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Emotion Detection from EEG Signal using KPCA and LSTM

Asma Rafique[1], Gagan Sharma[2]
[1]MTech Scholar, [2]Assistant Professor, Department of CSE,
Sri Satya Sai College of Engineering,
RKDF University, Bhopal, M.P, India

Abstract – *In this paper, three different feature reduction techniques such as PCA, KPCA and Fast-ICA are used to reduce features. LSTM with different classifier was evaluated and it was observed that LSTM with random forest classifier outperforms best. The result is analyzed on varying testing and training ratios. The classification accuracy of 97% were obtained by KPCA and LSTM with random forest classifier. The results showed that using appropriate feature for extraction emotional state such as Fast Fourier Transform (FFT) and suitable learner such as LSTM with random forest classifier, recognizer system can be accurately.*

Keywords –EEG Signal, Emotion Recognition, EEG, BCI, Feature Extraction, Feature Reduction, Classification, Accuracy.

I. Introduction

Understanding and recognizing emotions is crucial. Language, conduct, and facial expressions all effectively convey emotions [1, 2]. However, people are capable of misrepresenting these. Patients with paralysis, strokes, ALS [3], or brain disorders are unable to use these pathways effectively. Therefore, it is crucial for everyone, including those with conditions, to be able to recognize emotions. Consequently, it is crucial to research the physiological factors that change in response to emotions.

This work focuses on the detection of emotions based on electroencephalogram (EEG) signals. EEG is a way to record electrical signals from the brain [4]. EEG is a simple, rapid, non-invasive and convenient method that is widely used in biomedical research and medical diagnosis. Therefore, EEG is a preferred technique for classifying emotions [5].

Many researchers have given different models related to emotions. The first and foremost model was given by Darwin and was further developed by other two scientists named Plutchik and Ekman. According to Plutchik, there are basically eight emotions such as sadness, anger, joy, acceptance, disgust, surprise, fear, and curiosity [6] while Ekman suggested that all emotions comprises of six basic feelings that are happiness, anger, fear, sadness, disgust and surprise [7]. Figure 1.1 shows the basic emotions felt in our daily lives..

Figure 1 Basic Emotions

Russell, J.A. (1980) developed a circumplex model of affect describing the emotions in a two dimensional space. This model represents the interconnection of emotions like anger, fear, happiness, joy, depression and displeasure. The emotional states were considered as pleased along the x-axis and the level of activation along the y-axis. Words describing these emotions were placed in such a way that the like meaning words were closer to each other whereas the opposites lied diagonally [9-10]. This model was further modified by Lang et al. who represented the two dimensions as valence and arousal [11]. Figure1.2 shows the circumplex model of affect.

Figure 2 Circumplex Model of Affect

An Emotional Model consists of two dimensions- Valence on X-axis and Arousal on Y-axis. Valence and arousal are defined by Self-Assessment Manikin Method. SAM ratings range between 1 to 9.Valence can be represented as positive or negative state of emotions. The highest value of valence indicates a person is happy and lowest value of valence indicates a person is sad. Similarly, Arousal is defined on SAM scale from 1 to 9.The highest value of arousal indicates a person is excited and lowest value of arousal indicates a person is unexcited or calm.

A Brain-Computer Interface (BCI) could be a means that of communication that permits a subject to send commands to some device solely by the means that of brain activity [13]. And, therefore, they state that it's thought-about the sole means of communication for people who are suffering from some specific motor disabilities. The aim of a BCI is to “read” the user’s intent, that is usually done using classifiers that take some illustration of readings of brain signals and translate them into a category from a collection of states or intentions.

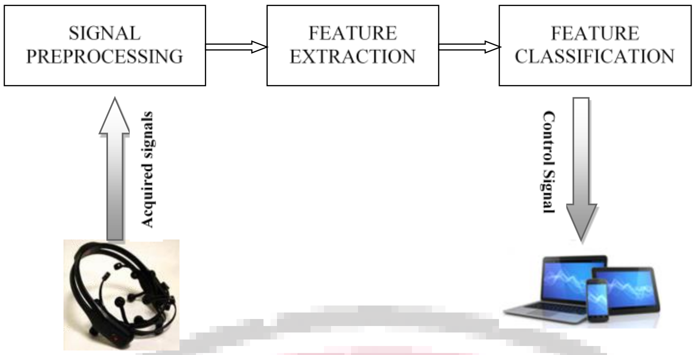

Figure 3 BCI Interface

II. Literature Review

A cluster of human affective states known as emotions are thought to arise in response to specific stimuli from interpersonal or environmental events [11]. The development of decision-making preferences and self-motivation are significantly influenced by various emotions [12]. The depiction of emotions includes discrete scales for emotions like rage, anxiety, satisfaction, boredom, etc. O level of awakening valence [13–15]. Two-dimensional coordinates are used in the latter case to explain the nature of emotionality at the core of affects [16]. Excitation dimension is being used to accurately measure multiple aspects of rest at excitation levels, while valence dimension indicates whether emotional responses are favorable (happy) or negative (sad) at the level of excitation-valence, where various discrete emotional states, p. It can be defined by combining various excitement levels and valence, for instance, cheerful, peaceful, disheartening, and frustrated.

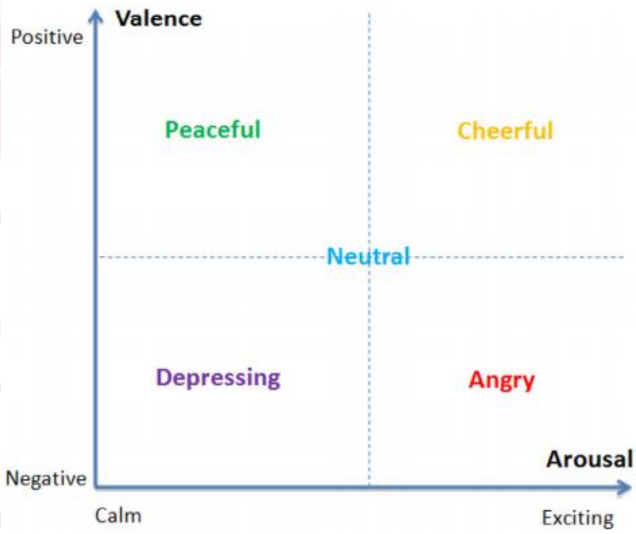

Figure 4 Arousal Valence Plane

Despite the fact that research on emotion detection using electroencephalogram (EEG) data is becoming very active in recent years, stimulus familiarity—a significant subjectivity issue—has received little attention. Capturing emotional signals from human responses, integrating emotional responses, and finally predicting the transient emotional state are the three main tasks of an estimator or classifier of intelligent emotions. The relevant approaches can be broadly categorized into two groups: facial/vocal signals and physiological signals. The generalizability of behavioral data may be constrained by specific users who are trained to have no expression. However, due to their reproducibility, objectivity, and captivating ease of use with a portable application on wireless communication devices, physiological parameters and real-time electrophysiological information of the central nervous system (CNS) or of the peripheral nervous system (PNS) will register. The feasibility of using different physiological signals to assess emotions has been investigated in a well-researched work. More specifically, the electroencephalogram (EEG) of many frontal as well as parietal cortical regions allowed for the identification of the variability of emotion.

(Joshi & Ghongade, 2021) [19] implies emotion detection based on Linear Formulation of Differential Entropy (LF-DfE) feature extractor and BiLSTM network classifier for Electroencephalography (EEG) signal. The EEG signal's nonlinearity and non-Gaussianity are successfully picked up by LF-DfE. The BiLSTM network learns spatial information from various brain regions and captures the long-term dependence of the EEG signal. On the SEED database, the developed framework is being used to distinguish between positive, negative, and neutral emotions, while the DEAP database uses valence and arousal. The SEED database's average accuracy of emotion detection has increased for subject contingent approaches by 4.12%, noncontingent approaches by 4.5%, and interdependent approaches by 1.3%.

(Kumar & Kumar, 2021) [20] introduces a brand-new automated emotion recognition system that uses deep learning principles to identify emotions from EEG signals from video games. 28 different participants' EEG data were collected using 14-channel Emotive Epoc+ wearable and portable EEG equipment. Each participant had access to 20 minutes' worth of EEG data while they played four different emotional computer games for five minutes each. The proposed framework is straightforward enough to divide emotions experienced while playing games into four categories. The outcomes show that the proposed framework for model-based emotion detection is a workable approach for identifying emotions from EEG data. The network attains 99.99 percent accuracy while taking less time to compute.

(Peng et al., 2021) [21] By adding an auto-weighting variable to the least square regression, I propose the GFIL structure to simultaneously accomplish these objectives. Contrary to the popular method of trial and error, GFIL automatically accomplishes the recognition after training. In particular, GFIL can 1) automatically identify the crucial frequency bands and channels, 2) adaptively discriminate the contributions of various feature dimensions, and 3) quantitatively rank as well as choose the features by the learned auto-weighting variable.

(Fu et al., 2021) [22] In this study, a conditional generative adversarial network (cGAN) is suggested to determine the relationship between EEG data connected to emotions, a coarse label, and an image of a facial expression. In order to achieve the fine-grained estimation and visualization of EEG-based emotion, a corresponding training strategy is also proposed. The experiments demonstrate the viability of the suggested technique for producing fine-grained facial expressions. The generated image's image entropy shows that the suggested method can successfully visualize fine-grained facial expressions.

(Sharma et al., 2021) [23] explains the benefits of a fully automated depression detection system, pointing out that manual EEG signal analysis is time-consuming, tedious, and difficult to do without a lot of practice. This study introduces a new EEG-based computer-aided (CAD) hybrid neural network for depression screening known as DepHNN (Depression Hybrid Neural Network). The suggested approach makes use of windowing, long-short term memory (LSTM), and convolutional neural network (CNN) architectures for the learning of sequences.

(Zhang et al., 2022) [24] introduce the generative adversarial network-based self-supervised data augmentation as a novel data augmentation structure (GANSER). The suggested scheme produces high-quality and highly diverse simulated EEG samples, making it the first to merge adversarial training with self-supervised learning for EEG-based emotion detection.

(Bao et al., 2021) [25] To build a transfer model for EEG-based emotion recognition, suggest a two-level domain adaptation neural network (TDANN). In particular, a deep neural network is used to extract deep features from the topological graph that preserve topological information from EEG signals. On the SEED data set, accuracy reached 74.93 percent. On the self-built data set in the cross-subject transfer experiment, the ability to distinguish accurately between sadness (83.79 percent), anger (84.13 percent), and fear (81.72 percent) was on par with the ability to distinguish accurately between joy and other emotions. The SEED data set's average accuracy was higher than WGAN-DA at 87.9 percent.

(Chen et al., 2021) [26] suggest the domain-invariant and domain-specific features are taken into account by the multi-source EEG-based emotion recognition network (MEERNet). Then, in order to extract domain-specific features, we construct numerous branches relating to multiple sources, and DA is then carried out between the target and every source. Initially, researchers assume that different EEG data share the same low-level features.

With an average accuracy of 86.7 percent and 67.1 percent, respectively, experimental results demonstrate that the MEERNet performs better the single-source methods in cross-session and cross-subject transfer scenarios.

(Kim et al., 2022) [27] aimed to acquire a new EEG dataset based on the discrete emotion theory, termed as WeDea (Wireless-based eeg Data for emotion analysis), and propose a new combination for WeDea analysis.

(Subasi et al., 2021) [28] presents a novel electroencephalography (EEG)-based automated framework for emotion recognition. The suggested approach is simple and is divided into four main stages: reprocessing, feature extraction, feature dimension reduction, and categorization. The pre-processing stage, which includes the use of a Symlets-4 filter for noise reduction, employs a discrete wavelet transforms (DWT) centered noise reduction technique, herein referred to as multi scale principal component analysis (MSPCA). As a feature extractor, a tunable Q wavelet transform (TQWT) is used.

(Rahman et al., 2021) [29] uses a convolutional neural network (CNN) to categorize the emotion because CNN has enhanced feature extraction abilities to suggest a method that converts EEG (electroencephalography) signals to topographic images that contain the frequency as well as spatial information. The suggested technique, which significantly improves classification accuracy, prepares topographic images from relative power spectral density instead of power spectral density. The suggested approach is used with the well-known SEED database and has produced results that are superior to those of the state-of-the-art.

Nicolaou et al. [30]used the audiovisual methods to detect the valence and excitement in the database of the week. They used the Support Vector Regression (SVR) and long-term bi-directional long-term recovery networks (BLSTM-RNN) to continuously capture emotions over time and in size. Nicolaou et al. It has also been proposed to use anrelevant vector machine (RVM) that attenuates the RVM output for continuous detection of emotions. Although they showed how they improved RVM performance for continuous emotion recognition, they did not directly compare their performance with the recurrent BLSTM neural network.

III. Methodology

This study aims to categorize various emotions, as shown in figure 5. The four important stages of the system's procedure are as follows. Acquisition of signals was the first step. The second stage was signal preprocessing, which eliminated unwanted files and background noise. Extraction of features from the EEG signals was the third step. The categorization of the signals to the associated emotions was the fourth step.

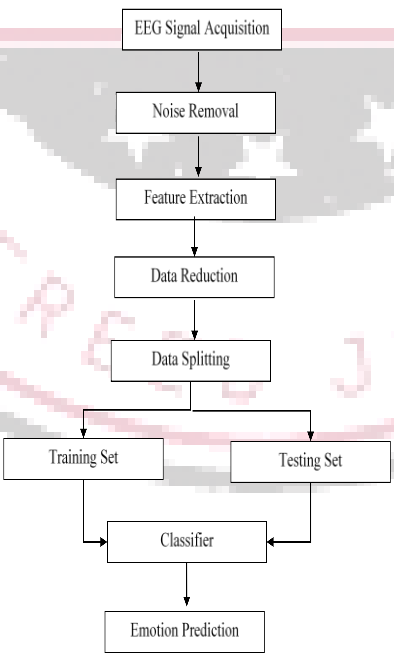

Figure 5 Flow Chart of Proposed Methodology

Signal Acquisition **-** EEG data from the participants are collected using the Emotiv EPOC device. Emotiv EPOC uses 14 channels. They are known by the channel numbers AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, and O2. The device uses sampling at a frequency of 128 Hz.

Preprocessing **-** To eliminate the undesired artifacts, a band pass filter using a Butterworth filter was applied to the EEG signals. Lowering the frequency band utilised, the number of channels (channel selection), and the selection of attributes has an immediate impact on lowering the processing time and raising memory utilization, both of which improve system performance.

Feature Extraction **-** Various methodologies for features extraction from the EEG signals were put into practice to compare. Numerous techniques, including time domain, frequency domain, and time-frequency domain methodologies, were employed because the EEG is a non-stationary signal. The most suitable method for feature extraction using time-frequency domain techniques was Fast Fourier transform (FFT).

Dimension Reduction and Classification of Emotion Signals **-** A feature vector for each trial, denoted by the notation Y = [y1, y2,... yn], is obtained after some suitable signal features have been extracted. The dimension of every feature vector that is fed to the classifiers needs to be decreased since the classifiers are cursed by dimensionality. It is possible to create a matrix Z with a column dimension (m) that is significantly smaller than the original matrix by minimizing the dimensionality of the matrix A, which has a matrix with size nm wherein the number of its rows (n) is greater than the number of its columns (m). The original matrix A projected into the vector Z through a linear transformation $Z = A^T Y$ and an initial vector Y, which allowed it to be reduced to a lower dimension.

This type of transformation causes some of the information in the original matrix to be lost, while classification is made simpler. In general, there is a trade-off between the amount of information lost and the degree of classification simplicity that must be taken into account. Numerous techniques, including Principal Component Analysis (PCA), Fast Independent Component Analysis (F-ICA), and Kernel Principal Component Analysis, have been used in studies to reduce the dimension of feature vectors (KPCA).

After the desired features have been extracted, LSTM network is used with Support Vector Machine (SVM), K Nearest Neighbor (k-NN), and Random Forest are just a few of the classifiers used to categorize EEG signals.

IV. Result Analysis

This section comprises with an analytical and numerical description of proposed algorithm for which is simulated to obtain the performance of the proposed algorithm. The result analysis is performed by analyzing the performance of different feature extraction techniques with LSTM. For evaluating the performance of these classifiers, the EEG emotion dataset is first of all cleaned. For cleaning purpose Butterworth filter is used to remove unnecessary noise from the dataset. Further data reduction techniques are used to reduce dimension of large dataset and finally dataset is divided into two groups i.e. training set as well as testing set. Figure 6-8 illustrates the performance analysis of different feature reduction techniques under different classifiers by varying training and testing dataset ratios.

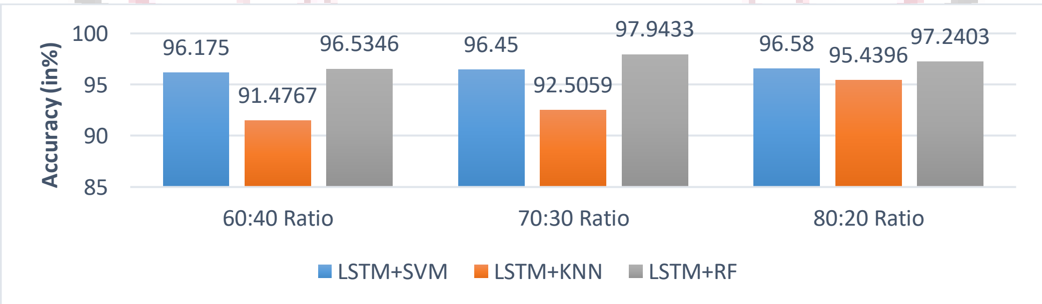

Figure 6 Performance Analysis on Feature Reduction Fast-ICA

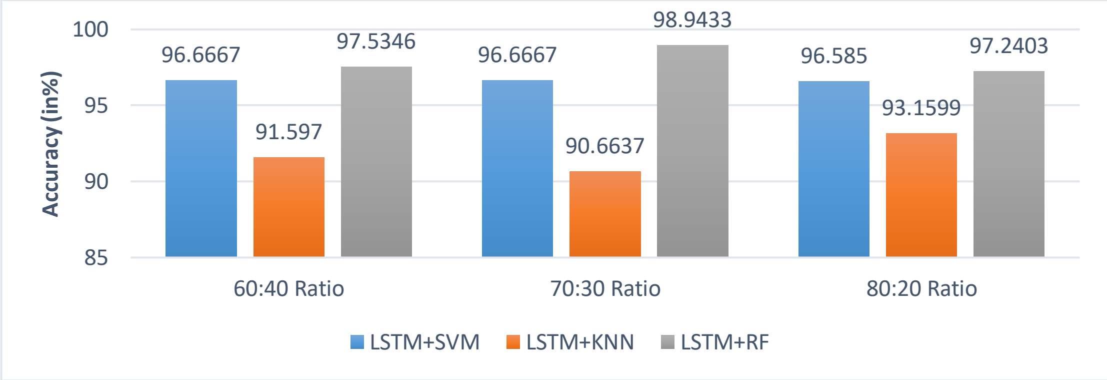

Figure 7 Performance Analysis on Feature Reduction KPCA

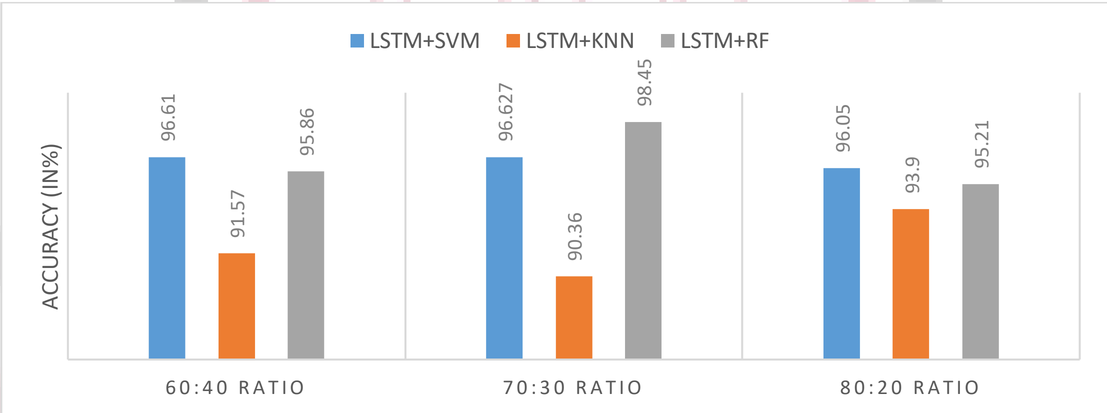

Figure 8 Performance Analysis on Feature Reduction PCA

Figure 9 Performance Analysis of SVM for KPCA, PCA and F-ICA

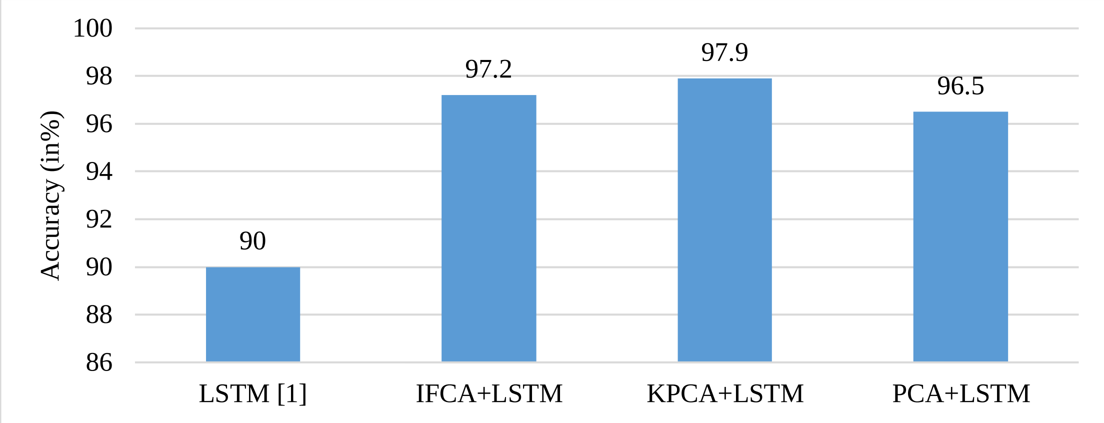

Figure 10 Comparative State-of-Art

V. Conclusion

In this paper, three different feature reduction techniques such as PCA, KPCA and Fast-ICA are used to reduce features. LSTM with different classifier was evaluated and it was observed that LSTM with random forest classifier outperforms best. The result is analyzed on varying testing and training ratios. The classification accuracy of 97% were obtained by KPCA and LSTM with random forest classifier

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