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An accurate EEG signal-based emotion recognition using deep intelligence techniques

B. Sankara Babu, Associate professor, GokarajuRangaraju Institute of Engineering and technology
Hyderabad, bsankarababu81@gmail.com

Abstract:
One of the first experiments to use EEG data to try and distinguish between real emotional emotions and performed ones is presented in this paper. For the first time, we've compiled an EEG dataset (accessible here) that includes recordings of people making real and false facial expressions. Real smiles are divided into three categories: genuine smiles, artificial or performed smiles, and neutral faces. The intrinsic features of three EEG emotional expressions, a genuine grin, a neutral grin, and a fake/acted grin, can be retrieved in several ways. Combining discrete wavelet transforms (DWT) with empirical mode decomposition (EMD) and DWT-EMD (DWT-EMD) over three frequency bands allowed us to extract EEG features from the data. The proposed strategies were then evaluated using a range of classifiers, such as k-nearest neighbours, support vector machines, and artificial neural networks (ANN). Our 28 volunteers were divided into three groups based on the way they expressed their emotions: genuine, neutral, and fake/acted. Better results were obtained by combining DWT and EMD than by using alone DWT or only EMD. There were distinct brain patterns in all frequency bands for each of the three emotional expressions, as revealed by the power spectral features derived from DWT, EMD, and DWT-EMD. We used only DWT or EMD to run binary classification trials and reached an acceptable accuracy of up to 84 percent for all types of emotions, classifiers, and bands... Classification accuracy in the alpha and beta bands was 94.3 percent on average for DWT-EMD and 84.1 percent for DWT-EMD in combination with ANN to identify real emotional expressions from false ones. As a result of our findings, future emotion research should include merging DWT-EMD and highlighting the link between the alpha and beta frequency regions.

I. Introduction:

Conscious or unconscious events cause emotional responses in the brain, which are known as emotions [1]. Emotions and their dynamics, according to some researchers, have an impact on cognition and behaviour [2]. A person's bodily and psychological conduct are greatly influenced by their emotions in particular [2]. Hence, the ability to recognise emotions is crucial in a variety of fields, including human-robot interaction, describing interest in learning, assessing happiness and contentment, and recognising levels of alertness on the road and in regards to safety. Emotions can be assessed using a variety of methodologies [4–7] that have been proposed in the literature. Emotions and emotional activity can be assessed most easily via self-reporting. Such techniques are inherently subjective and necessitate complete focus from the user. Facial expression, speech analysis, and physiological response analysis are objective metrics. We use a variety of emotional behaviours to communicate our feelings to computers and other people on a daily basis. The way we express ourselves spontaneously reveals a great deal about how we are feeling on a deep level. The most

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extensively used non-physiological markers for emotion identification are facial expressions and speech tone analysis. Automated facial expression analysis has been researched by Hoque and his colleagues [8] to distinguish between dissatisfied and joyful smiles. They were 92% accurate in identifying smiles from other facial expressions when presented with frustrated or joyful stimuli. Social circumstances, on the other hand, can frighten people into hiding their true feelings. Facial expressions and auditory characteristics may not disclose the genuine mental state of persons when trying to interpret their emotions [9]. False alarms are more common because these facial characteristics aren't usually accompanied by emotions. This is especially true. Furthermore, installing a camera and a microphone is necessary for analysing facial expressions and for analysing audio signatures, raising privacy issues. Research has combined spoken, facial, and physiological cues with multimodal techniques to better understand and identify emotions. Physiological signals, on the other hand, reflect true emotions, but facial and aural expressions may not reflect a person's inner mental state accurately. Changes in physiological signals associated with emotional emotions, in particular, are automatic and frequently go unnoticed. A more reliable assessment method, according to some, would be required for precise measurement of felt emotions. The question that emerges here is whether or not other objective methods can distinguish between genuine and acted-out emotional expression. Expressional activities are essential in everyday human relationships. Smiling, for example, conveys a sense of well-being. Even if someone is smiling, they may not be content. Smiling can also be a symptom of frustration, according to Hoque et al. A smile, in particular, is an ubiquitous and versatile facial emotion. It's time to delve deeper into the emotions hidden beneath smiles and other facial expressions. We can create better and more dependable human-computer interface systems by using modalities that recognise human emotional states at a deeper and more precise level. Electroencephalography (EEG) modality is used in this investigation to see if performed emotions can be distinguished from real ones. EEG is a widely utilised method for studying brain processes and disorders at a millisecond time scale. Many datasets have been utilised in research on emotion recognition. For investigating the basic rhythms in the signals, spectral analysis is one of the most commonly used methods of signal analysis. There is a great deal of non-stationarity in EEG signals. The non-stationary nature of EEG signals cannot be accommodated by conventional approaches such as Fourier transforms. When evaluating real-life signals, harmonic components are assumed to be present on a global scale. This could explain why. As a result, the Fourier spectrum becomes wider, and the energy frequency distribution becomes misleading . Signal analysis in time-frequency space, as opposed to spectrum analysis, may help capture quick dynamic changes in brain spectra. EEG time-frequency methods have been used by several research groups to classify emotions. The discrete wavelet transform (DWT) and empirical mode decomposition (EMD) have been used extensively in the literature to analyse EEG data. DWT is an excellent tool for capturing neurally specific domains in signals that have a regular frequency variation. DWT comes in handy. However, despite the fact that the EMD technique has been widely used for seizure detection and motor imagery classification, there has been minimal study on emotion recognition using it. A recent study in EMD uses this database to identify emotions from multidimensional input. The outcomes seemed good. EMD outperformed time-domain

approaches due to the higher frequency content information. Human-computer interface development is complicated by the lengthy processing times required by EMD-based techniques. New insights into the brain mechanisms behind the EEG signal could be gained, according to Sweeney-Reed et al. They've discovered that the frequency of oscillations associated with certain cognitive behaviours changes with time, according to the researchers. This suggests that EMD is beneficial in revealing the underlying physiological processes that are unique to the field of emotion research. There is a possibility of intermittencies when using EMD directly on raw EEG data. Other research has shown that combining EMD and DWT approaches can recover important properties from nonlinear signals. In order to discover and describe singularities in an EEG signal, using wavelet transform before applying EMD is recommended. EMD approaches, according to Munoz et al. softened signals and reduced noise. In this way, wavelet transformation noise can be suppressed with EMD. Wavelet analysis lacks adaptability, but EMD analysis can make up for it. Ji et al. used DWT and EMD-based methods for extracting non-linear characteristics to improve the classification accuracy of motor pictures derived from EEG data. In the current study, emotional expressions are being examined using EEG signals and machine learning technology. There were no problems with our method, which was developed to create realistic facial expressions using a two-dimensional model of emotions (arousal and valence). We next examined these emotional expressions using three different feature extraction methodologies, including DWT, EMD, and combining DWT with EMD (DWT-EMD). Because of their significant ties to emotions, this study's data analysis concentrates on theta, alpha, and beta frequencies. Using three different classifiers (KNN, SVM, and an artificial neural network (ANN)), we also tested the feasibility of recognising appropriate emotional expressions (ANN). This is the first study to distinguish between performed and actual expressions using three different time-frequency feature analysis methodologies on EEG data. Our key contributions to this project have been as follows as a result:
EEG signals can tell the difference between real emotional experiences and staged ones.
Experiment design and procedure development for hypothesis testing

EEG recordings of 28 persons with genuine and staged grins were used to generate a new database. The rest of the structure looks like this. Described in Section II are the study's stimuli, data collection methods, and preprocessing techniques. Section 2 of the report. Section III discusses feature extraction techniques, statistical analysis, and classification models. Section IV summarises the findings and conducts a categorization study. Section V summarises the findings and suggests areas for additional research. The study's conclusion, Section VI, summarises everything.

II. MATERIALS AND METHODS:

TITLES AND SUBJECTS This research involved 28 healthy students, 20 men and 8 women, all around the age of 20. There were no visual impairments among the study's subjects. A history of neurological or psychiatric disorders was not available for them to consult. Participants signed an informed consent form after being briefed on the study's protocols. All procedures were carried out in accordance with the principles outlined in the Helsinki

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Declaration. The study's procedure was approved by the institutional review board (IRB) of the American University of Sharjah.
To elicit emotional responses, researchers employed 246 still photographs from two big online public image collections as stimuli in Test Protocol B. Examples of this type of database include Open Affective Standardized Image Set (OASIS), as well as Geneva Affective Picture Database (GAPED). Three different types of image sets were used in this investigation (116-funny images, 70-neutral images, and 60-one-plain image). Human and animal infants in pictures made up the majority of the humorous images. Pictures of nature and plain books constituted the majority of the neutral images. Arousal-valence scale images were used for all photos in this investigation [26, 27]. Images were shown on a 19-inch LCD panel 50 cm distant from the individual. There was some randomness to the images' display order, but no image now being viewed belonged to the same category as the one that had just been rated. Each type of picture stimulus was given three separate event markers to indicate the epochs/trials in the experiment. FIGURE 1: The experiment's stimuli and tasks are shown. A plain image was displayed on the screen, and participants were instructed to type a keyboard response (i.e. "Q") while smiling in an acting pose as soon as the image came on the screen. These procedures were carried out in order to make the patient experience fictitious or acted-out emotion Participants had to act just once on emotional expressions such as honest grins (by pressing "P") or neutral emotions (by pressing "N"), if they considered their feelings had changed. A total of 246 experiments were conducted in order to arrive at the final results shown in Figure 1. Each session begins with a one-second drift check, followed by two extra seconds of viewing an emotionally compelling image. The entire experiment took about 13 minutes, however the number of trials varied from person to person based on how rapidly they replied. Study participants were only included if they had genuine, on-stage smiles after successful trials. Participants' responses were used to label each experiment.
SOURCE COLLECTION AND PRE-PROCESSING The EEG data was recorded using 64 Ag/AgCl scalp electrodes, in line with the standard 10–20 system (ANT waveguard system and ASA Lab 4.9.2 acquisition software, ANT Neuro, the Netherlands). Samples of the EEG data were taken at a rate of 500 hertz. All EEG electrode impedances were measured using the brain regions M1 and M2 on the left and right sides, respectively. FIGURE 2 depicts a typical experimental setup and data collection system. Using the EEGLAB toolboxes (9.0.4)[28], custom scripts were created in order to do preprocessing on the EEG data. We located and manually removed the eye blinks using EEGLAB's independent components analysis (ICA) technique. Removed artefact components such eye blinks, eye movements, and muscular activity helped recreate clean EEG signals. Eye blinking and eye movement-related independent components were removed from each subject. In order to eliminate noise in the EEG signals, we applied a 0.1 Hz to 40 Hz wideband finite impulse response (FIR) filter to all of them. Electricity line interference was eliminated with a 50-Hz cutoff filter. The decision was made to re-reference the EEG data to the newly created average reference. Data mean subtraction was performed to remove the baseline.

Fig:1 Layout of the experiment and data collection

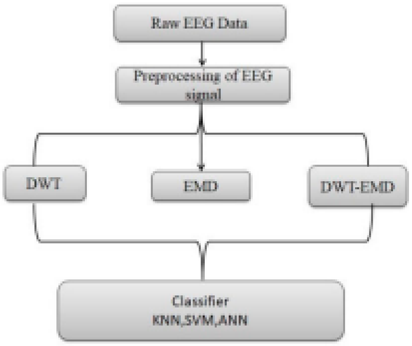

Fig:2 A framework for identifying and classifying features.

moreover, there is an alternating-current offset. After that, 1100 ms-long epochs were created from the clean signals. In total, 230 epochs were generated, with each matching to a different sort of visual stimulus. The same number of epochs were utilised to extract features for all three types of emotion (We used a total of 180 epochs, 60 for each type of emotion.).

III. FEATURE EXTRACTION:

This research proposes three different feature extraction algorithms. A combination of DWT and EMD as well as Discrete Wavelet Transform (DWT) are the approaches employed (DWT-EMD). The following sections will go over how to put the feature extraction approaches into practise. The rhythmic activity in the 4-30 Hz range is an important part of our cognitive processes research (i.e. theta, alpha and, beta bands). In the EEG frequency components' power spectra, changes are observed. FIGURE 3 depicts a schematic representation of emotion categorization and feature extraction. TRANSFORMATION OF WAVELETS IN AN IMPLICIT SPACE (DWT) Discrete wavelet transform separated the EEG signals into seven different levels (DWT). The Daubechies 4 (Db4) wavelet family was utilised in this study because of its near time-frequency localization and closeness to the EEG signal waveform. Each stage involves downsampling the signal twice.

For feature extraction, a subset of wavelet coefficients was chosen that matched theta, alpha, and beta frequencies (DWT decomposition levels 6 and 5 respectively). The mean power of EEG signals in the three frequency bands was calculated for each electrode using a moving time window of 1.1 seconds, as recommended by [30]:

$$P_j = \frac{1}{N}\sum_{n=1}^{N}\left|x_j(n)\right|^2, j = 1, 2, 3 \qquad (1)$$

theta band at j = 1, alpha band at j = 2j = 2, and beta band at j = 3 and N is the duration of the EEG signal reflect the segmented EEG signals Each participant now has 11160 characteristics (60 epochs 62 electrodes 3 frequency bands) to work with. The machine learning classifiers were fed the significant features from each frequency band as inputs, and the results were impressive.

DECOMPOSITION IN THE EMPIRICAL MODE

To break down clean EEG data into a limited number of intrinsic mode functions, EMD requires no prior definitions in comparison to predictive techniques (IMF). The EMD procedure makes use of a time-scale-based approach to energy extraction. • At most, there is a single crossing between extrema and zero for each IMF. Each IMF is a representation of a different frequency component of the originating signal. Local maximums and minimums generate an envelope whose mean is always zero. As soon as the iterative processes within EMD meet the two requirements described in, its ultimate function is represented in the time domain (2). We can get the entire energy distribution of the data by using the Hilbert transform to extract the IMF's instantaneous frequency and local energy. If you're working with stationery data, this is ideal [19]. Each of the EEG signal's three frequency bands' EMD is shown in the table below: (theta, alpha, and beta).

$$X(n) = \sum_{i=1}^{N} c_i(n) + r(n) \qquad (2)$$

IMF component ci is repeated N times and the residue component r is the result. THREE) DWT-EMD MODE The EEG data was separated into narrowband signals using wavelet modification before being used in this approach, which used EMD as the final step. To decompose the resulting intrinsic mode function into a more focused frequency, the suitable subband signal is first picked [32]. Using wavelet transform on a clean EEG data before EMD can help identify singularities and describe them [24]. Accordingly, we utilised the Daubechies 4 (Db4) wavelet to separate the clean EEG data into three frequency bands: theta, alpha, and beta (see Figure 2). In order to extract their IMFs components, we used EMD on each of the three frequency bands that had been decomposed (2). Using a 1.1-second time window, we retrieved the mean power characteristics from the first three components of the IMF (1). As a result, each individual had 11160 characteristics (representing 60 epochs, 62 electrodes, and 3-frequency bands) to work with. The machine learning classifiers employed significant information as input to separate the three categories of emotion. 62 electrodes were used to create a topography encompassing the scalp, representing the average of all features among patients. REDUCE THE SIZE OF A FEATURE We use feature dimension reduction to reduce the number of features and focus on the most critical ones. In order to get the best performance from machine learning classifiers, this step is frequently taken before them. As a result, numerous strategies for reducing the size of feature dimensions have been developed and published in the literature [33], [34]. In order to reduce the dimension of the feature, we used a paired-sample t-test. EEG data from participants in genuine, neutral, and fake emotional states were all compared using a paired-sample t-test to see which group had the strongest power characteristics. Before doing the t-test, we ran the Kolmogorov-Smirnov test [35] to verify that the data were normally distributed. Based on the paired-sample t-test results, there is a statistically significant difference between the two sample groups (p-value). A p-value of less than 0.05 guided our selection of emotion identification elements. performance categorization and analysis It took a lot of different classifiers to separate the three main kinds of feelings. A classification approach called support vector machines (SVMs) is frequently utilised when PSD features are the input. As a result, SVM was one of the techniques we used to classify emotions. A study in [37] employed artificial neural networks (ANN) to identify positive and neutral emotions as well as negative ones, despite the fact that SVM and KNN techniques have a higher accuracy. Hence, on our EEG dataset, we opted to test each classifier's efficacy: KNN [38], SVM [39], and ANN [40]. Classifier parameters are summarised in TABLE 1. These numbers were derived by doing validation on the training data. A real grin from a fake one could now be distinguished, as could an actual smile from a neutral look. To accomplish subject-dependent classification, we applied 5-fold cross-validation to each classifier. Each subject's selected traits were divided into five equal-sized subsets. Four different sets of data were used to train the classifiers, and the rest of the data was tested on just one. We repeated this approach five times to ensure that each subgroup was used for validation in order to collect all samples with predicted labels. Accuracy, sensitivity, and specificity were the measures we utilised to assess the classifiers' performance. There is a percentage ratio between correctly predicted samples and all samples that were included in the data set that was used to compute classification accuracy. The sensitivity measures the proportion of accurately anticipated true positive (TP) cases among all the true positives that were found.

TABLE 1. Units Values of the parameters used for each classifier.

SI No.	Classifier	Parameters	Value
1	Support Vector Machine (SVM)	Kernal Function	Linear
		Kernal Scale	1
2	k-th Nearest Neighbor (KNN)	Nearestneighbor	13
		Distance	Euclidean
		Distance Weight	Equal
3	Neural Networks (NN)	Initial Learning Rate	0.001
		Optimizer	Adam

The specificity is the projected proportion of true negatives (TN) among all of the true negatives and false positives, as well as erroneous results and false results. In Equations 3-5, the terms precision, sensitivity, and specificity are expressed mathematically:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (4)$$

$$Specificity = \frac{TN}{TN + FP} \quad (5)$$

IV. RESULTS:

EMOTIONAL MOODS HAVE AN IMPACT To visualise the mean power distributions for all patients, we created three topographical maps (FIGURES 4, 5 and 6). The topographical map has 62 electrodes, but electrodes M1 and M2 were removed from the study due to the fact that the majority of individuals had insufficient skin-to-skin contact with the device. FIGURE 4 depicts the patterns of cortical activity in three different moods as determined by discrete wavelet transform. This is what we found: In the right frontal, right temporal, right central parietal and left parietal brain regions, there is similar activity in the form of beta, alpha and theta bands that accompany emotional emotions. Emotional neutrality is activated in the central and right parietal areas in the beta, alpha, and theta frequency ranges in a comparable way. Across all three frequency ranges, the lowest activation levels were found in the occipital regions of the scalp. Topographical maps of false emotion exhibit a far lower brain activation pattern as compared to real and neutral emotions. Increased activity can be seen in the right temporal gyrus and left parietal gyrus. Observations from topographical maps using the EMD technique are shown in FIGURE 5. The following are their names: When people feel genuine emotion, the beta band in their brains shows higher activation in the right hemisphere than it does in the left. Particularly in the right parietal and occipital lobes. The alpha band is highly active in the right hemisphere and the left prefrontal electrodes. The alpha bands are more active in the prefrontal lobes. There are only a few electrodes in use by this band.

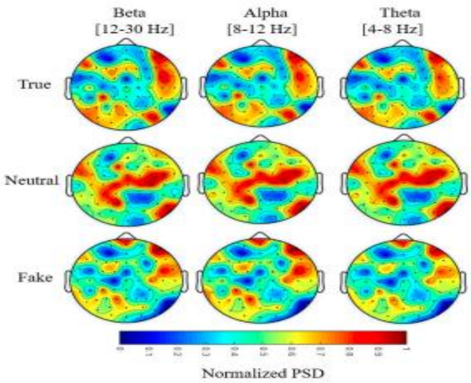

Fig 3: The DWT approach was used to find the mean power distributions in various emotional states and frequency ranges.

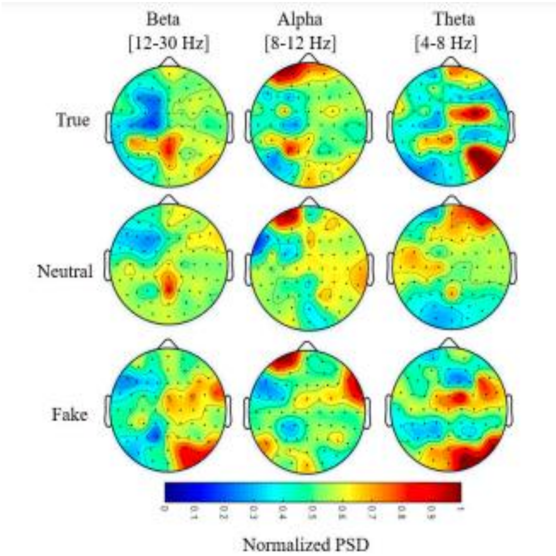

Fig 4: The EMD method was used to measure the mean power distributions in various emotional states and frequency ranges

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The frontal and parietal lobes of the right brain are most active. Although neutral behaviour has no emotional connotation, those with neutral feelings exhibit different patterns of brain activity than those without. The alpha band in the left prefrontal, right parietal, and central electrodes had the highest level of activity. The theta band activations are higher in the right frontal and left front-temporal regions than in any other part of the brain. Only the right parietal and occipital electrodes in the research of participants who had been taught to fake their emotions show greater activation energy across the beta band. The activation energy in the alpha band is higher in the left prefrontal and right temporal electrodes than in the other electrodes. It gets worse because of an error in theta

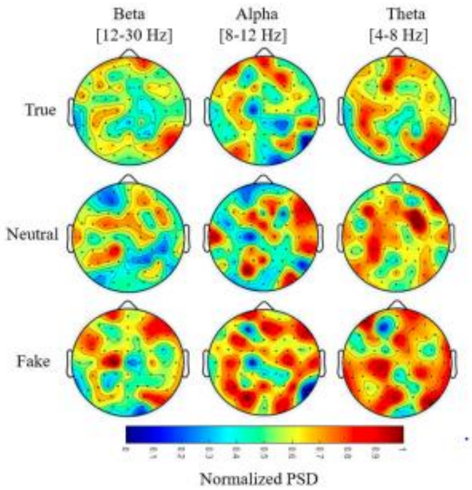

Fig 5: The DWT-EMD approach was used to find the mean power distributions in various emotional states and frequency ranges.

The band, right central, parietal, and occipital electrodes were the most active in comparison to other regions. DWT-power EMD's feature extraction topographical maps and results are shown in FIGURE 6. To summarise what we've learned thus far, consider the following: - Activation in the prefrontal, right parietal, and left prefrontal regions is more pronounced when using the beta band to analyse real emotion as compared to other regions. Brain electrodes on the right and left sides are more active in the alpha band in terms of prefrontal and parietal functions. The theta band reveals prominent activations in the left and right brain's frontal, central/parietal, and parietal areas. When the brain is in a neutral state, only the mid-central, right prefrontal, and left parietal lobes show significant beta band activation. The frontal lobes of the right brain, the right occipital region, and the left central-parietal region are all highly activated in the alpha band scans. In addition, in the theta band, greater cortical activity can be noticed in the right frontal and left parietal and central regions of the mind. Fake Emotion- Higher energy activations in the left central, right prefrontal, and right parietal lobes can be seen in the beta band during Fake Emotion. The most active electrodes in the alpha and theta bands, on the other hand, are located in the frontal, central parietal, and occipital regions. Within the three feature extraction methods examined thus far, the combined DWT-EMD strategy indicated stronger activations in the emotion and frequency bands than either the standalone DWT approach or the EMD approach, on average. Due to its higher activations, DWTEMD was able to identify new characteristics that could not be discovered using only DWT or EMD approaches. Image stimuli were found to be excellent at eliciting a wide range of emotions due to the fact that their cortical activations migrated around the brain when they were linked to various emotions. Emotion and frequency bands show higher brain activation using all three approaches.

V. DISCUSSIONS:

The study's objective was to use EEG data to distinguish between genuine and acted facial expressions. Using a paradigm, brain signals associated with three types of emotional expression were collected: true, false, and neutral for this study (the control condition). The choice of emotional stimuli utilised in the experiment substantially influences the results of emotion-specific studies. As a result, the visual stimuli we used were static images. Three different time-frequency analysis approaches were used to extract characteristics from the recorded EEG signals in order to study the generated emotional expressions. Additionally, machine learning was used with numerous classifiers to assess how well these emotions could be differentiated. According to the findings, EEG waves can be used to tell the difference between real, neutral, and artificial emotional responses. To the best of our knowledge, this is the first study to use EEG signals and machine learning methodologies to investigate emotions expressed as grin expressions. Using topographical maps to depict three different emotional expressions, we examined the brain activation patterns that accompanied each one. This type of map of EEG electrode activity has been made to give a clear understanding of where the electrodes are located under the different types of emotions. The three emotions were also classified subject-dependently using ANN, SVM, and KNN. There is a distinct brain pattern linked with each form of emotional expression, as shown in FIGURES 4–6. Our findings demonstrated that the prefrontal region of the brain was associated with mental processes and cognition activities in response to emotional inputs. For authentic emotion, the topographical maps showed increased activity in the frontal and parietal lobes. To our knowledge, this is the first study to show that specific brain patterns are linked to different emotions [22], [13], and [41]. A number of studies have revealed a link between happy memories and increased activity in the prefrontal and anterior cingulate cortex, both of which may be seen on fMRIs and PET scans. For feature extraction, time-frequency analysis was found to be the most accurate method when comparing a genuine smile to a fake one. As a result, the type of visual stimuli had a significant impact on brain reactions. According to an investigation of classification performance across the three EEG frequency bands, classifiers performed marginally better in the alpha and beta bands than in the theta band. In keeping with previous research, high-frequency bands have been demonstrated to better reflect emotional processes. Classification accuracy in the alpha band is highest for the DWT-EMD strategy, with 94.3 percent, 92.4 percent, and 83.8 percent for classifying actual emotional expression from a fake one using ANN, SVM, and KNN. The beta band of the DWT-EMD system identified emotional neutral expressions as either true or fraudulent. DWT-EMD, which worked in the theta band, could tell real emotional responses apart from fakes. All participants, as seen by the reduced standard deviation, benefited from our research's improved accuracy in the alpha and beta bands. Emotion classification research in higher frequency bands have already shown remarkable accuracy, and this work is no exception. We believe that EEG data can better predict emotional expressions when the alpha and beta frequencies are higher. Another important aspect is that the DWT transform method was employed before the EMD approach considerably increased the classification accuracy. Instead of just employing EMD or DWT, a discrete wavelet transform followed by empirical mode decomposition yielded better results. We found that DWT-EMD outperformed DWT by 27.9%, 19.7%, and 24.7 percent in the alpha band using ANN, KNN, and SVM. The increases were equivalent in the beta and theta frequency bands. DWT-EMD outperformed EMD by 13.1% with ANN, KNN, and SVM and by 12.9% with EMD utilising 14.1% in the alpha band, we found. When dealing with non-stationary signals such as EEG, the EMD method can provide a wide frequency range of coverage. To solve this problem, [45] recommends using DWT before decomposing into IMFs. Perhaps this explains why our system is now better at classifying EEG data. By using DWT before EMD, classifier performance is improved, making it a useful method for obtaining information from EEG signals. This study's DWT-EMD method significantly increased the rate at which people were able to recognise emotions. However, there are a number of downsides to this strategy. As a starting point, all of our analysis is based on photographs that have been left static. The recognition of emotions has long been aided by a range of indicators included in previous studies. For researchers, including various stimuli could help them better understand people's emotional expressions. Before we get too far, it should be noted that the entire study was completed in a single session. We should check to determine if the EEG responses are consistent throughout time. A deeper knowledge of how emotions work might result from this research. In this study, the dimensionality of the characteristics was reduced using a basic statistical test (the t-test). The test is a one-way univariate test, thus no multiple factors or interactions are taken into consideration for this calculation.. Many different methods for selecting feature sets should be examined in future study, including correlation-based [46], bispectrum [47], and the internal feature selection method of comparable spatial pattern (48). The classification accuracy can be improved even further by combining different modalities, such as EEG with eye tracking, EEG with functional near infrared spectroscopy, or a combination of the three modalities. It will be possible to develop a better model of human emotion perception by utilising the strategies described above. This means that future studies may look at how well the DWT-EMD technique works with different types of emotions such as melancholy, amusement, and so on.

VI. CONCLUSION:

We used EEG signals in this study to try and tell the difference between performed and real emotions. True, fake/acted and neutral emotional reactions were the focus of our experiment. We employed time-frequency algorithms on EEG recordings to extract useful information for differentiating between these three sorts of expressions. ANN, SVM, and KNN were all used as well as other machine learning techniques. There is a difference between how people exhibit genuine and performed expressions, according to the classification performance and power distribution data. The power distribution map revealed higher levels of activity in the prefrontal electrodes. Our ANN classifier in the alpha frequency range used the DWT-EMD approach and had a maximum classification accuracy of 94.3%. In our research, we observed that ANN and KNN classifiers produce the best results out of the three classifier algorithms employed for emotion recognition. Finally, we demonstrate the first time that EEG signals

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may be used to tell a phoney expression from a real one. Other researchers can use the dataset we obtained to further the state-of-the-art in this new field, which they designed and designed human subjective studies for.

REFERENCES:

[1] R. J. Davidson, P. Ekman, C. D. Saron, J. A. Senulis and W. V. Friesen, ”Approach-withdrawal and cerebral asymmetry: emotional expression and brain physiology I,“ Journal of Personality and Social Psychology, vol. 58, no. 2, pp. 330-341, 1990.

[2] R. J. Davidson, “What does the prefrontal cortex do in affect: Perspectives in frontal EEG asymmetry research,“ Biological Psychology, vol. 67, no. 1-2, pp. 219-233, 2004.

[3] J. A. Coan and J. J. B. Allen, “Varieties of Emotional Experience during Voluntary Emotional Facial Expressions,” Annals of the New York Academy of Sciences, vol. 1000, no. 1, pp. 375-379, 2003.

[4] J. A. Coan and J. J. B. Allen, “Frontal EEG asymmetry as a moderator and mediator of emotion,” Biological Psychology, vol. 67, no. 1-2, pp. 7-49, 2004. [6] H. J. Eysenck, S. B. G. Eysenck, Manual of the Eysenck Personality Questionnaire. London: Hodder and Stoughton, 1975.

[5] P. J. Lang, M. M. Bradley and B. N. Cuthbert, International affective picture system (IAPS): Affective ratings of pictures and instruction manual. Technical Report A-8, University of Florida, Gainesville, FL., 2008.

[6] V. Krajča, S. Petránek, I. Patáková and A. Värri, „Automatic identification of significant graphoelements in multichannel EEG recordings by adaptive segmentation and fuzzy clustering,” Int. J. Biomed. Comput., vol. 28, no. 1-2, pp. 71-89, 1991.

[7] F. v. d. van der Heijden, R. Duin, D. d. de Ridder, and D. M. J. Tax, Classification, Parameter Estimation and State Estimation: An Engineering Approach Using MATLAB. John Wiley & Sons, November 2004.

[8] R. O. Duda, P. E. Hart and D. G. Stork, Pattern Classification (2nd Edition). Wiley, 2000.

[9] T. Kohonen, Self-Organizing Maps. Third, extended edition. Springer, 2001.

[10] C. J. Jung, PsychologischenTypen. Rascher Verlag, Zurich - translation H. G. Baynes, 1921.

[11] A. J. Tomarken, R. J. Davidson, R. E. Wheeler and R. C. Doss, ”Individual differences in anterior brain asymmetry and fundamental dimensions of emotion,” Journal of Personality and Social Psychology, vol. 62, no. 4, pp. 676-687, 1992.