21, 25$	2	58	SVM	92.47%
			kNN	90.23%
$7, 23, 29, 32$	2	58	SVM	82.46%
			kNN	76.23%

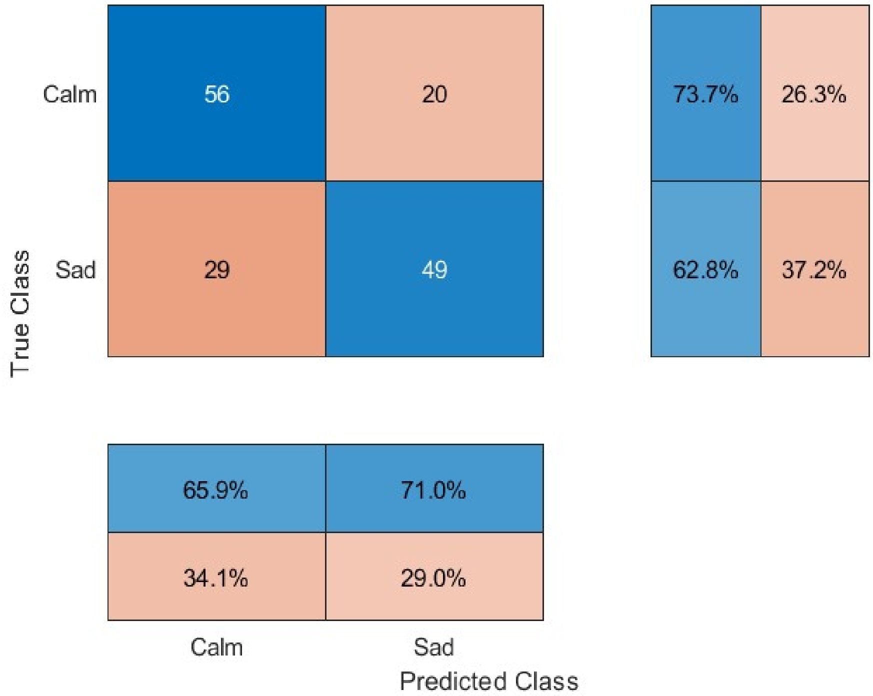

Figure 5.4: A 2X2 Confusion matrix of KNN

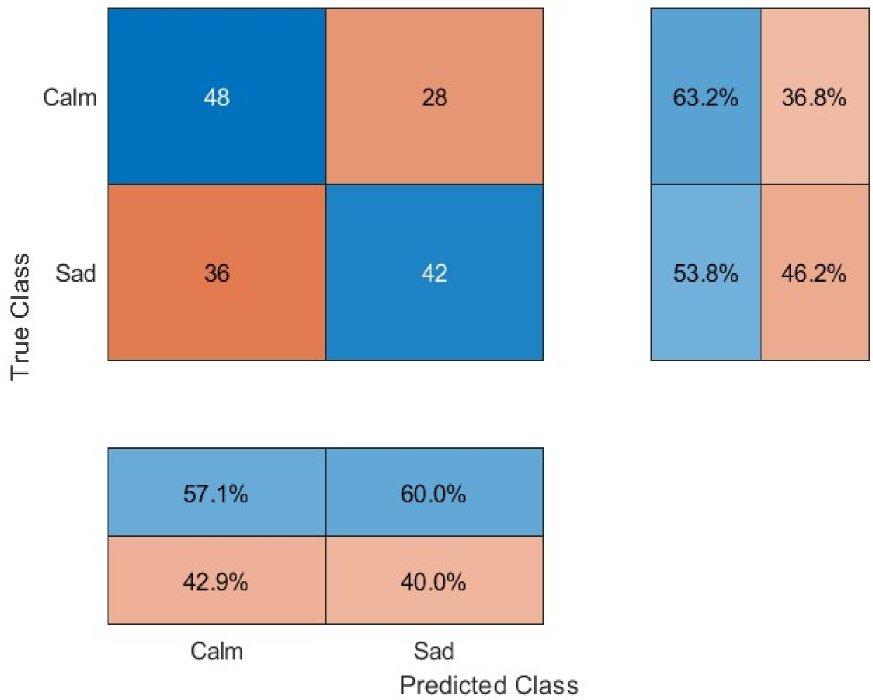

Figure 5.5: A 2X2 Confusion matrix of SVM

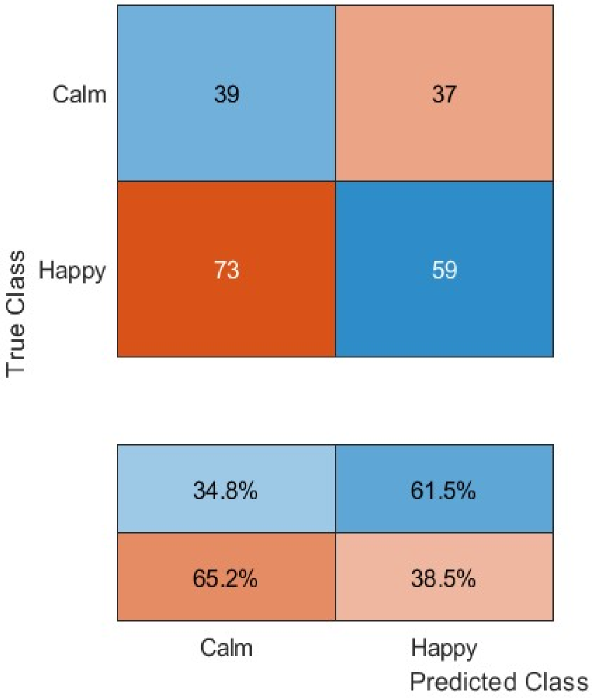

Figure 5.6: A 2X2 Confusion matrix of KNN

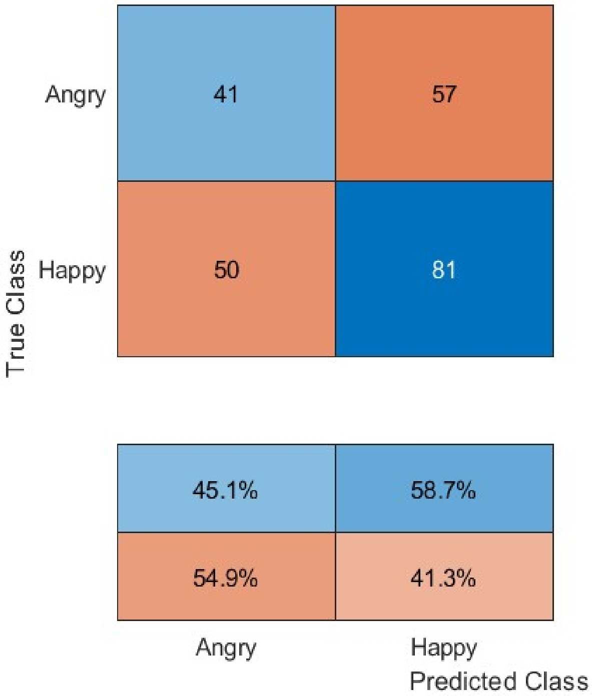

Figure 5.7: A 2X2 Confusion matrix of KNN

Figure 5.8: A 2X2 Confusion matrix of SVM

5.6 COMPARISON WITH PREVIOUS WORK

The accuracy of the proposed model is compared with the previous works that have been done on this area by other research enthusiasts.

Table 5.3: Comparison of the proposed models with the previous works

Author	Classifier	Classes	Accuracy
Li et al.[1]	CLRNN	2	74.12%
Horlings[13]	SVM	2	81%
Frantzidis et al.[17]	SVM	2	81.3%
Murugappan et al.[18]	SVM	2	71.3%
Brown et al.[26]	KNN	2	82%
Hosseini et al.[21]	SVM, KNN	2	82%
Schaaff et al.[25]	SVM	3	66.7%
Ackermann et al.[24]	Random forest	3	55%
Gupta et al.[22]	PNN	4	71.43%
Nakisa et al.[23]	Random forest	4	67.47%
Proposed work 1	SVM	**2**	**92.47%**
Proposed work 2	KNN	**2**	**90.23%**

5.7 SUMMARY

This chapter discussed the classification of different emotional states such as Angry, calm,happy and sad. This chapter verified the result obtained from the different experimentation conducted. Two methods of classification are used, KNN and SVM . Performance of the model is also analysed using various parameters. Each model selected in this work is comparable with any previous work as it can provide a better performance in categorization task

Chapter 6

CONCLUSION

6.1 CONCLUSIONS

The study that was conducted demonstrated the potential for using EEG waves with binary patterns to classify emotions. For feature extraction from the EEG signals, a novel method based on the application of one-dimensional local binary patterns (1D-LBP) was described. An excellent emotion categorization method requires the right features to be derived from EEG signals. It's crucial to remember that features are the condensed parameters that describe how the original EEG data behaved. The findings of the experiment demonstrated that the proposed method could classify emotions with a high degree of accuracy. With characteristics based on the 1D-LBP approach, various EEG data sets generally showed great accuracy. The computational effectiveness and applicability of the suggested methodology was one of its benefits. One of the best options for real-time signal processing is the 1D-LBP method because of its high performance and low computing complexity properties.

6.2 SCOPE FOR FUTURE WORK

In the future, investigate the 2 transition in 4 class method and 4 transition or any other transition method in LBP gives better performance than 2 transition.

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