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Stress Detection and Audio-Visual Stimuli Classification from Electroencephalogram

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ABSTRACT Electroencephalogram (EEG) is the graphical representation of Brain's electrical activity. Mental stress can be detected in many ways and EEG is one of them. Regular mental stress gives rise to many mental disorders and it may cause various physiological and psychological diseases. As a result, early-stage detection of stress is very important. In this research, brain activity was recorded through EEG headset during inducing different levels of stress from audio-visual stimulus. Again, for better interaction between humans and machines, it is essential to analyze the power spectrum of the brain in response to different audio and visual stimulus. To better evaluate visual and auditory stress, an automated system is designed to differentiate among various audio and visual evoked potentials. This may further help for designing different assistive devices for the people having visual and hearing disability. In this paper, we proposed a framework to classify different levels of stress in response to audio and visual stimuli and also classified between these two stimuli by analyzing EEG signals. Raw EEG data was collected in lab environment and the necessary pre-processing steps were applied for denoising. By extracting robust features from the denoised audio and visual data, binary and multi-level stress were classified. A binary classification between audio and visual stimuli was also successfully done in this research. We achieved highest accuracy for binary stress classification 97.14% from visual stimuli, whereas we achieved 94.51% accuracy for auditory stimuli. Again, we achieved the accuracy for four level stress classification 89.59% for visual stimuli and 82.63% for audio stimuli.

INDEX TERMS Brain-Computer Interface (BCI), Electroencephalogram (EEG) , Mental Stress, Audio stimuli, Visual stimuli, Machine Learning

I. INTRODUCTION

NOWADAYS,mental stress is an inevitable problem that has an impact on people all over the world. Numerous elements of everyday life, including job, habit, and restless times, can cause mental stress. Again, climate change, lacking of security in society, study pressure, different social and family issues induce stress severely [1]. It has an impact on both a country's economy and the efficiency of each person's daily tasks [2]. Mental stress has a direct impact on operators' emotions, conduct, and performance; it can even result in operational mishaps [3]. Psychosocial stress has been linked to poor quality of life by impacting people's emotional behavior, ability to function at work, and mental and physical health [4]. The sympathetic nervous system (SNS) and the hypothalamus-pituitary-adrenocortical (HPA) axis are both activated during stress [5]. The adrenal cortex releases glucocorticoids, or cortisol, in response to stimulation of the HPA axis. Cortisol is a key player in the control of several physiological processes, including blood pressure, glucose levels, and carbohydrate metabolism [5]. Many physical, immunological, and psychological health issues, such as anxiety, sadness, and post-traumatic stress disorder (PTSD), heart attacks, strokes, and immunological illnesses, are brought on by chronic SNS dysfunction [5]. Stress also modifies the anatomy and physiology of the brain.

Stress levels may be assessed in a variety of ways. The most often utilized technique for determining a person's degree of mental stress is standard questionnaire-based self-reporting [1], [2], [5], [6]. Additionally, physical, and physiological measurements have also been used as impartial techniques to evaluate stress. A few physiological characteristics that are responsive to stress include voice, eye focus, pupil dilation, blink rate, and facial emotions [6]. Some physiological biomarkers such as electroencephalography (EEG), electrocardiography (ECG), functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), galvanic skin response (GSR), positron emission topography (PET), and cortisol are also can be used for stress level detection [1], [3]–[5], [7]. Out of all these methods, EEG is chosen due to its many benefits, including its excellent temporal precision at millisecond scale, ease of use, inexpensive setup costs, and non-invasive data gathering [5]. EEG has emerged as the most extensively utilized neurophysiological signal in this industry because of all these benefits. Furthermore, EEG signal alterations are a more accurate, objective indicator of emotions since they are not subject to conscious manipulation [6].

Different kinds of stimuli were used to evoke stress. Montreal imaging Stress task (MIST) was used by Eduardo et al. [1] which is one of the most validated stress inducers. A modified version of the Trier Social Stress Test (TSST) was used by A. Akella [8] and his fellow researchers to generate a controlled stress response. A construction workers' EEG data was collected while they worked in the real construction sites and occupational stress was classified by H. Jebilli et al. [9]. A simulated drone piloting training session was used to evoke stress by Qunli Yao et al. [3]. Some authors performed mental arithmetic tasks for inducing stress [4], [5]. Different virtual reality environment based stroop test was also used to induce mental stress [10]. Instead of using only visual stimuli, some authors designed auditory stimuli such as music tracks to evoke stress [7], [11], [12]. Sometimes combination of both audio and visual stimuli such as movie clips were used to give rise to mental stress [13].

Most researchers worked on stress classification from visual stimuli. Out of them, many researchers worked on either binary stress detection or multi-level stress detection. Some of them worked on both binary and multi-level stress. G. Jun [14] and H. Altaf [15] worked on binary stress classification using visual stimuli and found highest accuracy 96% and 95% respectively. On the other hand, A. Akella [8], Q. Yao [3] and F. Al-shargie [5] used only visual stimuli and multi-level stress was classified successfully with the highest accuracy 91%, 89.88% and 94.79% respectively. E. Perez-Valero [1] and A. R. Subhani [4] employed visual stimuli but in their research work, both binary and multi-level stress was detected with good accuracy. Another important stress inducer in everyday life is auditory stimulation where people get emotionally attached listening to various problems. One research used various music tracks as auditory stimuli for inducing stress and they worked on both binary and multi-class stress [7]. However, no researchers used both visual and auditory stimuli for mental stress classification purpose.

Many researchers worked on classification among different types of stimuli. However, these works are not focused on stress detection. G. S. Mouni et al. [16] classified among three types of stimuli named- audio, visual and cognitive stimuli. They found best accuracy for the visual stimuli. Audio, visual and audio-visual stimuli multi class classification was done by Y. Dasdimir et al. [17]. But in this case, they found the best accuracy for the audio-visual stimuli. J. Leoni et al. [18] employed several types of stimuli but they found best accuracy for the picture and non-picture (audio-video) based stimuli. T. Agarwal et al. [19] employed LSTM method for classifying audio and visual stimuli. Dr. E. G. M. Kanaga et al. [20] did multi class classification among for auditory, somatosensory, and cognitive events and found the highest accuracy for somatosensory stimuli. These findings not only help neuroscientists identify ERPs more quickly and accurately, but they also open the door for BCIs to potentially offer users more features by utilizing the variety of stimuli that the system can identify. Since most BCI systems on the market today rely on visual cues or visual input, they might not be suitable for severely incapacitated patients who have lost their capacity to see or regulate their eye movements. D. Kim et al. [21] developed the first online ASSR-based BCI system, proving that a completely vision-free BCI system could be realized.

In this research, we collected EEG data using both audio and visual stimuli. Mathematical word problems having three difficulty levels were shown before participants. Advanced pre-processing pipeline was used for removing noise from the raw EEG data. Binary and multi-level stress was detected from both audio and visual stimuli was done in this work. Moreover, we performed binary classification of EEG data for audio and visual stimuli having significant improvement of accuracy. In the next consequent sections, we will discuss about detailed methodology, results and discussions and finally conclusion of the proposed work.

II. METHODOLOGY

The framework of the proposed research work is shown in Fig. 1. EEG data was collected from 30 subjects in two different session for audio and visual stress inducing stimulation. An optimal pre-processing pipeline was used in this work for removing noise from the raw EEG data.

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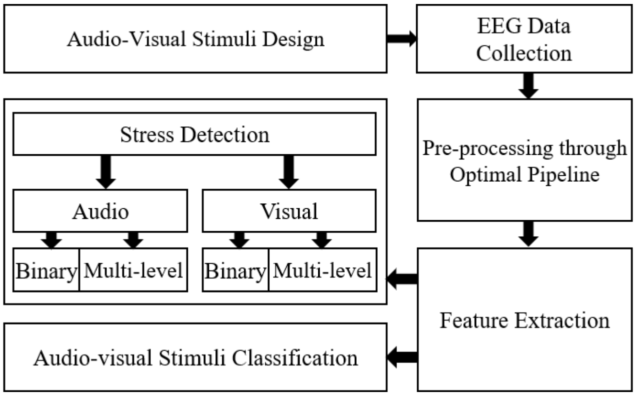

FIGURE 1. Framework of the proposed research work

After noise removal, we extracted necessary time domain and frequency domain features from the data. Finally in this research work, binary and multi-level stress were classified from both audio and visual data with necessary analysis. Again, binary classification between audio and visual stimuli was also done in this research work.

III. DATA COLLECTION

In this section, the whole data collection procedure will be described in details. This section includes three subsections having the dataset description, stimuli design and collection procedure.

A. DATASET DESCRIPTION

We used one dataset in this work. This dataset was made which includes EEG data collected by the authors at lab set-up following all the ethical requirements and data collection process was approved by the respective authority of Chittagong University of Engineering and Technology, Bangladesh. The whole data collection procedure followed the Helsinki protocol. To make this dataset, we needed to follow some steps. First of all, In order to build a proper comprehension of the EEG signal for stress classification purpose, we need to design different audio and visual stimuli by using EMOTIV Builder before starting data collection process. Participants should fulfill all inclusion requirements, including not having any physical, mental, or head injuries and abstaining from drug or prescription use prior to the trial. The EEG data was recorded by Emotiv EPOC flex headset which have 32 electrodes having two reference electrodes located at right and left mastoid. Total 30 subjects' data was collected in this dataset. The sampling frequency was 128 Hz and data were transmitted through Bluetooth communication. The number of channels were optimized, and we collected data from 16 channels named: Cz, Fz, Fp1, F7, F3, C3, P3, O1, Pz, Oz, O2, P4, C4, F4, F8 and Fp2. Because these channels are found very significant for mental stress classification in the previous literature [22]–[24].

B. STIMULI DESIGN

Obtaining EEG data while performing routine chores might provide a noisy signal. Conversely, if we apply multiple stimuli over an extended period of time, each stimulus may produce a strong peak, and the noise will be of average magnitude. The term "event related potential" (ERP) describes this behavior. For this reason, prior to collect data we designed visual stimuli where mathematical problems having three difficulty levels were given to evoke stress to subjects.

Different experimental stages of each stimulus were shown in Fig. 2. where the stimulus starts with the calibration phase. In calibration phase five seconds eyes close and five seconds eyes open data was collected followed by some general instruction phase. Then in the stimuli stage, audio or visual stimuli were heard or visualized by the subjects. Data was collected by using two kinds of stimuli- visual stimuli and audio stimuli.

Three difficulty levels math problems were shown or heard separately following a random order after finishing each difficulty level math. In the visual stimuli, stress free data was taken where the subjects were remained relaxed with their eyes closed for five seconds. Then the problem was shown to the subjects where they were allowed to view the stimuli image as much time as they need to solve the math problem. During calculating the math problem, the brain signal was recorded which was labeled as stressed data. The duration of the visual stimuli was on average 150 seconds In the audio stimuli, the five seconds eye closed data was taken by following the same way as visual stimuli. But in this case, the mathematical problem was heard by the subjects using an earphone where the participants heard it only once and has no opportunity to repeat the audio. The duration of the audio stimuli was almost 35-45 seconds. During this time the subjects need to listen the audio carefully and then solve the mathematical problem mentally without using any pen and paper. During calculating the math problem, the brain signal was recorded which was labeled as stressed data. Finally, the difficulty levels the subjects faced during solving the math problem was taken as feedback.

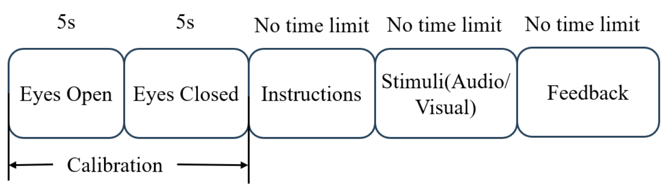

FIGURE 2. Experimental stages for single stimulus

C. COLLECTION PROCEDURE

Data has been collected from thirty participants, ages nineteen to twenty-five. Before providing any data, all participants were required to complete the authorization form. There was no history of brain disorders or visual issues among the patients. Alcohol or other narcotic substance

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addiction was absent in all of the individuals. They were all paid a little fee and gave their voluntary participation. The institution's CHSR committee and the Directory of Research and Extension, DRE, gave their approval to this initiative. The subjects entered into a noise-free room and all the subjects were given necessary instruction before collecting data. The lab set up was arranged for collecting EEG data. The room was organized with low lighting and electrical shielding, where participants were seated around 50 cm away from the computer display. A mouse and keyboard were provided to the participants so that the studies could continue. A mouse and keyboard were provided to the participants so that the studies could continue.

Visual and audio stimuli was used to collect data. There was almost three weeks gap between audio and visual data collection. Three kinds of mathematical word problems having three difficulty levels- easy, medium and hard were used to design the stimuli. In both the case of visual and audio stimuli, we collected two phase data- 5 seconds control data and stress induced data. After completing the whole experiment, the participants were given their feedback regarding how much difficulties they felt during solve the problem on scale 1 to 5 (very easy to very hard). Each subjects need to solve total six problems (three problems as visual stimuli and three problems as audio stimuli) and relaxed data was also separated from the raw data. As a result, we have total 12 files for each participants in our dataset. Finally we have total 360 (30*12) recording files in our dataset. In Fig. 3, real time EEG acquisition was shown in our lab set-up.

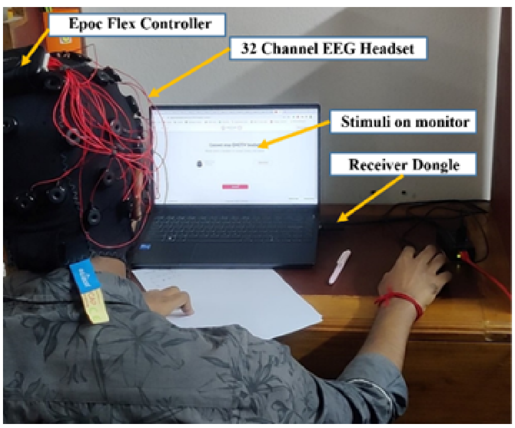

FIGURE 3. Real-time data collection scheme using 32-channel EEG

IV. EEG PRE-PROCESSING

In this paper, we used a new pre-processing pipeline proposed in two of our previous works [25], [26] to ensure the improvement in data quality without losing any significant channel information. As automated pre-processing pipeline loss a significant amount of information although the process is bit quicker. For this reason, we used our manual method instead of the automated one. The proposed pre-processing pipeline is shown in Fig. 4.

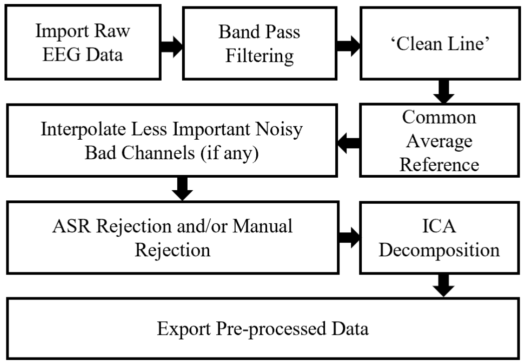

FIGURE 4. Proposed pre-processing pipeline

According to our proposed method, notch filtering using clean line function was used after band pass filtering the raw data with 0.5 to 45 Hz cut off frequency. The EEG data may contain some sinusoidal power line interference after bandpass filtering. We must make sure that the power line interference is eliminated as band pass filtering is not precise. Clean line function from EEGLAB 2022 in (MATLAB 2023a) adaptively assesses and removes sinusoidal noise (e.g., power line interference) from the ICA components or scalp channels using multi-tapering and a Thompson F-statistic [27]. Following that, we used a common average reference to re-reference the data. In addition, we identified and interpolated any noisy bad channels that were not essential to the application of interest. For EEG-based stress detection, any noisy poor channel—aside from the frontal ones—can be interpolated. Then, by examining the data, we did Artifact Subspace Reconstruction (ASR) rejection and/or manual rejection. ASR is a component-based method that requires little computation and may be used automatically [28]. Using the remaining components, the signal is rebuilt in this manner, eliminating the components with high variances. Using a reference data set devoid of artifacts, the ASR approach establishes criteria for choosing which components to reject. When the ASR rejection identified a sizable portion of the data that needed to be removed, we performed manual rejection by simply removing the considerably noisy component of the data. Following that, we eliminated muscular and ocular artifacts using ICA. Then, we divided our whole data into 4-second epochs with 10% overlapping. We got total 2180 epochs for visual stimuli and 1985 epochs for auditory stimuli.

V. FEATURE EXTRACTION

Several important EEG features are identified in previous literatures. For example, ten characteristics were employed by D. Shon et al. [27], including frontal alpha asymmetry, mean, standard deviation, and hjorth parameters for mental stress detection. 40 characteristics, such as mean, kurtosis, and hjorth parameters, were employed by M. J. Hasan [29] for various mental stress state detection. In our research, we took into account every attribute from each band and retrieved

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11 statistical features [27], [29]–[31] because these features are very significant for mental stress detection. Again, as traditional machine learning models were employed here, we selected easily understandable features by using trial and error method. Some explanation regarding these features are given below: Mean: The equation of mean is shown in equation 1.

$$\mu=\frac{1}{N}\sum_{i=1}^{N}X_i \tag{1}$$

Standard deviation: The standard deviation measures how widely distributed the data are in relation to the mean. When it comes to standard deviation, data with little or low standard deviations are centered around the mean, whereas high or great standard deviations are widely distributed. The equation of standard deviation is shown in equation 2.

$$\sigma=\sqrt{\frac{\sum_{i=1}^{N}(X_i-\mu)^2}{N}} \tag{2}$$

Variance: It means the statistical measurement of spreading of data with respect to the average value in a specific dataset. The equation of variance is shown in equation 3.

$$\sigma^2 \tag{3}$$

Kurtosis: This statistical feature is used to measure how tailed a distribution is. The frequency of outliers is known as tailness. Excess kurtosis is the tailiness of the distribution relative to a normal distribution. The equation of kurtosis is shown in equation 4.

$$\frac{1}{N}\sum_{i=1}^{N}\left(\frac{X_i-\mu}{\sigma}\right)^4 \tag{4}$$

Skewness: The skewness of a distribution indicates how asymmetrical it is. A distribution is considered asymmetric when its left and right sides are not mirror reflections. The equation of skewness is shown in equation 5.

$$\frac{1}{N}\sum_{i=1}^{N}\left(\frac{X_i-\mu}{\sigma}\right)^3 \tag{5}$$

One method for expressing a signal's statistical properties in the time domain is the Hjorth parameter, which contains three different types of parameters- Activity, Mobility, and Complexity. They provide details on the signal's amplitude variability, temporal dynamics variability, and spectral bandwidth variability [32].

Activity: The variance of the time function, or the activity parameter, may be used to determine the frequency domain power spectrum surface. In other words, if there are many or few high frequency components in the signal, the value of activity yields a big or small number [32]–[34]. The equation of activity is shown in equation 6.

$$\operatorname{var}(X) \tag{6}$$

Complexity: The complexity parameter shows how a signal's form resembles that of a pure sine wave [32], [33]. As the signal's structure becomes closer to that of a pure sine wave, the complexity value converges to 1. These three factors aid in time domain signal analysis in addition to providing information about a signal's frequency spectrum. Additionally, by using them, a lower computational complexity can be attained [32], [34]. The equation of complexity is shown in equation 7.

$$\frac{\text{Mobility }(X')}{\text{Mobility}(X)} \tag{7}$$

Mobility: The square root of the ratio between the signal's first derivative's variance and its own is the mobility parameter. This parameter has a power spectrum standard deviation percentage [32], [33]. The equation of mobility is shown in equation 8.

$$\sqrt{\frac{\operatorname{var}(X')}{\operatorname{var}(X)}} \tag{8}$$

Sample entropy: Sample entropy is the idea that a value from a series in an ordered system would be a suitable way to define it. It may be thought of as a measure of degree of randomness or regularity [35]. If there are more complex or non-ordered sequences in a series, the entropy will be higher, and vice versa. It lessened the bias brought on by self-matching [35]. The equation of sample entropy is shown in equation9.

$$\operatorname{SampEn}(m,r)=-\ln\frac{B^{m+1}(r)}{B^m(r)} \tag{9}$$

Spectral entropy: The spectrum complexity of a time series is measured by spectral entropy, which is derived from Shannon entropy. based on the inconsistent data buried in the EEG spectrum in the resting state [31]. The equation of spectral entropy is shown in equation10.

$$\begin{gathered}\hat{p}(f)=P(f)/\sum_{f=0.5}^{45}\mathrm{P(f)}\\ SH=-\sum_{f=0.5}^{45}\hat{p}(f)\log(\hat{p}(f))\end{gathered} \tag{10}$$

Differential entropy: Differential entropy, which is the entropy of a continuous random variable, is used to quantify the complexity of a continuous random variable. Minimum description length is also connected to differential entropy [30]. The formula for calculating it is as follows:

$$h_i(X)=\frac{1}{2}\log\left(2\pi e{\sigma^2}_i\right) \tag{11}$$

To determine each band's frequency domain component, a Welch periodogram was used. Three characteristics were retrieved from the frequency domain: average power, frontal alpha asymmetry, and valence [36] .

Valence: Asymmetrical frontal hemisphere activity was linked to mental stress as valence [36]. Positive and negative valence levels are associated with activation of the left and right prefrontal areas, respectively. The idea that frontal EEG asymmetry might serve as an index of valence is supported by a substantial body of research [36]. The equation of valence is shown in equation 12.

$$\frac{\beta(F3)}{\alpha(F3)} - \frac{\beta(F4)}{\alpha(F4)} \tag{12}$$

Frontal alpha asymmetry: The frontal lobes of the right hemisphere in the cerebral hemisphere are asymmetrical in the left hemisphere as opposed to the right. In EEG electrodes, Fp1 and Fp2 are utilized to detect frontal lobe differences. The pre-frontal cortex of the brain is referred to as Fp [27], [36]. Each electrode yields the alpha wave band's power, which is then taken and subtracted from the absolute value and the log. The equation of frontal alpha asymmetry is shown in equation 13.

$$\frac{\alpha(F4) - \alpha(F3)}{\alpha(F4) + \alpha(F3)} \tag{13}$$

Average power: The average band power, which is calculated as a single value that represents the frequency band's contribution to the signal's total power [37]. The equation of average power is shown in equation 14.

$$P_f = \frac{1}{N}\sum_{n=1}^{N} |X_n(k)|^2 \tag{14}$$

VI. RESULTS

Insightful findings and all the results are described in this section. Total five datasets were made by combining all the features extracted from the data. In first dataset only relaxed and stressed data features were combined for visual stimuli. In second dataset, three level stressed data features were combined for the visual stimuli. In third dataset, eye closed relaxed data and three level stressed data features were assembled for four class stress classification for visual stimuli. On the other hand , eye-closed and stressed data features for auditory stimuli were combined in the fourth dataset and three level stressed data features for auditory stimuli were combined in the fifth dataset. Again, eye closed relaxed data and three level stressed data features were assembled for four class stress classification for auditory stimuli in sixth dataset. Last but not the least, the seventh dataset was based on both the combination of audio and visual stimuli data features. In each case, 80% data was taken for training and 20% data was taken for testing purpose. We employed several machine learning models and four models outperformed out of all the models. Those four models were- Support Vector Machine (SVM), k-Nearest Neighbor (kNN), Decision Tree (DT) and Linear Discriminant. Our dataset was imbalanced initially as eye closed relaxed data was taken for five seconds whereas hard math problem solving involved higher time duration. Again in multi level stress detection dataset, three difficulty level math need different time time duration for solving. We did not fix the time limit for math solving because our target was to classify different levels of stress. If time limit was set for each level math solving, it will create e mental pressure for each case. In that scenario, different difficulties problems may exert same amount of stress. But our target was to classify multi-level stress. We also need to balance all the seven datasets before training ML models. SMOTE was used in this purpose to balance the dataset.

TABLE 1. Summary for binary stress classification from visual stimuli

Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Decision Tree	91.43	66	66	66
Linear Discriminant	93.93	73	83	77
KNN	97.12	94	83	88
SVM	97.14	94	86	90

TABLE 2. Summary for three level stress classification from visual stimuli

Model Name	Accuracy (%)	Macro F1 Score (%)	Weighted F1 Score (%)
Decision Tree	74.00	70	74
Linear Discriminant	73.15	71	74
KNN	84.35	83	85
SVM	89.01	87	89

TABLE 3. Summary for four level stress classification from visual stimuli

Model Name	Accuracy (%)	Macro F1 Score (%)	Weighted F1 Score (%)
Decision Tree	74.46	71.11	74.46
Linear Discriminant	73.48	73.10	73.48
KNN	85.27	85.14	85.27
SVM	89.59	88.52	89.59

TABLE 4. Summary for binary stress classification from auditory stimuli

Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Decision Tree	90.11	57	57	57
Linear Discriminant	80.77	49	52	49
KNN	93.96	73	67	74
SVM	94.51	82	76	79

The accuracy, precision, recall, and F1 scores for each machine learning model were shown for binary stress classification in Tables 1. and 4. In Tables 2. Table 3. Table 5. and Table 6, accuracy, macro F1 scores and weighted F1 scores for multi-level including both three level and four level stress classification were shown.

In Table 7, results were shown in a tabular format for audio and visual EEG data binary classification. The study found that the best classification accuracy for visual stimuli was 97.14% for binary stress classification, 89.01% accuracy for three level stress classification and 89.59% accuracy

TABLE 5. Summary for three level stress classification from auditory stimuli

Model Name	Accuracy (%)	Macro F1 Score (%)	Weighted F1 Score (%)
Decision Tree	68.00	66	68
Linear Discriminant	73.00	72	73
KNN	86.00	86	86
SVM	88.00	87	88

TABLE 6. Summary for four level stress classification from auditory stimuli

Model Name	Accuracy (%)	Macro F1 Score (%)	Weighted F1 Score (%)
Decision Tree	63.68	61.94	63.68
Linear Discriminant	69.74	64.43	69.74
KNN	79.47	73.90	79.28
SVM	82.63	78.64	82.44

for four level stress classification, while the best accuracy for auditory stimuli was 94.51% accuracy for binary stress classification, 87.7% accuracy for three level stress classification and 82.63% accuracy for four level stress classification. This indicates that compared to auditory and visual evoked potentials, visual evoked potentials were more accurate for both binary and multi-level stress classification.

By analyzing all the results in tabular format, we came to know that out of four machine learning models, SVM performed better in all cases of machine learning classification. As our dataset was linear in nature that is why SVM worked better. In Fig. 5, the best result found for binary stress classification was shown where the best accuracy was found 97.14% for SVM. Three level stress classification result was shown in Fig. 6. where three different level stress was classified. We found the best accuracy 89.01% for SVM classifier. Again, for four level stress detection from visual stimuli, the best accuracy was found for SVM and that was 89.59% which is shown in Fig. 7.

In the second steps of our work, binary and multi-level stress was classified from auditory stimuli. Here, mathematical word problem was heard by the participants in stead of viewing the problem in image format. The audio was played for only once and then they need to solve those maths mentally which induces stress. In Fig. 8, the best result found for binary stress classification was shown where

TABLE 7. Summary for binary classification between visual and auditory stimuli

Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Decision Tree	91.71	92	94	93
Linear Discriminant	95.07	96	96	96
KNN	97.48	98	98	98
SVM	98.32	99	99	99

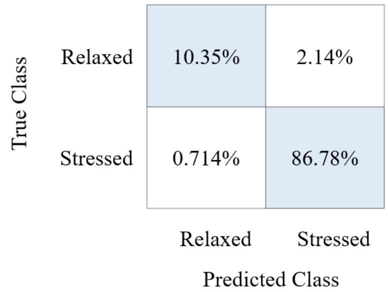

FIGURE 5. Confusion matrix for binary stress classification from visual stimuli

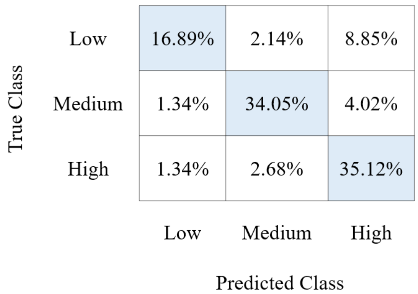

FIGURE 6. Confusion matrix for three level stress classification from visual stimuli

the best accuracy was found 94.51% for SVM. Three level stress classification result was shown in Fig. 9. where three different level stress was classified. We found the best accuracy 87.70% for SVM classifier. Finally, for four level stress detection from auditory stimuli, the best accuracy was found for SVM and that was 82.63% which is shown in Fig. 10.

In Fig. 6,7,9 and 10, there we noticed higher false values in multi-level stress classification comparing with the binary stress classification results because in binary classification, the highest stressed data and relaxed data was classified where the boundary line was more clear. On the other hand, in case of multi-level stress classification, three difficulty level math- easy, medium and hard problems were given to the participants where in few cases, some participants found the medium problem as hard and some hard problem seems medium level difficulty to them. As, difficulty level

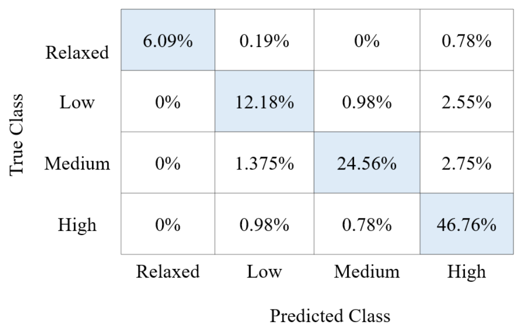

FIGURE 7. Confusion matrix for four level stress classification from visual stimuli

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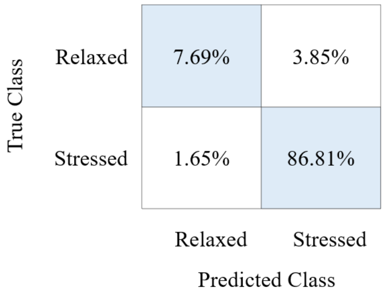

FIGURE 8. Confusion matrix for binary stress classification from auditory stimuli

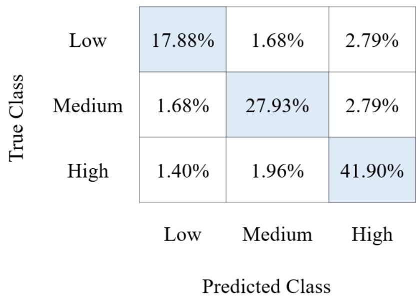

FIGURE 9. Confusion matrix for three level stress classification from auditory stimuli

varies from participants to participants in very few cases, that is why we got some false values during multi-level stress classification.

In the last stage of our research work, binary classification of EEG data between audio and visual stimuli was done. In Fig. 11, Confusion matrix for binary classification between visual and auditory stimuli was shown where best accuracy was found 98.32% for SVM.

From the comparison Table 8, we came to know about different types of stimuli used in previous works. Most of the authors used mental arithmetic task as visual stimuli but none of them used mental arithmetic task as auditory stimuli for inducing stress. Besides that, none of the works classified four level stress and it is still unchecked. In all of the works, the researchers employed traditional machine

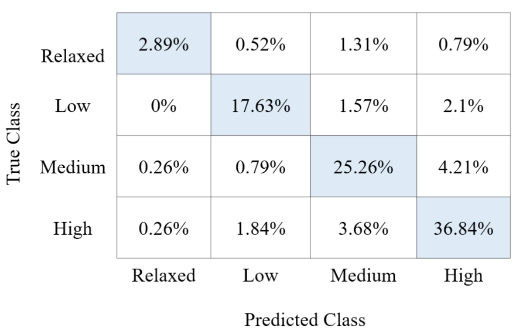

FIGURE 10. Confusion matrix for four level stress classification from auditory stimuli

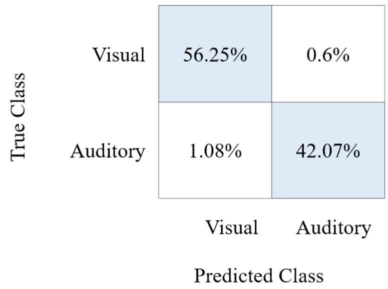

FIGURE 11. Confusion matrix for binary classification between visual and auditory stimuli

learning models and found satisfactory results. For visual stimuli, the highest accuracy for binary stress detection was 96% whereas in our research work we found 97.14% accuracy. Again, for three level stress detection, greatest accuracy was found 94.79% for visual stimuli whereas we achieved highest 89.01% accuracy. From audio stimuli, we got 87.7% highest accuracy for three level stress classification. We also successfully classified four level stress and found highest accuracy 89.56% for visual stimuli and 82.63% for auditory stimuli.

VII. SIGNIFICANCE OF AUDIO VISUAL STIMULI BINARY CLASSIFICATION AND FUTURE SCOPES

Brain-Computer Interface (BCI) is an augmentative communication that permits a person to control an electronic device using brain waves. The results of this research specially the audio visual stimuli classification are very significant for the BCI applications. As the whole system performed satisfactorily for the normal hearing and sighted people, this research's results can also be used for the blind and deaf people for classifying audio visual stimuli. Blind people can use this system for detecting visual stimuli and deaf people can be able to use this system for detecting audio stimuli. In traditional hearing and eye sight testing, the test decision is completely relied on subject's response and feedback how much they can hear or see any English alphabet. However, children and aged people sometimes give wrong feedback and as a result, the test result may also be wrong consequently. In this scenario, our audio visual stimuli classification system can be used for testing hearing and sighting condition for children and aged people and also the results can be compared with the traditional hearing and sight testing for better clarification of the test results.

VIII. CONCLUSIONS

In this research, binary and multi-level (three and four level) stress classification were done from both visual and auditory stimuli. A dataset was created by collecting real time EEG data from 30 subjects. We achieved highest accuracy for binary stress classification 97.14% from visual stimuli, whereas we found 94.51% accuracy for auditory stimuli. Again, we achieved highest accuracy for three level stress classification 89.01% for visual stimuli and 87.7% accuracy

TABLE 8. Comparison study for two and three level stress classification

Reference	Stimuli/Stressor Used	No. of Channels	No. of Subjects	Features No.	Classification type	Method	Accuracy
Altaf et al. [15]	Mental arithmetic exercises	1	30	12	Two-level stress	Naive Bayes	95%
Perez- Valero et al. [1]	Mental arithmetic task	8	20	2	Three level stress	SVM with smooth filter	94%
					Two level stress	Multi-layer protection without filter	81%
Islam et al. [24]	Mental arithmetic task	21	11	4	Two-level stress	Ensemble Subspace K-NN	77.3%
Akella et al. [8]	Mental arithmetic tasks	32	80	3	Three level stress	SVM	91%
Jun et al. [14]	Mental arithmatic task	14	10	-	Two level stress	SVM	96%
					Three level stress		75%
shargie et al. [5]	Mental arithmatic task	7	18	18	Three level stress	SVM with ECOC	94.79%
Hafeez et al. [39]	Montreal Imaging Stress Task-based mental arithmatic task	8	14	1	Three level stress	LSTM	70.67%
Chowdhury et al. [40]	Mental arithmetic task	1	5	1	Two level stress	Random Forest	86.9%
Ahn et al. [41]	Mental arithmatic task	2	14	4	Two level stress	SVM	77.9%
Rajendran et al. [42]	Mental arithmatic task	8	25	12	Two level stress	SVM	95.83%
Saidatul et al. [43]	Mental arithmatic task	19	30	2	Three level stress	kNN	84%
Proposed work	Mathematical Word Problem as visual stimuli	**16**	**30**	**14**	Two level stress	**SVM**	97.14%
					Three level stress		89.01%
					Four level stress		89.59%
	Mathematical Word Problem as audio stimuli				Two level stress		95.51%
					Three level stress		87.17%
					Four level stress		82.63%

for audio stimuli. For four level stress classification, we achieved highest accuracy 89.59% for visual stimuli and 82.63% accuracy for audio stimuli. A binary classification between audio and visual stimuli was successfully completed with highest accuracy 98.32%. These findings will help to detect mental stress at early stage and also it will further help the community having eye sight and hearing disability for classifying audio and visual stimulation.

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