Electroencephalogram Electrode Selection and Parallel Merged Recurrent Neural Network for Emotion Classification

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***Abstract*— The field of biomedical signal analysis for the development of Brain Computer Interface(BCI) has seen significant improvement recently through the development of modern Deep Learning Algorithms. The Electroencephalogram(EEG) signal is non-stationary, non-linear, and contains a lot of noise as a result of aberrations brought on by muscle action, blinking and poor electrode contact, making research in this field particularly difficult.The number of electrodes used to record EEG signals on non-invasive wearable devices raises the dimensionality and, consequently, the computing complexity of the EEG data. We propose the reduction of said dimensionality through extensive feature extraction and channel selection. The proposed model also employs Merged RNN with the help of Long Short Term Memory (LSTMs) applied on features from each selected channel.The Dataset for Emotion Analysis using Physiological Signals (DEAP), the research standard for emotion recognition, has been used to validate the model's applicability and accuracy.**

***Index Terms*— Band Power, BCI, DEAP, EEG, Emotion Recognition, Fractal Dimensions, Hjorth Parameters, Merged LSTM, Support Vector Machine(SVM).**

I. Introduction

Emotion Recognition is a key component of Brain Computer Interaction devices due to thier significance on routine human life.Emotion is a physiological state that represents human sentiments, ideas, and behaviour. It is crucial to how people form perceptions and reason through their actions. By examining non-physiological signs like oration [1], facial statement [2], text [3] and body poise [4] one can recognise emotions. These signs can be challenging to identify, though. The use of wearable sensors could solve this issue. Sensory data like Electrocardiogram(ECG), Elecromyograms(EMG) and EEG from wearable devices can be utilized as input for emotion analysis.These inputs are sometimes seen as being more trustworthy because they rely on unconsciously occurring bodily fluctuations that are difficult to alter and are controlled by the Sympathetic Nervous System.

The term "EEG" refers to signals collected by noting voltage fluctuations that occur on the skull's veneer due to the galvanic activity in the brain's active neurons. [5]. Clinically and for research purposes, EEG is the most utilized human activity measuring technique. Owing to the various advantages that can be gained by properly analyzing EEG signals, a lot of reasearch has taken place on the same. One of the primary research area includes emotion recognition in the field of health, gaming and advertisement sectors. In the health sector, EEG has proved useful in diagnosing mental stress [6], dyslexia [7] and other mental disorders. [8] whereas in the gaming sector it is studied with the aim of ultimately replacing controllers and joysticks. [9]

The four lobes of the cerebral cortex are the frontal, parietal, temporal, and occipital. According to the number of electrodes, EEG devices can be divided into three groups: low-resolution (1-32), medium-resolution (33-128), and high-resolution (128) [10]. It is normal practise to apply electrodes to the scalp using the worldwide 10-20 system [11], where each electrode is placed according to its relative location. By placing EEG electrodes on the regions of the brain that are most effective at perceiving emotions, it is possible to reduce the number of electrodes while increasing wearer comfort.

The most potent channels for EEG-based emotion recognition are still being worked out from the perspective of emotion recognition. As a result, the aim of this study is to present an alternative perspective on the problems that scholars currently confront with the aforementioned issues. For the purpose of identifying human emotional states, we in particular concentrated on investigating the most pertinent routes that subsequently reduce computing complexity and mitigate noise.

In this study we have employed feature extraction in all three domains namely statistical, frequency and time domain to reduce the number of features from each channel. Then we have employed channel selection based on the accuracy obtained by classifying through Support Vector Machine(SVM). The final feature vectors thus obtained were divided channel wise and merged RNNs was employed with LSTMs to perform the classification of emotions in two measures namely valence and arousal.

The remainder of the paper is organised as follows: In Section 2 we have presented related research work to feature extraction, channel selection and emotion classification from physiological signals. Section 3 presents a brief description of the DEAP dataset followed by Section 4 which deals with feature extraction techniques we have employed followed by channel selection method and the proposed merged LSTM model. In Section 5 and 6 we have jotted down the results obtained and conclusion and future work respectively.

II. Related Work

Two emotions were classified by Channel et al. [12]. To ascertain the participant's emotions, they used SAM. They employed Fisher discriminant analysis (FDA) and Naive Bayes (NB) as their classification techniques. For NB and FDA, the classification accuracy was found to be 72 and 70%, respectively.

Based on EEG data, Murugappan et al. [13] categorised five emotions. They each employed EEG information obtained from 64, 24 or 8 EEG channels.They achieved maximum classification accuracy of 83.26% and 75.21%, respectively, using the linear discriminant analysis (LDA) algorithm and the kNN technique. Researchers employed the DWT method to divide the EEG signal into the alpha, beta, and gamma bands.For the extraction of features, these frequency bands were examined.

PCA was used by Zhang et al. [14] for feature extraction. Characteristics from two channels were extracted (F3 and F4). The researchers found that 73% of the classifications were accurate.

Support vector machine (SVM) and LDA were used by Bhardwaj et al. [15] to identify seven emotions. Fp1, P3, and O1 were the three EEG channels used in this study. Theta, alpha, and beta subbands of the EEG signal were studied by researchers. With SVM, the average accuracy was 74.13%, while with LDA, it was 66.50%.

Zhang et al [16] investigation into a ReliefF-based channel selection technique for EEG-based emotion detection demonstrated that the number of channels needed to complete the classification job could be drastically decreased without suffering an unacceptable loss of accuracy. They carefully analysed several strategies and classified four emotional states in order to select the best channels (joy, fear, sadness, and relaxation). For instance, they looked into subject-dependent and subject-independent channel selection using mean-relief-channel-selection (MRCS) using an SVM classifier. The best classification accuracy was attained by 19 channels using the DEAP dataset, which was 59.13% accurate.

EEG channel selection technique Relief-FGSBS, studied by Zheng et al. [17], used a self-gathered data set as well as the publically accessible DEAP dataset to test the approach. The study's findings demonstrated that the best EEG channels are primarily situated in the posterior occipital area and frontal lobe. SVM was used on EEG signals from 10 channels to classify emotions, with an a mean classification accuracy of 91.31%

Manual channel selection can be done with the aid of prior research or by employing strategies that maximise the selection of the most relevant channels, which are frequently the ones with the highest weighting factors. The number of channels employed reportedly improves the classification accuracy of emotional states, according to Li et al. [18]. With the DEAP dataset's 10, 14, 18, and 32 channels—which were chosen based on the expertise of other authors—they explored the EEG classification. Entropy and energy were calculated as properties of the discrete wavelet decomposition of four frequency bands.

Examining emotions was done using the five EEG channels with the best performance: P3, FC2, AF3, O1, and Fp1. [19], another method in which channels are manually chosen.The study was performed on valence dimension i.e. degree of good or bad feelings. The writers showed the supremacy of preferring the MLPNN approach to the SVM.

According to a study published in [20], of the eight channels employed during emotional processing, the frontal (F8), parietal (P7), and temporal (T8 and T7) brain areas are most active . Additionally, it has been demonstrated that the brain regions surrounding the AF4, F8, O1, P7, T7, and T8 channels are engaged in response to emotional stimulus.Iteratively studying non-stationary and nonlinear time series was done using the EMD technique, which divides time-series signals into separate parts defined as Intrinsic Mode Functions (IMFs). To show the method's viability, the Linear Support Vector Classifier (LSVC) classification algorithm was used to three separate datasets: AMIGOS, DREAMER and DEAP.

Numerous articles examined the best selection method using the SEED dataset. Instead of using statistical parameters, the authors of [21] demonstrated a weighted distributions-based channel method of selecting channels. Using Differential Entropy (DE), which is obtained from an EEG signal made up of just 12 sensors, they demonstrated its competitive advantage to the initial whole pool of sensors(62). Four alternative profiles of the chosen electrode placements—four, six, nine, and twelve channels—are chosen in accordance with the traits of high peaks in the distribution of weight and asymmetric features in emotion processing. For instance, the other three profiles increase the number of channels on the four electrodes (FT7, FT8, T7, and T8). On the SEED dataset, Pane et al [22] Linear .'s Discriminant Analysis (LDA) classifier with the selected 15 channels produced the best results.

Xiaozhong Geng et al. [23] proposed combining of Independent Component Analysis(ICA), Wavelet Transform(WT) and Common Spatial Pattern(CSP) as an improved feature extraction algorithm for EEG signals. Rab Nawaz et al. [24] compared the different feature extraction algorithms. The best characteristics are found by extracting data from the EEG signals using Power entropy, Fractal Measurements, Statistical features, and Spectral(Wavelet) Energy.

In order to recognise human emotion from EEG signals, Rizon et al. [25] suggested an asymmetric ratio (AR) based channel selection approach. The results show that their strategy is effective at classifying and reducing emotional channels. The F-score index was utilised by Lin et al. [26] to determine the best EEG streams for emotion recognition. This statistic is derived from the ratio of variations within and across classes. He et al. [27] developed a genetic algorithm (GA) based on Rayleigh coefficient (RC) maximisation to select the ideal subset of routes for a motor-imagery BCI system. Multiwavelets decomposition-based features for EEG emotion categorization were proposed by Bajaj et al. [28], and the results are effective. Multiwavelet transform with MC-LS-SVM was the novel technique for emotion recognition introduced by Bajaj et al. [29]. Additionally, it offered categorization precision of 84.79% for emotions.

III. Dataset Description

Because they give researchers the opportunity to test their hypotheses on a variety of people of different gender, age, and cultural backgrounds, datasets are essential for the process of identifying emotions. The datasets include signals that were recorded using a range of measurement equipment, each with a different number of electrodes, sample frequency, etc. In this study we have made use of Dataset for Emotion Analysis Using Physiological Signals(DEAP) [30].

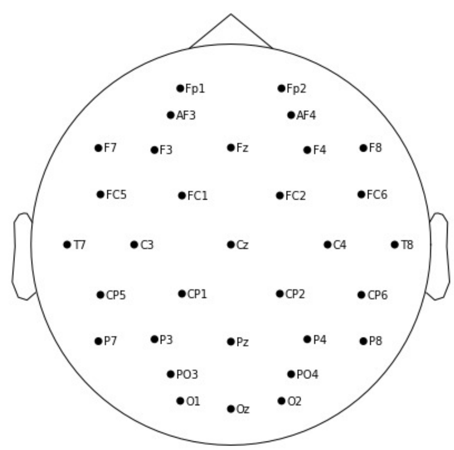

Fig. 1. Position of 32 electrodes in DEAP Dataset

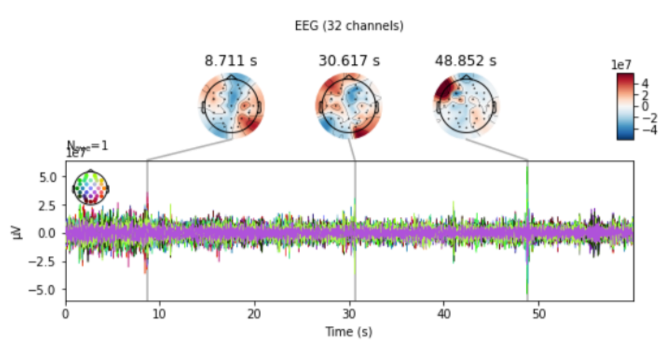

Fig. 2. Combined butterfly plot with scalp topography.

2012 saw the release of the DEAP dataset. Its production involved 32 individuals between the ages of 19 and 37 (mean age 26.9),while watching 40 one-minute films, 17 men and 15 women recorded EEG, EMG, EOG, and pulse blood volume data.(32*40=1280 samples) The three-second pre-trial baseline was subtracted from the EEG signals after they were recorded using the BioSemi ActiveTwo measurement equipment. The EOG artefacts were eliminated using the blind source separation approach. The raw EEG data was recorded at a frequency of 512 Hz but preprocessed data at 128Hz is also provided with the aforementioned noise and baseline removed. The dataset makes use of 32 elctrodes following the popular ”10-20” system for measuring EEG data. All the participants, after watching each of the videos, have rated it on a dicrete 9 point scale for valence, arousal, dominance and liking. For 22 participants, the frontal face video recordings are also provided.

In our study we have made use of the valence and arousal dimensions ratings provided by the subjects through a self assessment. The authors of the study have already provided us with preprocessed EEG data with EOG artifacts and baseline signal removed and downsampled using a band-pas filter(4-45Hz). The labels for each dimension are the ratings the participants gave themselves.If the self-assessment grade is less than 5, the valence/arousal/dominance label is assigned to low class, or ”0,” and to high class, or ”1,” if the score is larger than 5. [31] Valence, which ranges from miserable to happy, is a measure of pleasantness. From the least thrilled to the most excited, arousal rates the intensity of the emotions.

IV. Proposed Framework:EEG Electrode Selection and Parallel Merged Recurrent Neural Network

A. Data Pipeline: Feature Extraction

Before performing feature extraction, for this study, we have removed the EEG recordings from the first five and last five seconds with the reasoning that residual emotions from previous video plays a factor during the first period(avoiding mood swings) and the subject suffers from fatigue during the last period. [32] This also helps in dimensionality reduction to an extent.

The classification performance of BCI systems depends on extraction of features over EEG inputs. A feature, strictly speaking, is a distinguishing quality, a quantifiable amount, and a functional component formed from a segment of a pattern. Significant signal-embedded errors is minimised by extracted features. They also lessen the amount of resources needed to completely describe a significant amount of data. This is required to eliminate the potential requirement for information compression, lower the cost of information processing, and reduce implementation complexity.

For emotion identification with EEG, all of the retrieved features, which are described in more detail below, have been widely used. [33] [34] [35] [36]

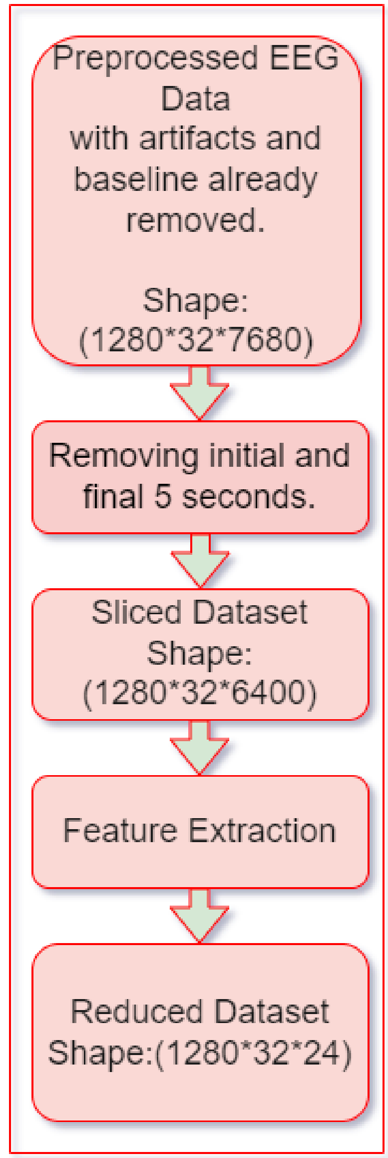

Fig. 3. Data Pipeline: Slicing and Feature Extraction

B. Statistical/Time Domain Features

We have made use of time domain/statistical features such as mean, median, variance,range, standard deviation, skewness(measure of assymetry of distribution), kurtosis(measure of ’tailedness’ of distribution), and related terms as the most basic aspects of the EEG signal. [37] ALong with the aforementioned basic parameters we have extracted the following complex features in the time domain-

1) Hjorth Parameters: The statistical characteristics of a time-series are represented by the Hjorth parameters [38] which are widely employed in signal processing. Complexity, activity and mobility are some of the parameters that are frequently utilised to find features when analysing EEG signals.

Activity Ao is the first Hjorth parameter, and it is used to compute the mean signal strength, which is the variation of the signal. The following is a mathematical representation of this-

$$Activity = var(y(t)) \tag{1}$$

The second parameter of Hjorth is mobility M_o, which indicates the power spectrum’s average frequency or standard deviation percentage. Its mathematical representation is as follows-

$$Mobility = \sqrt{\frac{var\left(\frac{d_y(t)}{d(t)}\right)}{var(y(t))}} \tag{2}$$

The third parameter of Hjorth is complexity C_o, which represents the change in frequency.The degree to which a time series resembles a pure sine wave can be determined using the complexity. It is depicted as-

$$Complexity = \frac{Mobility\left(\frac{d_y(t)}{d(t)}\right)}{Mobility(y(t))} \tag{3}$$

2) Fractal Dimensions: One approach to officially represent a dimension is as fractal, or self likeness. When working with fractals, we take an object and attempt to multiply or divide it into things that have precisely the same geometry as the original object but are only slightly smaller.

Fractal dimensions (FD) are used to quantify time series complexity. More complicated lines exhibit transients and other variations that interfere with the time series' tendency to resemble itself. [39]

In our work we have made use of the Petrosian and Katz Fractal Dimensions. Petrosian purported a quick way to calculate a bounded sequence's fractal dimension [40], which first converts the input to a binary sequence before computing the fractal dimension from time series. Katz suggested a different algorithm [41]. This became known as the Katz algorithm afterwards. Katz used FD to examine the EEGs taken in both the awake and sleeping states.

3) Entropy: A approach used in statistics to measure the degree of regularity and predictability of fluctuations over a time series of data is called approximation entropy. [42]. We have calculate Approximate Entropy(ApEn) and Sample Entropy(SampEn) respectively.

A modified and expanded version of the ApEn, known as the SampEn, has been used to identify emotions from EEG [43] [44], [50]. Its independence from data length and lack of self-similarity measurement make it superior to approximation ApEn [45]. More irregularity and complexity in the data are represented by bigger values of ApEn and SampEn, and vice versa [46]. The method used in this paper to calculate ApEn and SampEn is given in [47].

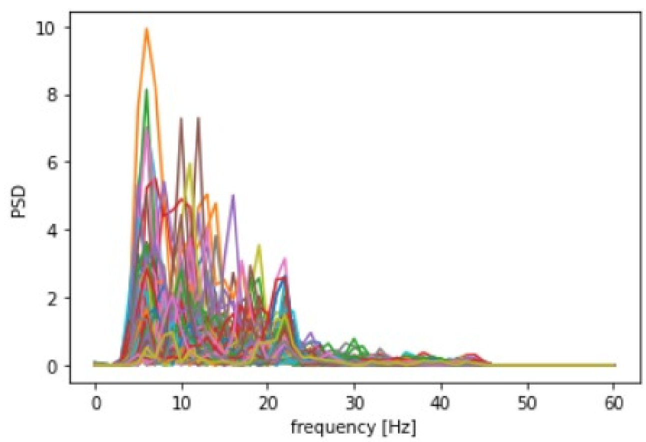

Fig. 4. Power Spectral Density againt Frequency for Channel FP1

C. Frequency Domain Features

The frequency domain features used in this paper are Spectral Entropy(SP) and Band power.

1) Spectral Entropy: The Fourier transform or more advanced methods like Wavelets are used to translate time-domain signals into the frequency domain, which is the basic idea underlying measuring entropy in the frequency domain. Power spectral density (PSD) of an EEG signal, which is produced by DFT, is necessary for spectral entropy. The power spectrum between two given frequency points of interest, let's say f1 and f2, is normalised, and spectral entropy is calculated and characterised by Shannon entropy. [48] where the sum is taken over all the frequencies between f1 and f2.

$$H(X) = -\sum_{i=1}^{n} P_i \log_2 P_i \tag{4}$$

2) Band Power: The five subfrequency bands that make up brainwaves are alpha (8–13 Hz), beta (13–30 Hz), gamma (30–100 Hz), theta (4–8 Hz), and delta (1 – 4 Hz). [49] In this study, we determined the averaged band power from the subfrequency bands to generate a single number that represents the average band power's contribution to the signal's overall power.

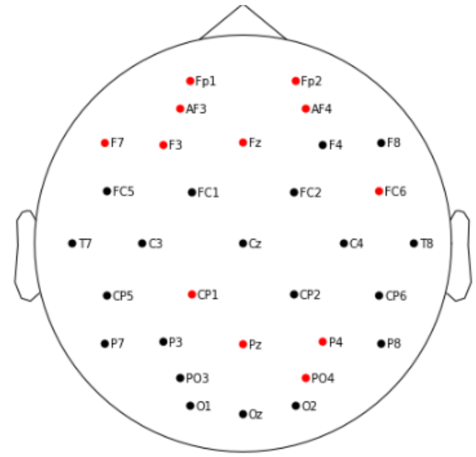

Fig. 5. Selected Electrodes positioning

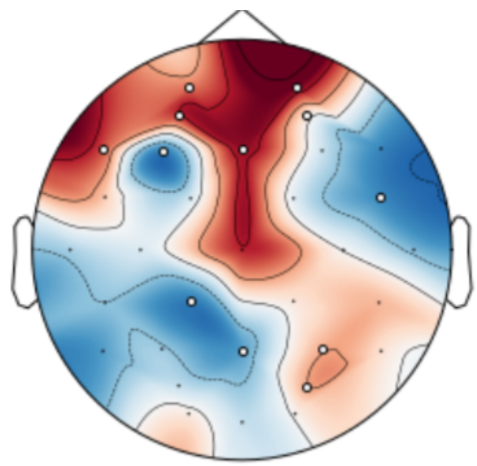

Fig. 6. Scalp topography of subject 30 at 10 sec. with selected electrodes marked.

We have made use of AntroPy [50],an open-source Python package for computing several entropy complexity metrics of time-series, for computing most of the aforementioned complex EEG features.

D. Channel Selection

The development of channel selection algorithms was prompted by the high volume of channel recordings that resulted from the accessibility of inexpensive interfaces. Channel selection aims to improve model performance, speed up processing, reduce dimensionality, and pinpoint the part of the brain that is responsible for class-event activity.

We have utilized a performance based metric for channel selection. Classification of emotion(both valence and arousal) is performed using SVM and the channels which provide us with the best accuracy are chosen as the primary channels that we finally employ as input to the merged LSTM model.

EEG signals from all 32 channels are fed into SVM and channels with the highest accuracy are chosen for further analysis. The number of electrodes/channels we have chosen are 12 which drastically reduces the need of high computational capacity.

From the frontal lobe, channels FP1, Af3, F3, F7, Fp2, AF4, Fz and FC6 are chosen whereas channels CP1, Pz, P4 and PO4 are chosen from the parietal lobes. Majority of electrodes selected from the frontal lobe aligns with previous studies which concluded that

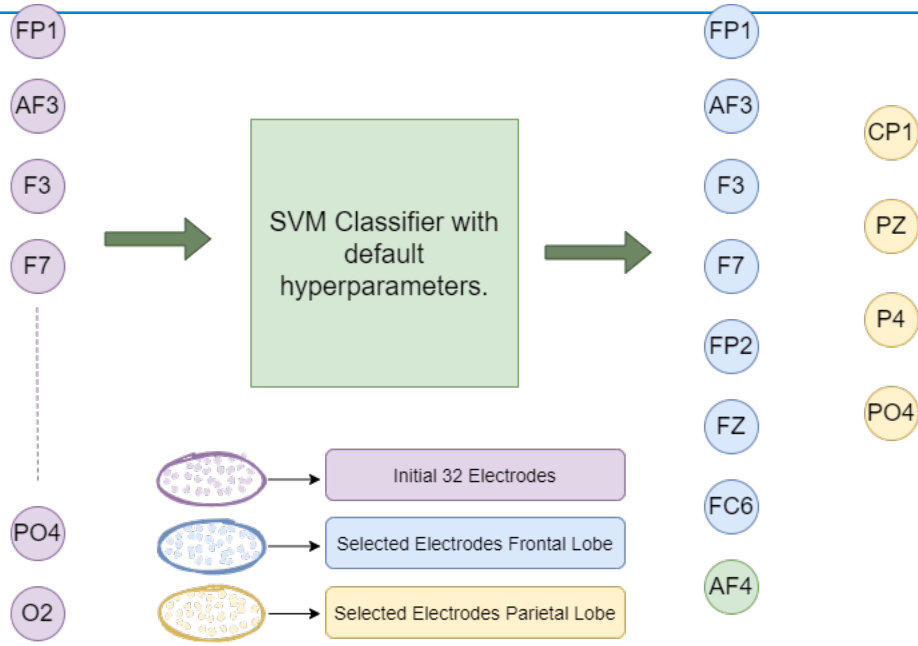

Fig. 7. Channel Selection Visualization

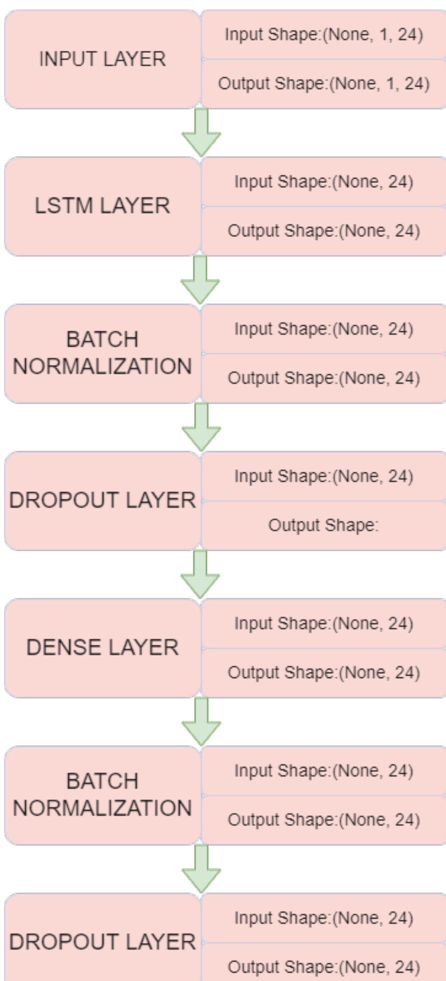

Fig. 8. Single Channel sub-model

Frontal lobe mainly deals with emotions inside the human brain (positive/negative,anxiety,fear etc). [51]. Fig.5 shows the positioning of the channels selected for input to the merged-RNN model described subsequently.

E. Merged LSTM Architecture

In our study, we have created a similar channel wise algorithm/model for all the selected channels. The number of LSTM units is set equal to number of extracted features i.e. 24. The LSTM layer is followed by two Dense Layers. Moreover each of the Dense Layers have a Batch Normalization and Dropout Layer following them.

The results of the final Dense Layer of all the channel wise sub-models are fed into a concatenation layer. Following that we have two hidden Dense Layers each with a Batch Normalization and Dropout Layer after their activation functions. The output dense layer uses 'sigmoid' as an activation function whereas hidden layers make use of the 'relu' activation function.

As the proposed model is a little 'complex' for only 1280 samples of data, the use of Dropout Layer was vital during model training. A dropout rate of 0.2/0.3 was used for all the single channel sub models and a rate of 0.7/0.8 was used after the concatenation layer of the merged model. Adding Batch Normalization after every hidden layer reduced the training time drastically and gave a stabilizing effect to model training.

V. RESULT

This section of the paper discusses and contrasts the outcomes of the suggested channel selection method with merged-LSTM model with previous similar studies.

Figure 10 and 11 demonstrates the loss curves for our model's training and validation against the number of epochs. It can be observed that the model's loss function plateaus in a zig-zag manner for both the valence and arousal dimensions after initial training. Potential solutions for this problem include using learning rate decay [58] or more sophisticated methods like ReduceLROnPlateau. [59] Moreover, although increasing the batch size increases the stability of the model, we have kept the maximum batch size of 128 for better

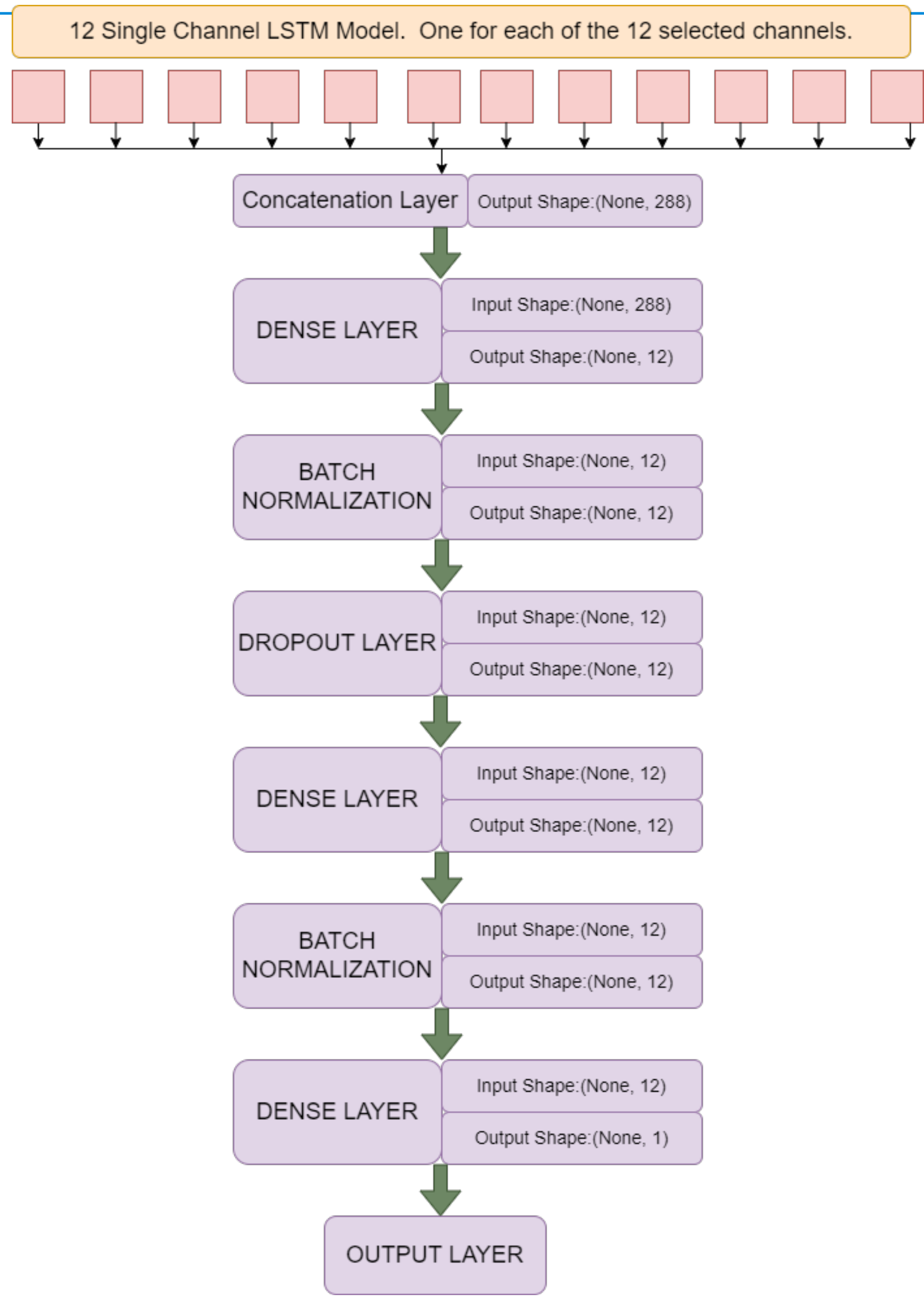

Fig. 9. Concatenated proposed Model

generalization [60] (for better classification performance on overall unseen data).

Table I shows the comparison table of accuracy obtained during different studies involving emotion classification and channel selection algorithms on the DEAP Dataset. In addition to the fundamental one, which is the study of the dataset authors [52], we picked studies that identify human emotions in two dimensions and in which the authors employed a smaller number of EEG channels, whether the channels were chosen manually or automatically.

Li et al. [18] investigates the impact of EEG signal accuracy in emotion identification on different frequency bands and channel counts. The results of classification using 10, 14, 18 and 32 channels were presented after passing all the four frequency bands through KNN classifier. The results show gamma as the superior frequency band for emotion classification and also that overall accuracy elevated when the channel count was escalated. When using features from all the frequency bands, classification accuracy of 85.74% and 87.90% was obtained using 18 channels and it reduced to 84.53% and 85.26% for 14 channels and further downgraded to 82.48% and 83.27% when 10 channels were engaged.

Özerdem et al. [19] used classification accurateness as a channel selection method and extracted features from the top 5 channels. KNN and MLPNN were then employed to get exactness of 72.92% and 77.14% respectively. The results for arousal dimensions were not studied/presented.

Wang et al. [55] suggests a channel selection strategy that uses normalised mutual information (NMI) to choose an ideal subset of EEG channels. Reducing the number of channels to 8 for valence

TABLE I
COMPARISON TABLE OF RELEVANT PAST STUDIES.

STUDY	No Of Channels Used	Classification Algorithm	Maximum Accuracy Achieved
Koelstra et al. [52]	32	Naive Bayes Classifier	V: 57.60% A: 62.00%
Li et al. [18]	18	KNN	V: 85.74% A: 86.46%
Özerdem et al. [19]	5	MLPNN	V: 77.14%
Wang et al. [53]	V: 8 A: 10	SVM	V: 74.41% A: 73.64%
Msonda et al. [20]	8	LSVC	V:67.00%
Menon et al. [54]	Feature Channel Vector Set	HDC	V: 76.70% A: 74.20%
Gupta et al. [55]	6	Random Forest	V: 79.99% A: 79.95%
Mert et al. [56]	18	MEMD + ANN	V: 72.87% A: 75.00%
Zhang et al. [57]	V:9 A:8	PNN	V: 81.21% A: 81.76%
Our Method	**12**	**SVM + Merged LSTM**	**V: 88.12% A: 90.56%**

Fig. 10. Loss curve for valence dimension

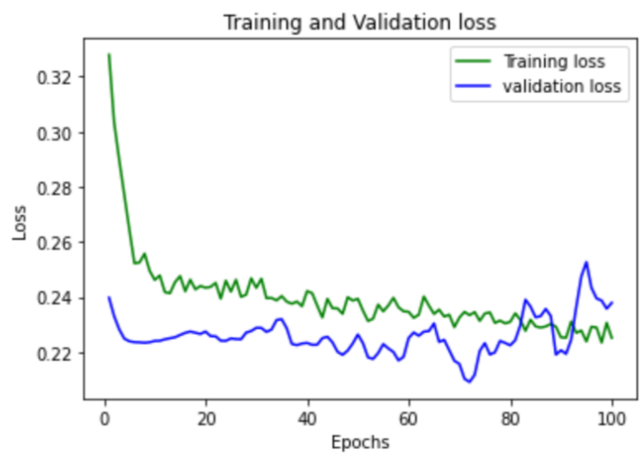

Fig. 11. Loss curve for arousal dimension

dimension and 10 for arousal exactness of 74.41% and 73.64% respectively was obtained.

Msonda et al. [20] studied the position of the fewest electrodes with the highest ”valence” discriminative power using a unique technique. Employing 8 most prominent EEG electrodes an AUC score of 67.00% was obtained for the valence dimension.

Menon et al. [57] engaged effective hyperdimensional computing (HDC) paradigm inspired by the human brain to create a feature channel vector set that reduced the vector storage by 98%. Correctness of 76.70% and 74.20% was obtained on the valence and arousal measures.

Gupta et al. [58] exercised flexible analytic wavelet transform(FAWT) on 6 channels as suggested by another study [61]. Engaging Random Forest(RF) as a classifier accuracies of 79.99%(valence) and 79.95%(arousal) were obtained.

Mert et al. [59] examines empirical mode decomposition's (EMD) and its multivariate extension's (MEMD) enhanced features for emotion identification. Engaging 18 channels from active brain regions for emotions [62] accuracies of 72.87% for valence and 75.00% for arousal were accomplished.

Zhang et al. [60] exercised probabilistic neural networks(PNN) to perform emotion categorization. ReliefF based channel picking method was used to select 9 channels for valence and 8 channels for arousal measures. 81.21% for valence and 81.76% accuracies were obtained and it was shown that 98% of the total classification accuracy can be achieved even after using a reduced number of channels.

To summarize, in our study we have made use of **37.5%**(12 out of possible 32 EEG based channels) of the total number of electrodes made available through the DEAP dataset. We have selected the same 12 channels for both the valence and arousal dimensions based on classification exactness obtained using SVM. The channels selected, all being from the frontal and parietal lobes, also points to the fact that for emotion classification analyzing these two brain regions can be most advantageous. Electrodes from temporal lobe like T7 and T8 came close to the electrodes from parietal lobes when used for classification using SVM but were eventually not used as employing the latter gave better accuracies with the merged LSTM model.

Although some previous studies have already reduced the number of required channels for emotion classification significantly, most of them employ complex channel selection algorithms and/or different set and number of channels for different emotion dimensions. [55] [60] We present a simple channel selection method based on the metric of accuracy using SVM.

We also removed the baseline signal and the initial and final 5 seconds of EEG data accounting for residual emotions and fatigue. Then, a total of **24** features were extracted from each channel data of each subject effectively reducing the data by **99.62%** (from 6400 to 24). This reduced data is fed into the merged LSTM model as visualized in Fig. 9.

Different batch sizes, dropout values and learning rate were experimented on as changing them slightly changed the model performance significantly. Final batch size selected was 128(for better generalization and smoother model training) and learning rate of 0.002 was the most efficient in reaching a minima for the loss function(mean square error). The classification accuracy we obtained for valence is **88.12%** and for arousal **90.56%**.

VI. Conclusion and Future Work

The use of an EEG headset with multiple channels raises the complexity of the gear and computers needed, which makes it harder to determine a person's psychological response because part of the channel adds superfluous noise to the EEG data and is irrelevant for evaluating emotions. According to this study, fewer channels may be required for emotion classification. A smaller number of channels are proposed in this study, which mitigates the problems that scientists currently face, as well as increases the accuracy of classification making use of only 12 electrodes. Also further fine tuning the learning rate and dropout number can still significantly improve the overall accuracy of our model.

As there is still a demand for additional studies in this area, we will use multiple data sources for both the model's validation and learning in our upcoming work to investigate the utility of our approach for cross-dataset application.

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