Webology (ISSN: 1735-188X)
Volume 19, Number 3, 2022

Human Stress And Pressure Detection Using A Machine Learning Approach With Eeg Signal

Kishor R Pathak[1] , Dr. Farha Haneef[2]

[1]Research Scholar, Oriental University Indore.

[2]Associate Professor, Oriental University Bhopal.

Abstract: This work intended to develop a unique multimodal prototypical by integrating several electroencephalogram (EEG) information sources subjected to neutral, undesirable, and optimistic aural stimulation to differentiate between Stress affected persons and controls. A depression identification model was constructed by fusing EEG data from many modalities using a feature-level fusion approach. Simultaneous EEG recordings were made on 86 Stress patients and 92 normal controls when exposed to various auditory stimuli. Then, lined and nonlinear characteristics were removed and chosen from the EEG data for each modality to generate modality-specific features. Additionally, a direct combination approach was employed to combine the EEG characteristics from various modalities to create a universal feature vector and identify numerous robust
factors.

The classification precision of each classifier, viz. the k-nearest neighbor (KNN), the decision tree (D.T.), and the support vector machine (SVM), is associated with positive findings. The KNN classifier had the maximum classification precision of 86.98 percent when optimistic and undesirable audio stimuli were combined, suggesting that the synthesis modality may attain a better rate of depression detection than the separate modality schemes. Additionally, feature weighting was accomplished using genetic algorithms to enhance the recognition framework's overall performance. This work may contribute to developing a new method for diagnosing depression.

Keywords: Depression recognition EEG, Multimodal Audio stimulus Fusion.

1. Introduction

Depression, often known as depressive disorder, is a frequent affective condition. The World Health Organization (WHO) estimates that over 340 million individuals worldwide suffer from depression. On the other hand, Chinese statistics indicate that more than 30 million Chinese residents are depressed [1]. Depression is ranked fourth in the world's top ten chronic disorders. Depression is predicted to overtake heart disease as the world's second leading cause of death by

2020 [2]. Depression is a severe psychiatric condition marked by negative feelings such as sadness, exhaustion, and despair. Severe depressive patients may even engage in suicidal conduct [3].

Since the mid-nineteenth century, clinical study on depression has been conducted steadily. However, clinical diagnosis has grown more challenging since the underlying brain mechanism and the pathogenic principle of depression are unknown. Specifically, a link between the brain and depression has been shown. As a result, more research uses electroencephalogram (EEG) technology to investigate impartial and ubiquitous depression diagnosis methodologies and procedures. EEG technology has been increasingly employed to aid in the identification of disorders such as schizophrenia [10], moderate reasoning impairment [11], epilepsy [12], and Alzheimer's disease [13]. Patients with depression have abnormalities in their cognitive abilities reflected in their EEG [14].

This essay is primarily concerned with the identification of depression

. While EEG knowledge is employed in the adjunct analysis of depression, the most often used EEG collection devices for study purposes are 128- and 256-electrode intelligence caps [15,16]. Before wearing the EEG gathering equipment, the brain cap must be soaked or the conductive paste applied to the appropriate electrode location. The experiment's functioning is rather complex, and the pollution generated is substantial. Moreover, since the individual is uncomfortable while wearing this equipment, it is simple for them to leave during the EEG monitoring, making a considerable sample size challenging to gather. In light of the circumstances and the degree of cooperation shown by the patient, this research will not use this apparatus. Additionally, Carmen CY et al. highlighted the importance of battery working duration and device size in influencing the utility of BSN sensors [17–19]. As a result, developing a ubiquitous and low-power EEG achievement sensor is critical for future study.

Additionally, complete prior investigations retrieved depressed EEG characteristics in the individual modality, often during rest. Multiple modalities have gained popularity in recent years in various fields by combining two or more modalities to attain superior consequences. The benefit of numerous modalities aids in growing usability when the shortcomings of one modality are compensated for by the assets of another [20,21].

As a result, this research sought to combine many modalities of three-electrode EEG information to develop a unique multimodal outline for determining the practical aspects of depressed EEG under normalization settings and for creating a depression cataloging model of ordinary EEG.

2. Related work

EEG signals are generated when neurons fire spontaneously and rhythmically from the scalp surface. In 1926, German psychiatrist Hansberg found it for the first time. He defined the waveform of electroencephalogram (EEG) signals with alpha and beta waves to understand the physiological foundation of psychological events. Science and technological advancements have resulted in some improvements in EEG technology research. Because EEG technology is safe, inexpensive, simple to use, and non-invasive, it has been used to diagnose brain illnesses. To begin, EEG can accurately describe the most psychological activity, and cognitive actions, like neuroscience, psychology, and reasoning science studies have shown [22,23]. Second, EEG indications are inextricably linked to human intellect activity and emotional state and may imitate real-time dynamic variations [24,25]. Harmon-jones et al. discovered that lower left frontal EEG activity was related to decreased happiness and increased undesirable emotions. Klinische et al. discovered that the electroencephalogram's alpha and theta wave oscillations might reflect reasoning and memory function performance [26]. Moretti et al. established a link between the EEG power ratio and moderate reasoning impairment memory performance [27]. Af-tanas et al. discovered that theta waves and low alpha waves in the prefrontal lobe of the human intellect reflect a pleasant emotional state and degree of attention [28]. Adeli et al. discovered correlation latitude differences between epileptic patients and healthy subjects in the Beta and Gamma wave subbands at higher frequencies in the EEGs of epileptic patients and healthy subjects [29]. Arns et al. investigation .'s established a difference in the ratio of theta to beta waves in the EEG between people living with ADHD and healthy individuals. Smit et al. established a link between EEG asymmetry in the human frontal lobe and anxiety illnesses. Siddiqui et al. think that electroencephalography (EEG) is a critical diagnostic technique for sleep disorders. Kühn et al. directed a meta-analysis of inactive EEG information from 470 applicants in 11 studies and discovered that patients with major depression have hyperactive prefrontal cortex. Leuchter et al. studied inactive EEG information from 121 discreetly stressed affected persons and 37 strong controls and discovered that Stress affected persons had a more significant total signal in the delta, theta, alpha, and beta bands than normal controls. Simultaneously, the prefrontal lobe's alpha band's power and synchronization were significantly different from standard rules.

Additionally, the researchers employed machine learning to identify EEG information from stressed and strong individuals based on the criteria presented by prior studies. Erguzel et al. classified 147 subjects with a classification precision of 89.12 percent using Backpropagation Neural Networks (BPNN). Spyrou et al. confidential the EEG information of 34 healthy individuals and 32 Stress affected persons using a random forest classifier with a 95.5 percent accuracy rate. However, these researchers collected EEG data in individual mode.

Data fusion from disparate sources has become a critical endeavor in recent years. It appears self-evident that a multimodal scheme that integrates several networks and signals would deliver more precise appreciation than a unimodal one. H. Ghasemzadeh et al. pioneered data synthesis in emotion detection and overall health, developing a revolutionary human equilibrium based on EMG signs for innovative neuromuscular system explanation. The findings indicated that irrespective of the genuineness of the training information, multimodal precision is superior to the second-best discrete modality.

While there is much research on separate modality EEG and unhappiness detection in general, there is minimal work on depression appreciation utilizing multimodal EEG information specifically. This study was designed to combine many modalities of three-electrode EEG information to develop a unique multimodal outline for deciphering the functional EEG characteristics of unhappiness and developing a depression cataloging model using general EEG.

3. Proposed method

We propose a multimodal depression identification model in this study based on the synthesis of EEG information recorded while listening to neutral, undesirable, and optimistic auditory stimuli. As seen in Figure 1, the synthesis is justified by the subsequent factors: (I) Subjective perceptions of favorable emotional stimuli are reduced in stress sufferers (optimistic feelings are weakened), (II) Affected persons suffering from Stress are more susceptible to undesirable emotional stimuli, as shown by more significant consideration to unpleasant feelings and an elevated demonstrative reaction (unpleasant emotions are improved), (III) Individual differences impair the accuracy of the information collected in each modality (optimistic or pessimistic audio stimulation). In light of the difficulties, merging the characteristics of various modalities may effectively compensate for the absence of distinct modality characteristics.

In this article, we accomplish a feature-level synthesis of EEG information. Our fusion process is shown in a block diagram in Fig. 2. It comprises six mechanisms: depression appreciation with neutral auditory stimulation, depression appreciation with negative auditory stimulation, depression appreciation with optimistic auditory stimulation, feature-level synthesis, feature collection for synthesis, and feature weighting.

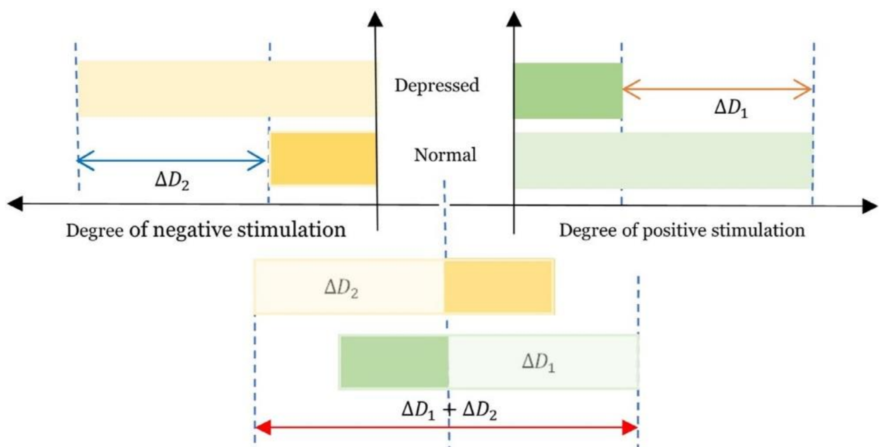

Fig. 1. the Mechanism of multimodal fusion.

The EEG achievement equipment is used to gather the subject's EEG information concurrently with neutral, undesirable, and optimistic auditory stimuli, and then the EEG information is preprocessed. (II) NeuEF is for features removed during neutral acoustic stimulation; negEF stands for components extracted during negative audio stimulation, and posEF stands for components extracted during positive audio stimulation.

3.1. Participants and research

3.1.1. Investigational equipment

Earlier research has implicated the amygdala and orbitofrontal cortex in both happy and undesirable feelings. Harmon-Jones et al. discovered that anger and reasoning dissonance, negative feelings, and motivational method orientations are all significantly related to the increased left-frontal activity. Additionally, the EEG sign obtained in the non-haired forehead location has a low impedance, low distortion, and good usefulness. As a result, the optimal scalp positions in the current investigation were FP1, Fpz, and Fp2. As seen in Fig. 3, three-electrode EEG information from frontal FP1, Fpz, and Fp2 was recorded concurrently in this work, with the earlobe serving as an orientation electrode. A Bluetooth connection was used to save the data on the PC. Fig. 3 illustrates a ubiquitous three-electrode EEG acquisition sensor created separately by Lanzhou University's Ubiquitous Alertness and Smart Solutions Lab. The device was very adaptable and could be used in various configurations to suit the application. The sampling rate was 250 Hz per channel, the sampling accuracy was 24 bits, the resistance of all electrodes was 50 kΩ, and the standard model refusal ratio was 110dB.

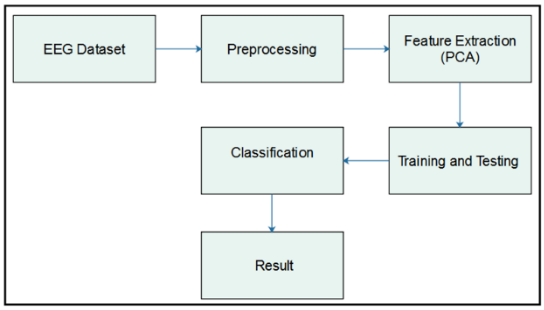

Fig. 2. Method flow diagram.

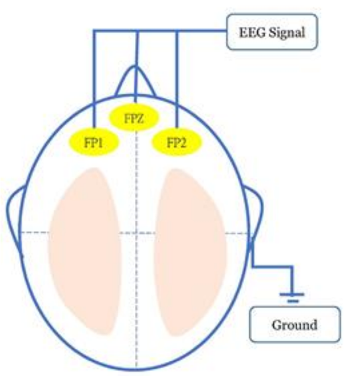

Fig. 3. Diagram of EEG-sensing device Electrodeposition of Fp1, Fpz, and Fp2.

3.1.2. Inclusion measures

To guarantee the validity and trustworthiness of the trial data, this article attempts to pick experimental samples that span the whole sample in amount and kind. The investigational procedure was followed precisely.

Professional psychiatrists used assessment techniques to choose people with Stress. The following are the inclusion criteria:

Patients with unhappiness: Patients with despair satisfied The Mini-International Neuropsychiatric (MINI) diagnostic criteria, and their Patient Health Questionnaire (PHQ-9) value was more than or equivalent to 5.

Well control group: The MINI did not detect any mental disorders, and the findings of all other balances were ordinary.

All focuses must also encounter the following criteria: No other psychological problems, no other significant or persistent bodily illnesses, and no psychotropic drugs were used during the two weeks before the study.

The study's participants were identified using the 973 National Key Investigation and Expansion Program's screening criteria. 86 stress-affected persons, and 92 regular controls were used to construct data sets.

3.1.3. Experimental procedure and materials

It has been shown that the emotional reaction of Stress patients to external stimuli is distinct from that of normal controls. Positive emotional stimuli are somewhat insensitive to depressive individuals, whereas negative emotional stimuli are very responsive. As a result, three distinct modalities were employed in this study: three distinct forms of auditory stimuli eliciting distinct emotions. The subjects' EEG signals were recorded and analysed using five sections of auditory stimuli: two unbiassed stimuli, two undesirable stimuli, and one optimistic stimulus. The stimulus was obtained from the International Affecting Digitized Sounds, 2nd version, a standardised collection of 167 naturally happening sounds, each lasting 6 seconds, frequently used to study emotions.

The whole experiment took place in a purpose-built laboratory that was silent, soundproof, glare-free, and adequately aired. There is no significant electromagnetic interfering present in the investigational setting, and there are no additional noise properties present throughout the trial. The following was the specific investigational protocol (Fig. 4):

The complete procedure for experimenting is provided below:

(I) Ascertain if the individual is awake and meets the requirements for enclosure;
(II) Explain to the participant the purpose of the experiment, the procedure, and any precautions that may be necessary;
(III) Wear the participant's three-electrode EEG sensor;
(IV) Ascertain that the electrodes were positioned correctly and in excellent contact;

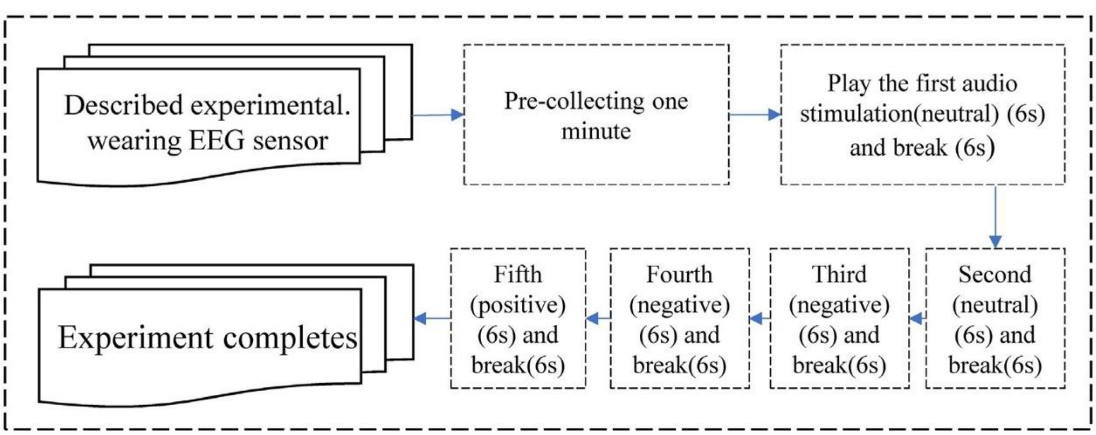

Fig. 4. Process of EEG signal acquisition.

(V) One minute of pre-collection was used to verify that the right EEG signs were gathered and that the gadget was modified appropriately if aberrant signs were discovered;
(VI) After the pre-experiment is completed successfully, the trial is formally begun;
(VII) Simultaneously with each section of acoustic stimulation, capture the participant's EEG

data. The individual rests for 6 seconds after each auditory stimulus. The following sequence was followed during playback: first neutral audio stimulus, second neutral audio stimulus, first negative audio stimulus, second negative audio stimulus, and finally positive audio stimulus;

(VIII) Notify participants that the trial has concluded and inspect the data excellence. If the information is of low superiority, it must be re-collected.

3.2. Data processing

Numerous sounds were unavoidably added during the collection of EEG signals. Noise is often comprised of two types: power occurrence noise generated by the surroundings and apparatus and other sounds generated by the body's functional signals, such as an electrocardiogram (ECG), electrooculography (EOG), and electromyogram (EMG). Preprocessing of the raw EEG signals was used to acquire reasonably pure EEG data. First, the noise in the power occurrence range was mainly created by the device's power source, which operated at a 50 Hz frequency. A 50-Hz notch filter was employed to eliminate the 50 Hz sign during the procedure. Second, the ECG was produced by the heart's rhythmic activity, which had a considerable amplitude. The ECG signal sent to the scalp decreases because the heart is placed farther away from the head. Extraction of features Traditionally, clinicians undertake EEG signal analysis based on their clinical experience, which is subjective. As a result, it is possible to overlook a significant quantity of data throughout the diagnostic procedure. The general EEG examination is primarily lined to extract specific frequency, power range, and peak properties. Numerous investigations, however, have shown that EEG signs are nonstationary and unpredictable and that a simple lined analysis cannot cut all of the data confined in these indications. As a result, the preprocessed EEG data's linear and nonlinear aspects were retrieved to conduct a complete analysis of the EEG signs.

(1) EEG lined features:

The relative centre occurrence, absolute centre occurrence, relative power and full power of theta, alpha, beta, and gamma waves, the total power, centre occurrence, skewness, kurtosis, and the peak of the whole band, are all EEG linear properties.

(2) EEG non-lined features:

Variation, Hjorth's movement, power spectrum entropy, Kolmogorov entropy, Shannon entropy, correlation measurement, and c0-complexity of the entire band are nonlinear aspects of the EEG.

4. Experimental consequences

In this part, we develop a model for unhappiness identification using a feature-level synthesis of multimodal EEG information, addressing three matters: (I) Validating the linear combinations of characteristics; (II) Comparing model performance in single and synthesis modalities; (III) Developing a paradigm for common recognizability of unhappiness. Throughout the model's creation, classifiers such as KNN, SVM, and D.T. were used to assess the presentation of each modality and the synthesis modality; moreover, tenfold cross-validation was utilised to assess each classification model's generalizability.

Classification techniques

KNN	63.11	64.88
DT	54.58	61.69
SVM	52.16	62.27
Average	56.62	62.95

Experiment with the technique of feature synthesis

Concatenating the feature environments of the several modalities to create a new sole feature vector is the simplest kind of fusion. However, as additional modalities are added, the measurement of the feature vectors rises.

This research conducts a comparative experiment employing two techniques to address this problem within the multimodal fusion depression recognition system. (I) combine the feature matrices extracted in various modalities to generate a new feature environment; (II) Using the lined grouping formula presented in Segment 3.4, for instance, construct a fusion feature matrix.

4.1.1. KNN

KNN is a widely used technique for classifying multiple variables. Its fundamental concept is to compute the distance between an unidentified sample and Decision Trees (D.T.s), a non-parametric managed learning technique used for cataloguing and regression. The objective is to build a prototype that accurately forecasts a goal variable's worth by inferring basic decision instructions from information attributes.

SVM

In 1995, Vapnik et al. introduced the SVM. Its fundamental concept is to categorise samples by determining the hyperplane with the most significant distance between them. It has excellent nonlinear properties.

The parameters of the classification algorithm

Then, other classifiers, including KNN, SVM, and D.T., are evaluated to assess if the lined grouping is optimal for feature-level synthesis. We compared these two feature matrices using the same feature selection and weighting.

Fig. 6 compares the presentation of two distinct techniques on three different classifiers. The linear feature combination consequences are superior to those obtained by combining all features from two modalities. In contrast to the merging approach, the fusion method of features linearly combines performance. For our specific data sets, the utilisation of particular modality attributes does not adequately answer our issue. As a result, we hypothesised that the lined grouping of characteristics in the synthesis modality might augment the capacity of different modality geographies to express themselves.

Individual modality characteristics' classification accuracy.

(a) Combine characteristics from distinct modalities and comparison the classification precisions of the synthesis modality features. The optimal mix of individual modalities is shown below.

4.1. Experiment with the presentation of appreciation models

This article performed two comparative studies to find the great depression appreciation model using three-electrode EEG information. (I) Identifying the optimal cataloguing modality among distinct modalities and modalities infusion. (II) Developing the optimal cataloguing model for depression EEG cataloguing according to cataloguing modality.

4.1.1. Experiment on synthesis modality

Classification findings for individual and synthesis modality characteristics.

For assessment, Fig. 7 depicts individual and synthesis modalities' classification performance. The best cataloguing accuracy was obtained for the individual modalities using the features of positive audio stimulation; for the fusion modalities, the best cataloguing precision was found using the fusion of optimistic and undesirable acoustic stimuli.

Additionally, the effect of various combinations of specific modalities was studied in this work. The combined presentation of the many bonded modalities and their constituent modalities. As previously shown, the synthesis modality of optimistic and undesirable auditory stimuli outperforms the two-component modalities. However, the findings indicate that the precision of the synthesis modality of optimistic and neutral acoustic stimuli and negative and neutral audio stimuli is not significantly higher than the accuracy of the two separate modalities. As a consequence of the findings in Figure 7, this research believes that the optimal synthesis modality is the synthesis of optimistic and undesirable auditory stimuli.

4.1.2. Experiment on classifiers

Three classic classifiers were utilised in this work, including KNN, SVM, and D.T.; the classifiers' parameters are provided.

As a result, this article believes that the KNN classifier is better suited for depression EEG classification.

The best depression appreciation modality in separate modalities is optimistic acoustic stimulation, with an average precision of 71.08 percent to determine the optimal classification modality. The best depression recognition modality infusion modalities synthesise optimistic and undesirable acoustic stimuli with an average precision of 76.04 percent. The fusion modality's average precision is 5% greater than the individual modality's average accuracy.

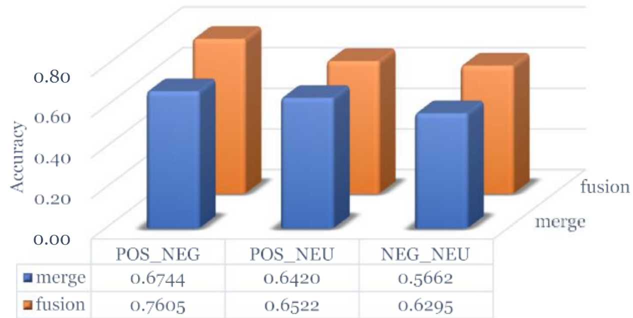

Fig. 6. the performance comparison of two types of strategies on three classifiers.

Additionally, to determine the optimal depression appreciation model and modality, we list the optimal classifier for the optimal separate and synthesis modality. The optimal classifier is KNN, and the optimal fusion modality's depression recognition accuracy is approximately 13% higher than the optimal discrete modality's.

As described before in this article, depression detection study has traditionally been restricted to multiple electrode EEG and sole modality data. For our specific data sets, the usage of different modality attributes does not adequately address the issue of depression detection. Not only does three-electrode EEG information simplify the depression detection model, but feature-level modal synthesis also improves the expression capacity of separate modalities' characteristics. Associated with the other modalities, the fusion modality of positive and negative auditory stimuli has greater accuracy for all classifiers than the separate modality and the other two synthesis modalities. We discovered that KNN had the most effective classification precision rate among the three classifiers, both in the separate and synthesis modes. The KNN classifier achieved the highest accuracy of 86.98 percent in recognising depression using optimistic and undesirable auditory stimuli fusion modality. As a result, this article claims that the KNN classifier is better suited for distinguishing between the Stress and regular groups when optimistic and undesirable acoustic stimuli are combined.

5. Discussion

As one of the world's most serious health problems, early detection and treatment of depression is critical and may even save a patient's life. Depression is now recognised based on the experience of the physician. Recently, several studies have begun to use EEG technology to detect depression. However, most of this research used EEG information from a single modality (resting state) and a significant number of electrodes. Classification of 70 Stress affected persons and 23 normal controls utilising 21 electrodes in the resting state resulted in a 91.3 percent classification accuracy. Lei et al. analysed the most excellent classifier accuracy, estimated to be 97.67 percent, using 128-channel EEG data.

Additionally, Hosseinifard et al. achieved the maximum precision of 83.3 percent by analysing data from 19 electrodes. In comparison to prior investigations, the current research compared the classification precision of several separate modalities and synthesis modalities for depression detection using three-electrode EEG information. In particular, we utilised a ubiquitous three-electrode sensor because it is tiny, convenient to wear, function, and very flexible.

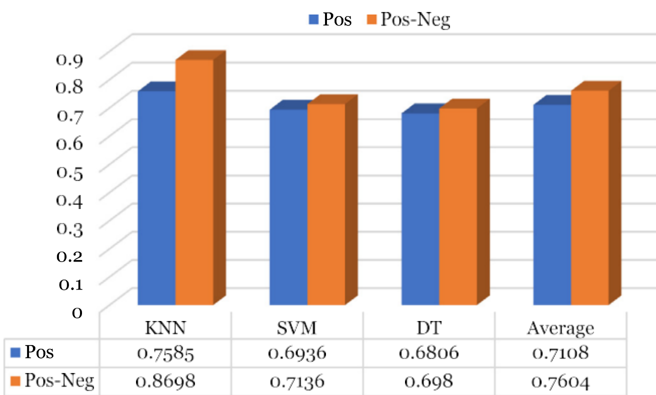

Fig. 7. the accuracy of the best individual modality and the best fusion modality.

As a result, three different modalities of feature extraction were applied in the current work: optimistic acoustic stimulation, undesirable acoustic stimulation, and neutral acoustic stimulation. We examined the classification accuracy of three-electrode EEG characteristics in individual and fusion modalities between Stress affected persons and normal strong controls. In the affirmative, the KNN classifier had the best accuracy rate.

6. Conclusions

The complete classification system in this work was divided into three steps, beginning with the EEG information for the three modalities (neutral acoustic stimulation, undesirable acoustic stimulation, and optimistic acoustic stimulation). The feature extraction step was the first. This step included recording EEG information from 86 Stress affected persons and 92 healthy people using three modalities and extracting EEG characteristics, with linear measures such as EEG comparative power and release power and nonlinear variables like c0-complexity and correlation dimension. The second step included the merging of distinct features. At this step, the EEG features collected from the various modalities were linearly merged using the feature-level synthesis approach, and new features were chosen to contribute to the classifier using the t-test from the linearly combined features matrix. Classification completed the third step. In this step, we tested and compared three well-known classifiers, KNN, D.T., and SVM, using tenfold cross-validation. Additionally, feature weighting was accomplished using G.A. When the classification performance of all classifiers was compared in various fusion modalities, it was discovered that the KNN classifier performed the best in the synthesis of optimistic and undesirable auditory stimuli, with a precision rate of 86.98 percent.

Compared to earlier research, the current study discovered a novel method for identifying depression via modality synthesis and three-electrode EEG information and produced a much greater classification precision. The EEG sign may be an effective tool for researching depression and differentiating stress sufferers from normal controls.

References

[1] C.J. Liao, Z.Z. Feng, Mechanism of affective and cognitive-control brain regions in depression, Adv. Psychol. Sci. 115 (3) (2010) 1325–1335.
[2] A.H. Kemp, E. Gordon, A.J. Rush, et al., Improving the prediction of treatment response in depression: integration of clinical, cognitive, psychophysiological, neuroimaging, and genetic measures, CNS Spectr. 13 (12) (2008) 1066–1086.
[3] A.S. Zigmond, R.P. Snaith, The hospital anxiety and depression scale, Acta Psychiatr. Scand. (1983).
[4] W.H. Organization, The ICD-10 Classification of Mental and Behavioural Disorders: Clinical Descriptions and Diagnostic Guidelines, World Health Organization, 1992.
[5] A.P. Association, Diagnostic and Statistical Manual of Mental Disorders (DSM-5), American Psychiatric Pub, 2013.
[6] A.J. Mitchell, A. Vaze, S. Rao, Clinical diagnosis of depression in primary care – authors' reply, Lancet 374 (9704) (2009) 1817–1818.
[7] J.R. Lave, R.G. Frank, H.C. Schulberg, et al., Cost-effectiveness of treatments for major depression in primary care practice, Arch. Gen. Psychiatry 55 (7) (1998) 645.
[8] M.M. Hassan, S. Huda, M.Z. Uddin, et al., Human activity recognition from body sensor data using deep learning, J. Med. Syst. 42 (6) (2018) 99.
[9] M.Z. Uddin, M.M. Hassan, Activity recognition for cognitive assistance using body sensors data and deep convolutional neural network, IEEE Sens. J. (2018).
[10] N.N. Boutros, C. Arfken, S. Galderisi, et al., The status of spectral EEG abnormality as a diagnostic test for schizophrenia, Schizophr. Res. 99 (1) (2008) 225–237.
[11] M. Baker, K. Akrofi, O. Schiffer, et al. 52 The Open Neuroimaging Journal, 2008, 2, 52-55 EEG patterns in Mild Cognitive Impairment (MCI) Patients Open Access. 2013.
[12] S.J.M. Smith, EEG in the diagnosis, classification, and management of patients with epilepsy, J. Neurol. Neurosurg. Psychiatry 76 (suppl 2) (2005) ii2-ii7.
[13] J. Jeong, EEG dynamics in patients with Alzheimer's disease, Clin. Neurophysiol. 115 (7) (2004) 1490–1505.
[14] S. Olbrich, M. Arns, EEG biomarkers in major depressive disorder: discriminative power and prediction of treatment response, Int. Rev. Psychiatry 25 (5) (2013) 15.
[15] F.Y. Fan, Y.J. Li, Y.H. Qiu, et al., Use of ANN and complexity measures in cognitive EEG discrimination, International Conference of the Engineering in Medicine & Biology Society, IEEE, 2005.
[16] Geriatric depression symptoms coexisting with cognitive decline, A comparison of classification methodologies, Biomed. Signal Process. Control 25 (2016) 118–129.
[17] C.C.Y. Poon, B.P.L. Lo, M.R. Yuce, et al., Body sensor networks: In the era of big data and beyond, IEEE Rev. Biomed. Eng. 8 (2015) 4–16.

[18] E. Jovanov, C.C.Y. Poon, G.Z. Yang, et al., Guest editorial body sensor networks: from theory to emerging applications, IEEE Trans. Inf. Technol. Biomed. 13 (6) (2009) 859–863.

[19] R. Gravina, P. Alinia, H. Ghasemzadeh, et al., Multi-sensor fusion in body sensor networks: state-of-the-art and research challenges, Inf. Fusion 35 (2017) 68–80.

[20] S. Kumar, M. Yadava, P.P. Roy, Fusion of EEG response and sentiment analysis of products review to predict customer satisfaction, Inf. Fusion 52 (2019) 41–52.

[21] S. O'Regan, W. Marnane, Multimodal detection of head-movement artefacts in EEG, J. Neurosci. Methods 218 (1) (2013) 110–120.

[22] J.P. LachauX, N. AXmacher, F. Mormann, et al., High-frequency neural activity and human cognition: past, present and possible future of intracranial EEG research, Prog. Neurobiol. 98 (3) (2012) 279–301.

[23] D.L. Schacter, EEG theta waves and psychological phenomena: a review and analysis, Biol. Psychol. 5 (1) (1977) 47–82.

[24] J.A. Coan, J.J.B. Allen, Frontal EEG asymmetry as a moderator and mediator of emotion, Biol. Psychol. 67 (1–2) (2004) 7–50.

[25] Y. Liu, O. Sourina, M.K. Nguyen, Real-time EEG-based human emotion recognition and visualization, in: 2010 International Conference on Cyberworlds, IEEE, 2010, pp. 262–269.

[26] W. Klimesch, EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis, Brain Res. Rev. 29 (2–3) (1999) 169–195.

[27] D.V. Moretti, D. Paternicò, G. Binetti, et al., EEG upper/low alpha frequency power ratio relates to temporo-parietal brain atrophy and memory performances in mild cognitive impairment, Front. Aging Neurosci. 5 (11) (2013) 63.

[28] L.I. Aftanas, S.A. Golocheikine, Human anterior and frontal midline theta and lower alpha reflect emotionally positive state and internalized attention: high-resolution EEG investigation of meditation, Neurosci. Lett. 310 (1) (2001) 57–60.

[29] H. Adeli, S. Ghosh-Dastidar, N. Dadmehr, A wavelet-chaos methodology for analysis of EEGs and EEG subbands to detect seizure and epilepsy, IEEE Trans. Biomed. Eng. 54 (2) (2007) 205–211.

[30] M. Arns, C.K. Conners, H.C. Kraemer, A decade of EEG theta/beta ratio research in ADHD: a meta-analysis, J. Atten. Disord. 17 (5) (2013) 374–383.

[31] D.J.A. Smit, D. Posthuma, D.I. Boomsma, et al., The relation between frontal EEG asymmetry and the risk for anxiety and depression, Biol. Psychol. 74 (1) (2007) 26–33.

[32] M.M. Siddiqui, S. Rahman, S.H. Saeed, et al., EEG signals play major role to diagnose sleep disorder, Int. J. Electron. Comput. Sci. Eng. 2 (2) (2013) 503– 505.

[33] J.R. Hughes, E.R. John, Conventional and quantitative electroencephalography in psychiatry, J. Neuropsychiatry Clin. Neurosci. 11 (2) (1999) 190–208.

[34] S. Kühn, J. Gallinat, Resting-state brain activity in schizophrenia and major depression: a quantitative meta-analysis, Schizophr. Bull. 39 (2) (2013) 358–365.

[35] A.F. Leuchter, I.A. Cook, A.M. Hunter, et al., Resting-state quantitative electroencephalography reveals increased neurophysiologic connectivity in depression, PLOS One (2012) 7.

[36] T.T. Erguzel, S. Ozekes, O. Tan, et al., Feature selection and classification of elec-

troencephalographic signals: an artificial neural network and genetic algorithm-based approach, Clin. EEG Neurosci. 46 (4) (2015) 321–326.

[37] I.M. Spyrou, C. Frantzidis, C. Bratsas, et al., Geriatric depression symptoms coexist- ing with cognitive decline: a comparison of classification methodologies, Biomed. Signal Process. Control 25 (2016) 118–129.

[38] S. Alghowinem, R. Goecke, M. Wagner, et al., Multimodal depression detection: fusion analysis of paralinguistic, head pose and eye gaze behaviors, IEEE Trans. Affect. Comput. 9 (4) (2016) 478–490.