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Semi-Skipping Layered Gated Unit and Efficient Network: Hybrid Deep Feature Selection Method for Edge Computing in EEG-Based Emotion Classification

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ABSTRACT In this article, we propose a novel feature selection method based on hybrid neural networks for emotional classification avoiding expensive computation. With the development of neural networks for machine learning tools, the Electroencephalogram (EEG)-based classification of human emotions is increasingly important in providing health-care for Edge Computing in support of multiple Internet of Things (IoT) applications. However, classifying emotions through EEG signals is very challenging due to the low temporal boundaries and non-linear nature of EEG signals. Regarding non-linearity, we propose a hierarchical Semi-skipping Layered Gated Unit (SLGU) besides Efficient Network (ENet) for feature extraction. For faster processing, we have introduced a semi-skipping layer for Gated Recurrent Units (GRU) in Recurrent Neural Networks (RNN). The entered layer automatically skips the divergent factor during network training. Preprocessed EEG signals are sent to the hybrid SLGU-ENet model for deep feature extraction. To overcome the computational cost, an optimal function reduction method called the Bag of Visualized Characteristics (BoVC) is used. The entire facility is verified against two publicly available datasets. The results show that the classification performance of the proposed model achieves superior classification precision in a short processing time compared to the state-of-the-art models. The proposed algorithm required around 1.2-5 seconds, suitable for real-time IoT applications.

INDEX TERMS Edge computing, efficient network, electroencephalogram (EEG), emotion classification, Internet of Things, recurrent neural network.

I. INTRODUCTION

Human-Computer Interaction (HCI) has become a major topic in recent years due to advances in machine learning tools. HCI can play an important role in the provision of health services in smart cities [1]. With the advent of the fourth industrial revolution, new technologies are being studied to integrate emotional intelligence into existing IoT applications [2]. In Edge computing, HCI uses emotional behavioral data to control devices and enable multiple IoT applications. HCI reads brain activity by acquiring physiological signals generated by neurons in the brain [3]. Electroencephalogram (EEG) is a non-invasive technique that uses a bio-amplifier [4] to capture brain signals. Inner feelings can be related to many human-computer interactions, such as hypertension and epilepsy, etc. With advances in

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signal processing tools, EEG-based systems can efficiently classify human emotions. Compared to other techniques such as speech and image for emotion classification, EEG-based emotion classification can provide superior classification performance [5]. EEG signals can directly reflect brain activity.

With the growing demand for mobile applications, human emotions are becoming essential. Emotions can be classified on a two-dimensional scale as Valence and Arousal [6]. This two-dimensional scale describes the state of emotions of how happy or sad a participant is. EEG-based sentiment classification is more effective than voice and image-based sentiment classification [7]. However, understanding human emotions using EEG signals remains a difficult task due to the nature of EEG signals. The non-linearity of the signal can lead to misclassification, which is computationally expensive. Also, it can be subjective that each participant behaves differently in the same scenario. EEG signals have a low signal-to-noise ratio (SNR) and are often mixed with a lot of noise when received. The more difficult problem is that the EEG signal is temporarily asymmetric and abnormal, unlike the image or audio signal. Therefore, in the EEG-based classification of emotions, the choice of the characteristic values of the desire emotional state is very important. Many studies on emotion recognition are possible, but few can classify emotions with less processing time. The trade-off between classification accuracy and computational cost is competitive. Therefore, there is a need for a system capable of classifying human emotions in a short processing time with good classification performance.

Our main concern in this article is the selection of features to effectively classify emotions. We proposed a hybrid method of feature extraction and selection based on recurrent networks to identify and understand emotional behavior with less complexity and computational cost. With regard to edge computing, there is a research tendency to estimate the emotions caused by the visualization of stimuli in different IoT applications.

Many decomposition methods are used to deal with the non-linearity of the EEG signal. Reference [8] uses empirical mode decomposition (EMD) to classify emotions using the EEG signal. EMD-based decomposition forms an intrinsic mode function (IMFs) with reduced noise effects. They used the entropy of the sample based on the classification. The precision obtained with this method in the DEAP dataset is 92.03%. Reference [9] also uses EMD-based signal decomposition. Subsequently, the classification performance of the proposed model was calculated using the matching technique. References [10] and [11] used multivariate EMD (MEMD) and bi-variate (BEMD) to divide the signal into multiple and bi variants.

Recent advances in machine learning tools are prompting researchers to classify emotions using DNNs. Authors in [12] uses CapsNet for multi-class EEG-based emotion recognition. CapsNet is a deep capsule network that reduces the EEG input signal using a network of convolutional layer capsules. They have analyzed the DEAP dataset and achieved an excellent overall ranking.

The ability of EEG signals to classify emotions has been extensively studied in [13], [14]. The authors of [15] reported the use of EEG signals for emotion recognition, using power spectral density as characteristic and Support Vctor Machine (SVM) and k-Nearest Neighbors (k-NN) as classifiers. Reference [16] represents a 3D convolutional neural network (CNN) for character extraction. They also used the DEAP dataset and achieved a classification accuracy of 87.44% and 88.49% in terms of valence and arousal. The selection of functions based on entropy is also a major concern for many researchers. Entropy measures the predictability of features that occur in RAW EEG signals. The spectral entropy of the power is calculated as the characteristic vector [17]. This entropy function recognized eight emotional states. PSD (power spectral density) and higher-order statistics. Reference [18] were also used to characterize the EMD-based attenuation signal.

The classification of the characteristics extracted from the reference was performed using the Naive Bayes model, linear discriminant analysis (LDA), and SVM. Machine [19], [20] was trained using a repetitive neural network LSTN (Long Short Term Memory) with an accuracy of 79.26%. This model is combined with an intelligent multi-channel detection system for human emotions. Emotional mapping can be done using 3D vectors like Valence, Arousal, Dominance (VAD) [21].

Reference [22] has applied a bagging tree to classify human emotions based on characteristics extracted from the DNN model. Feature selection is the basic process for finding quality attributes. Various functions are essential for downsizing with a high sort of performance. In the literature, [23] constructed a phase lock value (PLV) by dismantling various functions to analyze the function. The GSCCA (Group Sparse Canonical Correlation Analysis) method proposed by [24] maps classes into linear relationships and analyzes EEG signals for feature selection. They extract 5 bands from the EEG signal and compare the frequencies in the SEED dataset. This mapping also helps you understand your emotional behavior. References [25] and [26] also select features from the SEED and DEAP datasets. They both use RNN to extract and select features, and SVM to classify emotions.

The selection of functions is an important point in the recognition of human emotions. This step is very important to extract high-quality features for a good sentiment rating. Selection of existing positions can be based on consent, mutual information, statistical analysis, and thrifty learning [27]. These methods are not efficient and require information before making a decision. In reference [28], the authors used a non-negative Laplace value to estimate the values of the characteristics. Similarly, authors in [29] used PCA to select attribute values based on their unique ID. Fisher's Discriminant Ratio (FDR) [29] is also a traditional feature selection method that selects high-quality features based on high FDR values. Likewise, [30] proposes a dynamic search strategy to optimize the set of statistical functions. The sparse selection algorithm proposed by [31] selects feature properties based on a sparse learning methodology. The selected function is used in sentiment ranking modeling with a fair ranking performance for SEED and DEAP datasets.

CONTRIBUTIONS

The summary of the proposed scheme is as follows.:

- EEG signals from two publicly available datasets are used to classify human emotions into valence and arousal domain. During preprocessing, the EEG signal is first decomposed using one-dimesional Discrete Wavelet Transform (1D-DWT) to remove unwanted signals and reduce the effects of noise from the EEG signal. The next step is to choose a good channel by evaluating the differential entropy of each channel. Therefore, choosing a channel can shorten the training time of the network and achieve good qualifying performance.
- In the second step, the pre-processed EEG signals from both datasets are sent to two different neural networks for feature extraction. Using the GRU concept in RNN, we introduced a semi-skipping layer into the existing GRU model to prevent the gradient effect from disappearing during training. Second, using Continuous Wavelet Transform (CWT), we use previously trained ENets to acquire spatial characteristics in the time-frequency domain. Therefore, the name of the proposed network is SLGU-ENet.
- The features extracted from the two models are then combined to have a single feature vector, a hybrid feature vector. Then, using the concept of a bag of features, we reduce the functions to get only a high-quality histogram of features.
- The trained network is then classified for precision using Support Vector Networks (SVN), Naive Bayes (NB), and k-Nearest Neighbor (k-NN). The accuracy of the system is checked against the two available datasets and compared with the latest trends in emotion classification.
- Capable networks are useful for many IoT applications because they require less network training and processing time (suggested skipping layers).

So far, we have discussed the introduction and literature on the use of brain wave signals to identify human emotions. For the remainder of this article, the II section defines the datasets related to our work and the settings made for experiments like preprocessing and channel selection. The III section describes the suggested operation parameters for selecting the hybrid immersion function. IV describes the classifier used in the proposed methodology to classify human emotions. The section V describes the experimental results and compares different models of emotional perception, then the VI section concludes the article.

II. EXPERIMENTAL SETUP

This section describes the experimental setup used for emotional classification. The work uses two publicly available datasets for the validation of the proposed model. Each dataset with different preprocessing techniques is described in the following sections. EEG-based sentiment classification requires intensive processing to eliminate the effects of artifacts.

A. DEAP DATASET

DEAP: A database for emotion analysis using physiological signals [32] is obtained using electrodes placed on the human skull. 32 users participate in this acquisition process by placing 32 electrodes on the head of each participant. Each participant must watch 40 tagged videos for 1 minute to obtain the desired EEG signal. The DEAP dataset uses four emotional states of Valence and Arousal. The four emotional states are High Arousal (HA), Low Arousal (LA), High Valence (HV), and Low Valence (LV). These for the condition indicate different conditions of internal emotional behavior. Participants who viewed other categories of movies are manually tagged with Self-Assessment Minikins (SAM) [33], as opposed to their actions. The EEG signals collected from each participant are sampled at a frequency of 128 Hz. Artifacts are somehow removed by using the low-pass and band-pass frequencies to achieve the wave of the EEG band.

B. SEED DATASET

The second publicly available dataset is the SEED [7] dataset. Unlike DEAP, SEED is a 15-participant dataset with 62-channel EEG electrodes. There are three emotional states in the SEED dataset: positive, negative, and neutral. The positive and negative states represent a happy and sad state, respectively, while the neutral state represents the normal behavior of the participant. The SEED dataset is also used to capture the EEG signals by showing the participant a 4-minute video clip. From which 45 seconds of SAM and rest are an emotional state.

TABLE 1. Dataset overview.

Dataset	Participants	Channels	Experiments	Trials	Class
DEAP	32	32	1	40	HL HV AL AV
SEED	15	62	5	3	Positive Negative Neutral

The proposed method is validated separately using two datasets to obtain a high-quality feature selection approach. A full overview of the dataset description can be found in Table 1.

C. PRE-PROCESSING

The two datasets used for this work have already been pre-processed by the dataset vendor using a 0-75 Hz bandpass frequency filter to remove a wide variety of noise signals from the EEG data without process. The dataset provider

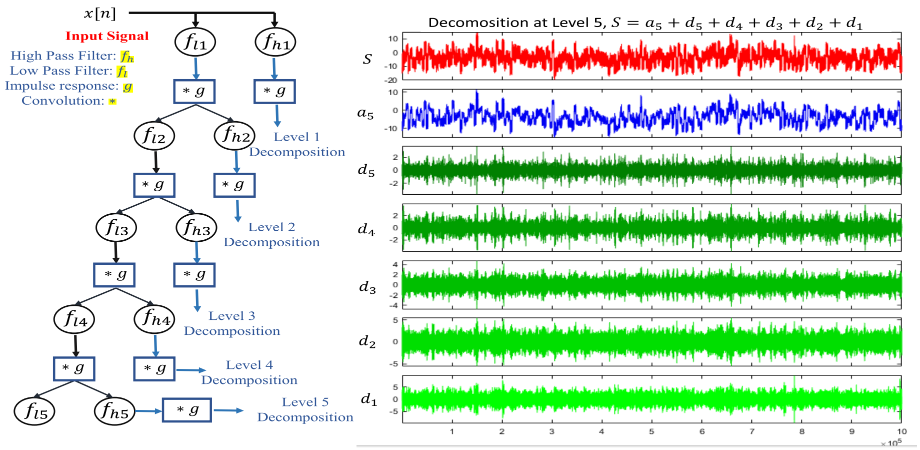

FIGURE 1. One dimensional discrete wavelet transform.

collected the data in a quiet and comfortable environment to avoid movement. In addition, equipment with a gyro sensor was used to ignore the subject's response to movement. Since the filtering process is different for each data set, we will use one-dimensional Discrete Wave Transform (1D-DWT) in this task to further reduce the impact of noise on both datasets. The raw EEG signals from the two datasets available in the preprocessing were first decomposed using a 1D-DWT [34]. Compared to the Fourier transform, DWT moves a flexible window that provides good temporal resolution. The Figure 1 shows the 5-step decomposition of the input signal $x[n]$. For a 5-step decomposition, the input sample must be greater than 224. The Daubechies wavelet is used to calculate the fifth level of decomposition, each level having twice the resolution of the previous one. The five-stage decomposition consists of a set of low-pass and high-pass filters at each level. $d_1 - d_5$ is the decay EEG signal for each level shown in Figure 1. S represents the sum of the decomposed signals analyzed to check the quality of the decomposition. For a more detailed analysis, we use a 5-step decomposition. This step is a pre-shrink method to remove unwanted signals from the data set that could lead to misclassification.

D. CHANNEL SELECTION

To overcome the dimensional curse and limit the execution time of the hybrid model feature extraction, we first select only those channels that recognize good differential entropy. The channels are selected from both datasets using the equation 1. A total of 12 channels out of 32 are selected for the DEAP dataset and 24 out of 62 channels are selected for the SEED data set with a threshold of 1.84. Channels with lower entropy values are discarded to save feature extraction and training execution time.

$$P_n(e) = \log_2 \frac{C(x[n])}{P(x[n])}$$

$$Entropy\ (E) = -\frac{1}{N}\sum_{n=0}^{N-1} P_n(e)\ \geq 1.84 \tag{1}$$

where,
$N\ =\ Total\ number\ of\ samples$
$P\ =\ Probablity,$
$C\ =\ class\ index/state,$
$and\ E\ \in\ (P|N \oplus C)$

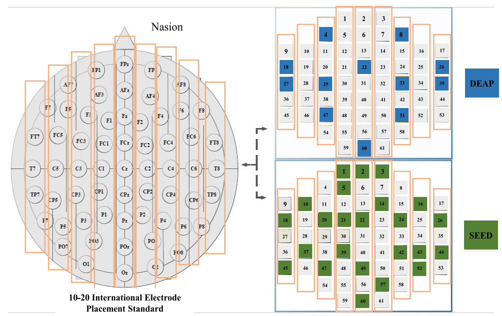

FIGURE 2. Selected channels for SEED and DEAP.

Channel selection is very important to eliminate channels with irrelevant information while maintaining the quality of the EEG signal. The number of channels selected for both datasets are shown in Figure 2 using the 10-20 International Electrode Placement Standard [35].

III. PROPOSED PARADIGM FOR EMOTION CLASSIFICATION

This section describes the proposed method for selecting hybrid features. The general structure of the proposed model is shown in Figure 3. In this work, along with ENet feature extraction, we introduced skipping layers in GRU (SLGU) to extract features in a shorter processing time. We analyze the features together to obtain a vector of deep hybrid features. After de-duplication, use BoVC (reverse function) to select high-quality features, the hybrid deep features are further reduced. Vectors with reduced characteristics are classified for validation using three well-known classifiers. The complete architecture is detailed in the next section.

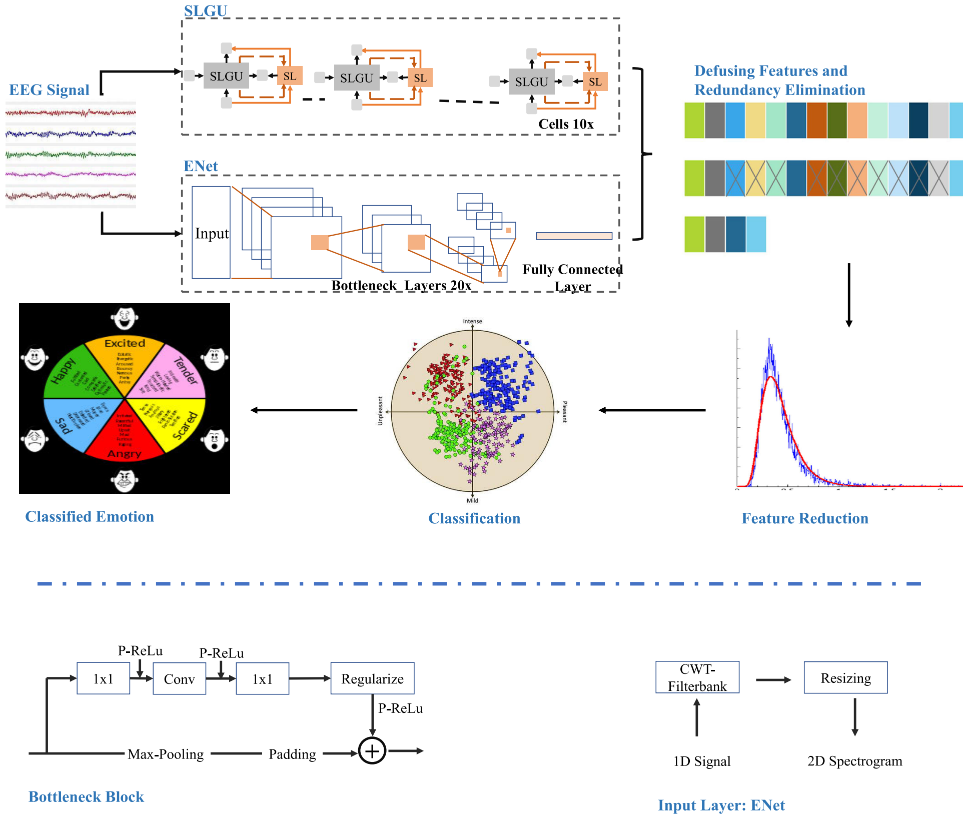

FIGURE 3. Framework of the proposed emotion classification model.

A. FEATURE EXTRACTION

In the feature extraction step, the EEG data of the selected and pre-processed channel is transferred to two different neural networks. After extraction, they dissect together to obtain a single feature vector (hybrid deep feature vector).

1) SEMI-SKIPPED LAYERED GATED UNIT (SLGU)

RNN put a big twist on neural networks. Most NN techniques require input size adjustment when processing serial data [36]. If the input is not linear, this is done to get a fixed-size input scale, which adds complexity to the system. In this case, the RNN offers a good advantage as it accepts inputs that do not require fixed-size data. Therefore, the RNN does not have a predetermined limit on the input signal. Therefore, it can be used for any EEG signal without increasing the complexity of computation. Adding a semi-skipping layer gives a modified version of the GRU [37]. Introduction of a skipping layer (sL) to avoid the problem of the vanishing of the gradient in RNN and GRU. Skip simplifies the network efficiently by using fewer layers in the initial formation phase. This allows us to speed up learning by reducing the gradient fading effect since fewer layers need to be spread. sL omits the high-frequency components of the EEG input signal. In any EEG interval, the high-frequency component is due to eye movements or EMG signals that can interfere with emotional stimulation. The skip criterion is based solely on the frequency component of the input EEG signal. The network then gradually recovers the skipped layers as it learns the functional space. If all the layers are turned off at the end of the workout, they will stay closer to the collector and learn faster. This comes off the collector and is more susceptible to disturbances that require additional training data for recovery. The gradient descent may disappear due to non-linear EEG signals. To avoid this, we have introduced a skipping layer in the GRU. The modified GRU, which introduced three skipping layers, is called SLGU (semi-skipping layered gated unit), since this layer is not omitted for every EEG signal interval, the word semi is used. Skipping layers prevents the disappearing gradation effect that often occurs with non-linear signals. SLGU helps to quickly recognize human emotions while maintaining overall ranking performance. The SLGU uses three sLs (Skip Layers) in each GRU block. The structure of a single SLGU block compared to GRU is shown in Figure 4. In the figure 4, the upper part represents the internal structure of a single GRU and SLGU cell. Since GRU cells use three activation functions, a skipping layer is introduced into each activation function of the GRU cell. Therefore 3 jump layers are added to form the SLGU cell. The lower part of the figure is the typical architecture of the SLGU and GRU blocks, where the input x_t produces the output of the function. The sL in SLGU cell skips the higher frequency component for the x_t input.

GRU has a switching mechanism, so it has fewer parameters compared to LSTMs. The skip layer can be easily jumped

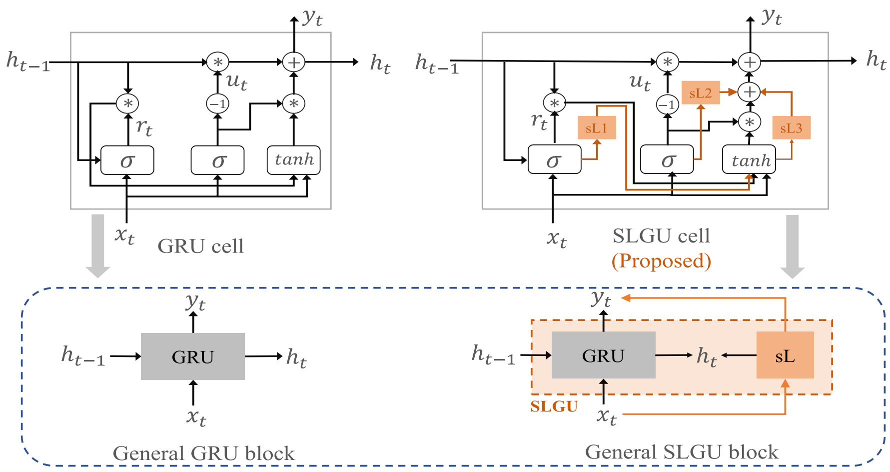

FIGURE 4. GRU vs proposed SLGU single cell architecture.

to the branch network to avoid faded gradient effects. 10-cell SLGU blocks are used to extract high-value functions. The input x_t is fed to the SLGU to extract the output characteristic y_t. The hidden state h_t and the previous hidden state $h_(t-1)$ are used as memory. A single SLGU contains 3 activation layers and 3 transmission layers attached to each activation layer. Two sigmoid functions with a hyperbolic tangent function are used to create a vector of GRU characteristics. Simialrly, a complete architecture uses 10 SLGU cells for feature extraction. The operation of the SLGU cell is the same as that of the hidden layer used in DNN. SLGU has a memory that stores the converted information in each cell, as well as the skip criteria. For the input x_t, we first calculate the current state h_t in equation 2 using the initial conditions for the previous state h_{t-1}. The reset gate vector r_t and updated gate vector u_t are calculated using equation 3 and equation 4. Hence the output with optimized vectors y_t is calculated using equation 5.

$$h_t = (1 - u_t) \odot y_t + u_t \odot h_t - 1 \tag{2}$$
$$r_t = \sigma(w_r.x_t + w_r.h_{t-1} + b_r) \tag{3}$$
$$u_t = \sigma(w_u.x_t + w_u.h_{t-1} + b_u) \tag{4}$$
$$y_t = tanh(w_n.x_t + w_n(r_t \odot h_{t-1}) + b_y) \tag{5}$$

sL skips the given layer with higher frequency component for this the final y_t becomes:

$$y_t = \begin{cases} tanh(w_n.x_t + w_n(r_t \odot h_{t-1}) + b_y) & \text{if } noSkip \\ tanh(w_n(r_t \odot h_{t-1}) + b_y) & \text{if } sL1 \\ tanh(w_n.x_t + b_y) & \text{if } sL2 \\ tanh(w_n.x_t + w_n(r_t \odot h_{t-1})) & \text{if } sL3 \end{cases} \tag{6}$$

This model has been shown to significantly outperform many competitive emotion classification techniques in terms of accuracy, and the remaining problem is computational costs solved with BoVC.

2) EFFICIENT NETWORK

Unlike other DNNs discussed in the literature, working ENet [38] can work well in real-time applications. The structure of the ENet architecture is shown in Figure 3. ENet is up to 18 times faster, requires 75 less FLOPs, has 79 less parameters, and provides similar or better accuracy to existing models. ENet consists of an input layer, a bottleneck layer, and an output layer. The input layer consists of a bank of CWT filters that convert one-dimensional EEG signals into two-dimensional space-time spectrogram images. This will shrink the image to $16 \times 256 \times 256$. The bottleneck layer is used for data transfer for object extraction, and the structure of the bottleneck layer is also shown in Figure 3. Each bottleneck layer consists of a 1×1 pass for resolution reduction, a maximum clumping layer, and a convolutional layer with a ReLU activation layer. Use a fully connected layer before the output layer to connect the pull function in a single row. Obtain a characteristic value in one row for each EEG image or channel. The output dimension of ENet is $(channels \times class \times subject \times experiment) \times 512$ see table 1. That is, for the DEAP dataset, the output dimension is $61,440 \times 512$ and for SEED it is $16,200 \times 512$.

B. FEATURE DEFUSING AND REDUNDANCY ELIMINATION

This section describes the decomposition of properties obtained from SLGU-Enet. The hybrid feature vector is a combined feature of SLGU and ENet. The dimensions of the input signal are 15360 and 5400 for the DEAP and SEED datasets, respectively. After feature extraction, the 15360×61440 features are extracted from the SLGU for DEAP data sets and 5400×16200 for SEED data sets. The dimensions of ENet are 15360×1000 and 5400×1000 for the DEAP and SEED datasets, respectively. The two features are separated from each other to have a hybrid deep feature vector. The fuzzy feature vectors can contain similar or overlapping features taken from different models. To reduce this, the size of the feature vector has been further reduced.

This step is very important when it comes to computational costs and learning opportunities. De-duplication disrupts both the computational costs and the classification performance of the proposed model. Reducing the functional dimension has also been shown to increase the efficiency of the system. The function is eliminated according to the value using the difference equation.

C. FEATURE REDUCTION

The characteristics obtained so far are dimensional, resulting in a dimensional curse in the emotion classification process. We use k-means to cluster to group similar features. This is an iterative process, the process starts with a random centroid value 'k' and then the average of each centroid is calculated to correctly cluster the features. The sum of the mean square errors is also calculated to find the exact value of k after a few iterations. In the graph we can see that at $k = 12$ all values are clustered with fewer errors.

1) BAG OF VISUALIZED CHARACTERISTICS (BoVC)

As discussed in the literature section, there are many traditional methods for reducing features such as PCA, PSO, and GS. This type of feature reduction method has been used to somehow smooth the feature vector, but it has limitations in collecting high-quality features from non-linear signals, so feature smoothing was not used. Inspired by Bag of Features [39] and Bag of Deep Features [40], concepts that are used to measure the vocabulary of all function values, The Bag of Visualized Character (BoVC) is a highly functional visualization quality. BoVC is a two-step process of *(i) measuring visual vocabulary* and *(ii) calculating characteristic histograms*. The hybrid feature vectors of the two datasets are too heavy to be used for real-time application advertising and cannot efficiently classify emotions. Therefore, this step is an essential step to apply human emotion analysis in real-time.

a: VISUAL VOCABULARY MEASUREMENT

Visual vocabulary measurements allow us to visualize characteristics with similar values. This is done by clustering k-means. K-means grouping is used to group similar characters and display them as a single attribute value. Correct grouping begins with a starting value of $k = 2$. Choose a value to evaluate the sum of the squared errors. After several iterations and trials, we found that the sum of the squared errors is minimal at $k = 12$. In the vocabulary assignment of $k = 12$, 12 groups were formed to group similar values. It repeats until all the values are correctly grouped. This mapping method helps understand the difference in attributes between different classes and reduces the dimension of the object vector. The grouped values are known as a vocabulary that represents a unique characteristic of an emotional state. This process is done separately for all datasets.

b: CHARACTERISTIC HISTOGRAM CALCULATION

The vocabulary characteristics histogram is calculated by taking the difference between the vocabulary and the total number of features. The histogram is the number of vocabularies in the hybrid feature vector. This process helps eliminate ungrouped characteristics that are poorly characterized by vocabulary measures. The output of BoVC is determined by the equation 7.

$$S = V \times (C_i \times k) \tag{7}$$

where,
$S = Selected\ Features$
$V = Vocabularies$
$C_i = Emotional\ state$
$and,\ k\ is\ the\ cluster\ size$
For DEAP dataset with 4 classes the output selected features vector is 2385×48 and for SEED are 841×36 with three classes/emotional state.

D. NETWORK TRAINING AND TESTING

The hybrid feature extraction and selection method are trained on the Windows 10 operating system on MATLAB R2020a using the Adam optimizer with a batch size of 128. To save training time, the proposed experiment was run on a graphics processing unit (GPU) GTX 1080 with 8 GB of RAM. The dataset is first divided into a test set and a stream set. The train set is used to train the network, whereas the test set is used to test the validity of the network. To reduce training and randomness, a 10-fold cross-validation scheme is used. Training multiple networks with nearly 1.2 million layers simultaneously is too big for a single GPU. So we extract functions from different models at different times, remove redundant features, and then combine the extracted features. The selection of features is important because it reduces calculation costs. Also shortened the validation time to perform emotion classification with a new dataset after selecting items with smaller dimensions.

IV. EMOTION CLASSIFICATION

Emotion classification and outcome evaluation are performed using three well-known kernel-based classifiers. As discussed above, the two datasets used for this work have 4 and 3 classes, so the multi-level classifier used should work well for lower-class identification.

A. SUPPORT VECTOR NETWORKS

For supervised learning of advanced machine learning tools, SVN [41] analyzes data based on various classes. Due to the validity of the high-dimensional space, SVN generates support vectors from a subset of the training data. The selected functions of the proposed model are used to classify the two datasets individually. Sorting based on the RBF kernel is done to achieve good classification performance. The performance of both the datasets is given subjectively and combined (average) in Figure 5 and 6.

B. NAIVE BAYES CLASSIFIER

The Naive Bayes classifier [42] is a probability-based statistical classifier. The Bayesian theorem is applied to naively

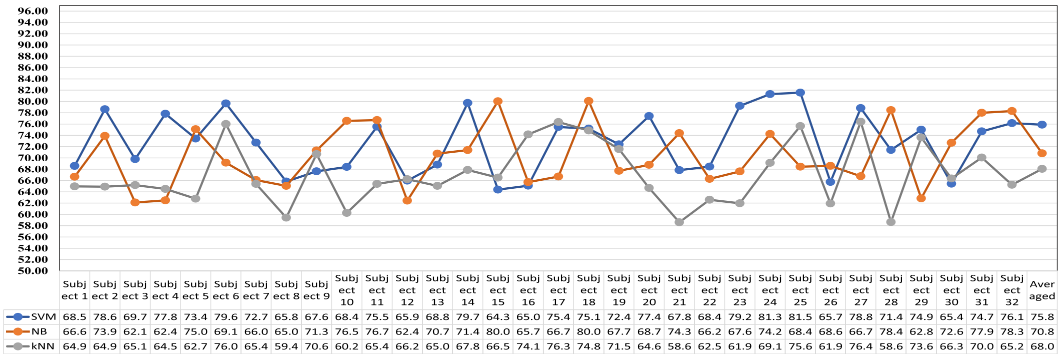

FIGURE 5. Classification accuracy of 32 subjects and averaged (DEAP).

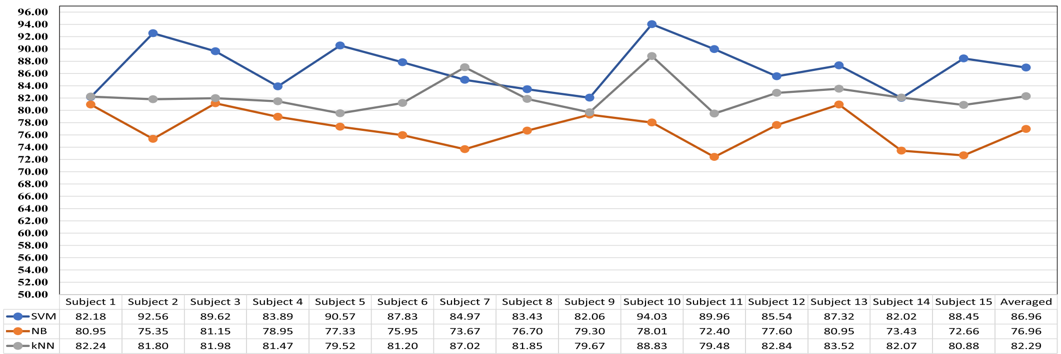

FIGURE 6. Classification accuracy of 15 subjects and averaged (SEED).

TABLE 2. Training execution time of GRU vs proposed scheme.

Technique	Dim.	Accuracy	-p	Ex. Time(s)
DEAP Dataset				
GRU-ENet	15360 × 61440	80.4	0.63	954
GRU-ENet-BoVC	6743 × 48	79.2	0.41	41
SLGU-ENet (Proposed)	8470 × 61440	84.3	1	484
SLGU-ENet-BoVC (Proposed)	2385 × 48	82.6	0.79	3
SEED Dataset				
GRU-ENet	5400 × 16200	84.3	0.33	522
GRU-ENet-BoVC	2540 × 36	87.6	0.71	124
SLGU-ENet (Proposed)	4321 × 16200	97.6	0.97	383
SLGU-ENet-BoVC (Proposed)	841 × 36	94.7	0.91	1.2

TABLE 3. Overall average classification performance.

Dataset	Classifier	Accuracy	F1-score	Precision	Recall
DEAP	SVN	82.6	0.81	0.91	0.72
	NB	80.1	0.77	0.86	0.82
	kNN	77.4	0.78	0.73	0.73
SEED	SVN	94.7	0.93	0.92	0.94
	NB	81.2	0.79	0.87	0.8
	kNN	89.5	0.83	0.81	0.86

distribute the values of different features according to the class index. Using the Bayesian Stochastic Theorem, the equation 8 specifies the conditional probabilities of the inputs X_n and S_i indices of the emotional state as follows:

$$P(S_i \mid X_n)$$
$$P(S_i \mid X_n) = \frac{P(S_i).P(X \mid S_i)}{P(X)} \tag{8}$$

where i for class number and n is the total number of features for each class/state.

C. K-NEAREST NEIGHBOR

Sorting via k-NN [43] provides the best classification performance when validated against SEED and DEAP datasets. The K-NN classification classifies objects according to the value of the nearest neighbor. It calculates the distance from each property value in each class. This algorithm uses the Euclidean distance method to find the closest neighbor. The sorting performance was achieved using an accurate Gaussian kernel.

V. EXPERIMENTAL RESULTS

This section describes the results obtained with the three classifiers listed above. The network is trained using the previously extracted hybrid deep function. The validity of the network is verified using test equipment and classifiers to obtain the best classification accuracy. To confirm the results, other statistical analyzes were performed on the extracted characteristics a follows:

A. PERFORMANCE METRICS

The following statistics were performed to evaluate the results. To save over-fitting problem, the dataset is usually divided into random parts with equal volume. The method is then trained with M parts and tested with the remaining part.

TABLE 4. Recent trends vs proposed method.

Sr. no	Technique	Description	Reference	Channels DEAP/SEED	Classifier	Accuracy DEAP/SEED	Facilitate real-time applications
1.	Sample Entropy	EMD based decomposition uses 4 IMF to calculate corresponding sample entropies. **(2016)**	[8]	2/-	SVM	93.20	✘
2.	EMD	Multidimensional IMFs are used as features. **(2017)**	[9]	8/-	SVM	71.99	✘
3.	MEMD	A multivariate EMD-based emotion classification act as a features. **(2018)**	[10]	-	DNN	87	✘
4.	BEMD	A bi-variate EMD based model to extract zero-mean oscillating components. **(2007)**	[11]	18/-	k-NN - ANN	67-75	✘
5.	MLF-CaspNet	Multi-level features guided capsule network which can simaltaneously extract features from Raw EEG signal.**(2020)**	[12]	32/-		94.59	✘
6.	3D-CNN	3D-CNN for extracting the spatiotemporal features in the EEG signals. **(2018)**	[16]	32/-	CNN	87.44	✘
7.	Non-linear features	Power spectral entropy and correlation dimensions are used as features. **(2017)**	[17]	IAPS	SVM	82.22	✘
8.	Domain Adaptation	Cross dataset adaptation technique to design model on one dataset and test on other. **(2018)**	[18]	32/62	subject-independent classifier	+7.25 - +13.40	✘
9.	LSTM-RNN	DWT transformation and LSTM based techniques applied on real time acquired signals. **(2019)**	[19]	own	CNN	62.01	✘
10.	LSTM	The MMResLSTM network shares the weights across the modalities in each LSTM layer to learn the correlation between the EEG and other physiological signals. **(2019)**	[20]	32/-	MMResLSTM	92.87	✘
11.	CNN	Applied CNN model on VLSI hardware to extract features and analyze EEG emotions. **(2019)**	[21]	12/-	SVM	83.88	✔
12.	CNN	Time-frequency domain analysis to acquire spatial features. **(2019)**	[22]	-	SVM	94.6	✘
13.	PLV	Adopted a multiple feature fusion approach to combine the compensative activation and connection information for emotion recognition. **(2019)**	[23]	14/20	SVM	66/83	✘
14.	GSCCA	Group sparse extension of the conventional canonical correlation analysis (CCA) method to model the linear correlation between emotional EEG class label vectors and the corresponding EEG feature vectors. **(2017)**	[24]	-/20	GSCCA-SVM	80.07-75.97	✘
15.	LSTM	Frequency domain and power features are selected for extraction **(2020)**	[25]	32/-	SVM	93.13	✘
16.	BoDF	Proposed Feature selection method to reduce feature dimension. **(2019)**	[40]	32/62	SVM - k-NN	77.4/93.8 73.6/91.4	✘
17.	SLGU-ENet (Proposed)	Proposed Skipping layers in GRU to enhance the classifying method.	This work	12/24	SVN - NB - k-NN	82.6/94.7 80.1/81.2 77.4/89.5	✔

The overall metric is calculated as stereotype of the metrics on the M times training. Using confusion matrix, we calculated accuracy (equation 9), precision (equation 11), recall (equation 12), f1-score (equation 10), cross entropy (equation 1) and p-score. All the metrics performed are represented in table 2 on both datasets. We calculate above parameters by using below keywords

$T_{positive}$ is when emotion is expected and is present.
$F_{positive}$ is when emotion is expected and is not present.
$T_{negative}$ is when emotion is not expected and is not present.
$F_{negative}$ is when emotion is not expected and is present.

3 emotional states for SEED and 4 emotional states for DEAP dataset are classified using two well known classifiers. The results are validated using the accuracy from selected features on each subject of both datasets. The accuracy, precision, recall, F1-score, p-score and specificity of the training set is given by:

ACCURACY

$$Acc = \frac{T_{positive} + T_{negative}}{positive + negative} \tag{9}$$

F1-SCORE

$$f1 - score = 2 \times \frac{prec - recall}{prec + recall} \tag{10}$$

PRECISION

$$Prec = \frac{T_{positive}}{T_{positive} + F_{positive}} \tag{11}$$

RECALL

$$recall = \frac{T_{positive}}{T_{positive} + F_{negative}} \tag{12}$$

CROSS-ENTROPY

The cross-entropy [44] is used to analyze the loss function of the selected feature values. Cross-entropy calculates the total entropy between distributions. Processing time is reduced due to the number of features selected. Using the SLGU structure, feature selection, and feature reduction method proposed in this work, it is possible to recognize emotion in a short processing time without disturbing the overall performance of the classification. The 2 table shows the execution time of a trained network.

$$Entropy = -\frac{1}{F_t}\sum_{s_i=1}^{S}([F_s \times ln(f)] + [(1 - F_s) \times ln(1 - f)]) \tag{13}$$

where,
F_t is the training features
F_s is the features of specific emotional state
S represents the number of emotional states
s_i is the state index
f is the selected feature value

p-SCORE

A t-test is performed on the selected feature vector to measure the p-score (probability score). The t-test checks if the selected function is useful. This test is used to evaluate whether the selected feature vector differs from the original or actual feature vector. The p-value is determined by calculating the mean difference between the selected object and the original object vector. Higher p-values indicate the quality factor of the selected feature.

B. CLASSIFICATION PERFORMANCE

Now the selected function is ready to classify emotions. We have used three modern multiclass classifiers that are known in this way. The classifications obtained from the SVM and NB classifiers show good classification precision, as shown in Table 3. KNN ranks well for the DEAP dataset as indicated in the table.

C. RECENT TRENDS IN EMOTION CLASSIFICATION

The performance of the SLGU-based emotion classification process is verified based on two sets of benchmark data. We then measure the performance of the proposed technique by classifying the selected objects from SVM, k-NN, and NB. The results show that the combined and selected functions work best in the model. The higher the precision of the combined and selected function, the higher the quality. So with this method, you can get accurate precision in a shorter processing time.

Table 4 shows a comparison of our study with previous techniques using EEG-based techniques for SEED and DEAP datasets. This table clearly shows that the precision achieved by our model is much better than the model used previously with the same dataset and decomposition technique.

VI. CONCLUSION

Classification of human emotions based on EEG is a difficult task due to the non-stationary signals. The resulting large feature vector causes a dimensional curse, which increases the training time of the neural network. Feature selection is very important to obtain high-quality features for good sort performance with shorter processing times. In this work, we have introduced a semi-skip layer in the Gated Recurring Unit (GRU) to avoid the vanishing effect of the gradient. The proposed SLGU-ENet method and BoVC (Bag of Visualized Characteristics) improve the sorting performance of emotions sorting when sorting using SVN (Support Vector Networks), NB (Naive Bayes), and k-NN (k-Nearest Neighbor).

The SLGU-ENet is validated with two publicly available datasets, DEAP, and SEED. Channel selection and feature selection help researchers explore changes in the sentiment analysis framework through the integration of neural networks and the introduction of a skipping layer. As a result, our feature selection method has been shown to intentionally improve overall classification performance with less computational costs. Hence, can be accurately useful for real-time IoT applications in providing emotional health care to mankind. Sorting performance has been greatly improved compared to the previous model. SLGU-ENet, better than normal GRU, implements parallel computing so that it can accelerate computing to a greater extent, suitable for real-time applications. The proposed model took less time to test and train the network. The number of layers in SLGU is based on the "hit and enforce" method. Therefore, it is better to develop a more systematic way of choosing the right layer.

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