Classifying Electroencephalogram (EEG) Signals Via Brain Activity Mapping to Distinguish Identified vs Unidentified Information

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Abstract-Conventional lie detectors have often been questioned for their accuracy and reliability, which can lead to wrongful accusations. These Inaccurate results may compromise legal decisions, threaten national security, or hinder the justice system. Electroencephalogram (EEG) is a technique used to record electrical activity in the brain, which has become a major focus for researchers, especially in the development of lie detection systems. Therefore, the research aims to explore complex patterns in brain activity that play an important role in distinguishing identified and unidentified information by using brain activity mapping as a novel approach. The required data are taken from channels T3, T4, T5, T6, O1, and O2 related to human memory. A total of 30 participants are involved in the study, where their brain activity is analyzed in the Alpha, Beta, and Gamma subbands. Brain activity visualization parameters are based on energy wavelet feature extraction values. The visualization results for each participant in the three subbands are then classified using the Naïve Bayes algorithm with a Gaussian distribution approach. The results of the machine learning method achieve 72% accuracy, with test scenarios using 80% training data and 20% testing data. The research introduces brain heat mapping as an innovative visualization technique to interpret EEG-based deception detection better, offering a more intuitive and explainable approach compared to traditional feature-based methods. The findings contribute to a deeper understanding of brain function and provide a foundation for improving the effectiveness and reliability of EEG-based lie detection in investigative contexts.

Index Terms-Electroencephalogram (EEG) Signals,

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Brain Activity, Identified Information, Unidentified Information

I. INTRODUCTION

NTERROGATIONS are carried out by authorities to reveal hidden information in security, investigative, criminal, and social contexts [1]. In the interrogation process, the polygraph is a tool that has long been used to monitor a person's physical reactions when lying. However, its accuracy and reliability are often questioned [2]. In the modern context, the Electroencephalogram (EEG) has become a promising research focus [3-6]. EEG records electrical activity in the brain and can provide insight into a person's honesty. Integrating EEG with lie detector technology can increase accuracy in detecting lies by identifying patterns of brain activity associated with lying. The information revealed in lie detection can be done by distinguishing information that is and is not identified by the brain so that research on EEG continues to be developed to analyze patterns of brain activity recorded via EEG [7–14].

In analyzing brain activity patterns, feature extraction is done to extract information hidden in the EEG signal [15–19]. Furthermore, many researchers are using machine learning to distinguish between normal brain activity patterns and design scenarios that trigger brain reactions. For example, previous research [20] has classified EEG signals based on known and unknown information using machine learning resulting in good accuracy. Furthermore, another previous research [21] uses a combination of feature extraction

and tries several machine learning algorithms to determine differences in brain activity when given familiar and unfamiliar image stimuli. It is followed by another previous research [22] which uses energy wavelet feature extraction and Shannon entropy to analyze differences in brain activity when faced with familiar and unfamiliar objects. The energy wavelet values in the research show quite a prominent difference in these two conditions.

The research has integrated the concept of EEG visualization to compare brain activity mapping, including previous research [23] which calculates the similarity of brain activity images in groups of EEG data when the eyes are closed and the eyes are open. It then classifies and produces quite good results. Other studies have also shown the benefits of using brain visualization in identifying certain neurological conditions through non-invasive methods [24-26]. The feature extraction results are then integrated into brain activity mapping, which can now be applied to developing a more sophisticated lie detection system. Brain activity mapping identifies brain areas involved in the lying process, such as the prefrontal cortex and anterior cingulate cortex, which are active when someone is processing false or contradictory information. Activity in these areas indicates cognitive conflict, self-control, and decision-making related to lying behavior [27].

After the integration of brain activity mapping, the classification process is also an important method for distinguishing the characteristics of EEG signal patterns from others. Many studies use several classification algorithms to classify data from EEG signals. Some of the classification algorithms used include Support Vector Machine (SVM), K-Nearest Neighbors (KNN) [28], Logistic Regression, Convolutional Neural Network (CNN), Random Forest [14, 28-30]. Another classification method, namely the Decision Tree, is used by [31] in the development of a lie detector system by analyzing changes in pupil diameter and eye movements. The use of classification algorithms also succeeds in classifying face recognition carried out [32] by trying several algorithms including Long Short-Term Memory (LSTM), Hierarchical Long Short-Term Memory (H-LSTM), Recurrent Neural Network (RNN), Deep CNN, and SVM. Another effective classification method is Naïve Bayes, which can be used to classify images [33-36], EEG signals [37–41], and various other types of data with the simple assumption that each feature is independent of the other.

Based on several previous studies by combining information from EEG and brain activity mapping, the research aims to explore more subtle and complex patterns in brain activity related to distinguishing iden-



Fig. 1. Research methodology. It has Finite Impulse Response (FIR), Independent Component Analysis (ICA), and Discrete Wavelet Transform (DWT).

tified information from unidentified information using energy wavelet feature extraction so that it can be used as a reference in developing a lie detection system. Next, to evaluate the effectiveness of the method used, the researchers apply Naïve Bayes machine learning algorithm, as it is capable of classifying EEG signal data and produces relatively good accuracy [42, 43]. Several similar studies have not explored the proposed scenario, brain activity mapping feature extraction method, and classifier algorithm, thereby creating a research gap in the research.

II. RESEARCH METHOD

In this stage, the methods and data used in the research are described. Figure 1 presents the five stages, starting from data collection, data pre-processing, feature extraction, visualization, and classification. The details are explained in the following sub-chapters.



A. Data Collection

The research uses an OpenBCI product using the 10-20 system. This system is a method of placing electrodes that refer to specific locations on the scalp, and it is used to measure brain electrical activity according to international standards. Figure 2 shows that six channels are applied. The four channels used are the temporal area on the side of the head consisting of the right temporal lobe (T4 and T6) and the left temporal lobe (T3 and T5). The other two channels are the occipital area, which is at the back of the head, namely the left occipital lobe (O1) and the right occipital lobe (O2).

The selected EEG channels related to memory in the human brain provide important insights into visual processing, color perception, object recognition, and other visual processes that occur in the brain [20– 22, 44]. In the EEG recording process, the stimuli used are images of people and places identified and not identified by the respondents. The respondents in the research are 30 healthy students, consisting of 16 females and 14 males, with an average age of 19 years. Before the recording, respondents are asked to fill out a health questionnaire and provide informed consent. To ensure familiarity with the stimuli, respondents are selected based on their ability to identify the given stimuli. In the first recording stage, respondents are presented with images of two people and two places that they can identify. In this recording, a scenario is created using a quiz-like system. If the respondent can identify the stimulus, they will click the "Yes" button, with each image being displayed for seven seconds to answer the question. The stimulus system created is designed in such a way that the respondent minimizes movement except for mouse movements "Yes" or "No". After the first recording stage, the respondent recovers for one minute. Next, the second stage of recording is carried out, respondents are presented with two pictures of people and two pictures of places that they cannot identify.

B. Data Preprocessing and Feature Extraction

Data preprocessing is a crucial step in preparing raw EEG data for further analysis. Since the EEG signal is often affected by noise, eye blinks, and muscle activity, it is essential to clean and filter the data to ensure accuracy [5, 41, 45, 46]. During the research, the analysis applies a Finite Impulse Response (FIR) filter to eliminate Direct Current (DC) offset and extract the desired frequency signal. This filter process combines band pass and FIR filters to remove noise and unwanted frequency components while preserving relevant frequency components. Next, artifacts, such as eye blinks, from the EEG signal are removed using the Independent Component Analysis (ICA) method. ICA is a method in statistics that separates mixed signals

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into independent signals [47–50]. After obtaining clean data from the ICA process, amplitude filtering is applied. If the amplitude value exceeds 100, it is limited to 100. Figure 3 provides an example of clean EEG data from each channel.

The next process is band decomposition using Discrete Wavelet Transform (DWT). The EEG device has a sampling frequency of 256 Hz, which is then reduced by a factor of 2 to 128 Hz through band decomposition using DWT. This reduction is carried out for several purposes, including reducing the computational load and eliminating high-frequency noise without sacrificing important information. The use of DWT is suitable for non-stationary signals which has advantages compared to all types of spectral analysis [51–55]. With DWT, every non-static time domain signal x(t) can be solved in Eq. (1) [56, 57]. It has $\gamma(t)$ as DWT of x(t), a as scale parameter, b as shift parameter, and $\psi(t)$ as mother wavelet.

$$\gamma(t) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{2^a}} \psi\left(\frac{t - b \times 2^a}{2^2}\right) dt.$$
 (1)

The approximate and detailed coefficients are calculated using Daubechies mother wavelet (db4). The db4 mother wavelet is selected because it effectively captures detailed signals by balancing time and frequency resolution. This mother wavelet has orthogonal and compact support properties, ideal for analyzing non-stationary signals because it can detect frequency changes efficiently [58]. Band decomposition using DWT is illustrated in Fig. 4.

The research focuses on the Alpha, Beta, and

Gamma sub-bands. These bands are related to frontal and occipital brain activity as well as emotional and mental reactions. After getting the coefficient values representing each subband, the energy value is calculated. Following decomposition, the wavelet sub-band energy is computed as follows in Eq. (2). It has N as number of samples in the signal X_i .

$$E = \sum_{i=1}^{N} |X[i]|^2.$$
 (2)

C. Visualization

After getting the feature values of each subband, a heatmap is plotted to visualize these features. The visualization is generated using Python visualization with MNE (Magnetoencephalography (MEG) and EEG data analysis) library. The following is the stages of the process that are conducted.

- Import Libraries: The script first imports the necessary libraries, including NumPy for numerical computing, matplotlib for data visualization, MNE for EEG data analysis, and Operating System (OS) for file system manipulation.
- Data: EEG data is represented as data_list, which has several lists (each representing data from one measurement session). Each sublist contains a series of amplitude values from several EEG channels.
- Channel Information: channel_names is a list containing the names of the EEG channels used in the measurement. It is used to create informa-

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Fig. 4. Implementation of 5-level Discrete Wavelet Transform (DWT) decomposition.

tion objects that store metadata about EEG data, such as channel names, sample frequencies, and channel types.

- Montage: The montage (the physical arrangement of the electrodes on the head) is determined using the make_standard_montage function of MNE. These montages are then organized into information objects.
- Visualization: Iteration is performed through each measurement session in the data_list. For each session, a topomap image (amplitude spatial distribution map) for the given data are created using mne.viz.plot_topomap. The channel names are placed on top of the plot using the coordinates of the info object. Each image is saved in the appropriate folder.

D. Classification

After plotting the heatmap, a classification method is applied to identify patterns in the visualization. The Naïve Bayes method with a Gaussian approach is used as the classification method, based on Bayes' theorem, which assumes that each feature is independent of the others. This method is suitable for cases where the data features are continuous and are assumed to come from a Gaussian (normal) distribution. It works by assuming that the feature values in each class are drawn from a Gaussian distribution, with a different mean and variance for each class [59].

In the research, the classifier is trained using an 80:20 train-test split, where feature values extracted through wavelet-based analysis are assumed to follow a Gaussian distribution with class-specific means and variances. The formula for this calculation is shown in Eq. (3). It has x as a continuous feature vector, C_k as class, and the posterior probability for the class C_k . It shows $P(C_k)$ as prior probability for class C_k , μ_{ki} as the average of the *i*-th feature in the class C_k , and σ_{ki}^2 as variance of the *i*-th feature in the class C_k .

$$P(X = x_i \mid C = C_k) = \frac{1}{\sqrt{2\pi\sigma_{ki}^2}} \exp\left(-\frac{(x_i - \mu_{ki})^2}{2\sigma_{ki}^2}\right)$$
(3)

Confusion matrix is an important evaluation tool in the context of classification in machine learning that displays model performance with detailed predictions for each target class. This matrix shows the number of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), providing insight into how well the model differentiates target classes with pinpoint accuracy as shown in Eqs. (4)–(6). It is a key instrument in assessing model reliability and identifying areas that can be improved to increase

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TABLE I Mean Wavelet Energy Values.				
Subband	Channel	Classification		
		Identified	Unidentified	
Alpha	Т3	125.3	229.2	
	T4	122.0	224.0	
	T5	126.1	223.8	
	T6	130.3	216.0	
	01	130.2	232.0	
	O2	126.7	222.9	
Beta	T3	251.4	449.7	
	T4	251.6	457.8	
	T5	250.8	444.5	
	T6	255.5	433.8	
	01	252.6	461.8	
	O2	241.4	450.5	
Gamma	T3	519.6	941.9	
	T4	520.9	945.9	
	T5	516.4	924.7	
	T6	515.9	995.1	
	01	526.2	937.0	
	O2	523.7	962.0	

accuracy.

Accuracy =
$$\frac{TP + TN}{TP + TN + FP + FN}$$
, (4)
Precision = $\frac{TP}{TP + FP}$, (5)
Recall = $\frac{TP}{TP + FN}$. (6)

III. RESULTS AND DISCUSSION

A. Result

As previously explained, the research uses values from energy features obtained from the band decomposition process using DWT. The results of extracting the average value of the energy feature for 30 respondents for 6 channels each for the Alpha, Beta, and Gamma subbands are shown in Table I.

In Table I, the average wavelet energy values in the unidentified condition tend to be higher than the identified condition in all channels and subbands. The value of the unidentified condition is almost twice the value of the identified condition. This increase in wavelet energy is seen consistently in various EEG channels and in all frequency subbands of the wavelet decomposition results. The results strengthen the indication that the signal characteristics in this condition have a significantly different pattern compared to the identified condition.

Next, the researchers interpret the distribution in a boxplot to compare the distribution of several data groups (Fig. 5). The boxes in the boxplot represent the Interquartile Range (IQR), namely the range between the first quartile (Q1) and the third quartile (Q3). This covers the middle 50% of the data. Figure 5 shows that the distribution values for several data groups in



the unidentified condition are higher when compared to the values in the identified condition. These distribution values are grouped based on each subband and channel, combining data from 30 participants. In the condition when participants are given a stimulus that they can identify, the lowest energy wavelet value in the Alpha subband is 43.6 and the highest value is 288.4. While the lowest value in the Beta subband is 99 and the highest value is 536. In the Gamma subband, the lowest value is 238.5 and the highest value is 1,110.2. The result shows that when participants are given a stimulus that they cannot identify, the energy wavelet values in all subbands tends to be higher and has more variable compared to conditions where the stimulus can be identified. This increase in wavelet energy values may reflect increased cognitive activity or brain effort in trying to identify an unidentified stimulus. Additionally, greater variability in the unidentified condition also suggests a wider range of responses among participants, which can result from individual differences in cognitive and perceptual processes.

Next, the extracted feature values from each respondent is visualized into a heatmap map. Table II shows the results of heatmap visualization from respondent 13 as an example in the Alpha, Beta, and Gamma subbands in the identified and unidentified information conditions. In the research, each respondent produces three heatmap images of Alpha, Beta, and Gamma subbands. So, in the image classification test using the Naïve Bayes algorithm, the total image data consists of 180 images (90 for identified labels, and 90 for



Fig. 5. Distribution of wavelet energy values in the Alpha, Beta, and Gamma band frequencies for identified and unidentified conditions.

unidentified labels).

In Table II within the Alpha subband, the identified condition shows high energy concentrations in frontal and parietal areas, indicating memory and attentionrelated activity, while the unidentified condition shows a more uniform distribution of energy, reflecting broader cognitive effort. In the Beta subband, the identified condition displays intense activity in frontal and central areas, indicating a large allocation of cognitive resources to information processing, while the unidentified condition has a more homogeneous energy distribution, indicating additional effort to understand the unidentified stimulus. In the Gamma subband, the identified condition shows high brain activity across areas, especially temporal and parietal, associated with complex information processing, whereas the unidentified condition has a more even distribution of energy, indicating a diffuse cognitive effort to recognize the unidentified stimulus.

Table III shows the performance of the Naïve Bayes algorithm using the Gaussian distribution approach with a scenario of 80% training data and 20% testing data. The algorithm achieves an accuracy of 72%. It demonstrates its effectiveness in classifying identified and unidentified conditions based on wavelet energy features extracted from the heatmaps.

Next, the researchers also test other classification

TABLE III Evaluation Metrics Values.

Evaluation Metrics	Percentage (%)
Accuracy	72
Precision	75
Recall	66

TABLE IV Performance Comparison of Different Classification Algorithms.

Algorithm	Accuracy (%)
Naïve Bayes	72
Convolutional Neural Network (CNN)	69
Support Vector Machine (SVM)	69
Random Forest	63.8
K-Nearest Neighbors (KNN)	61

algorithms, including CNN, SVM, Random Forest, and KNN as classifiers. However, the results obtained from these algorithms are lower than Naïve Bayes. Therefore, the researchers focus on the best results found as the core of the discussion. Table IV presents a comparison of the performance of various classification algorithms that have been tested in the research.

A classification system must measure its performance using a confusion matrix. Confusion matrix is a table that records the results of classification work.



Fig. 6. Confusion Matrix Naïve Bayes model with a Gaussian distribution approach

Figure 6 displays the confusion matrix from Naïve Bayes with a Gaussian distribution approach with a positive value of 14. It means that from the testing data of 18 heatmap maps on brain conditions, 14 correct values are identified, and 4 predicted label values are incorrect. The data testing test value in the identified condition produces fewer FP values when compared to the data testing test value in the unidentified condition. In the unidentified condition, the false value is only 6, and the heatmap incorrect value is 12. In simpler terms of the 18 images that should have been unidentified, the model incorrectly classifies 6 images as identified and succeeds in classifying 12 images correctly.

The FP cases occur when participants do not recognize an image, but the model incorrectly classifies it as "identified". It may occur due to similar brain activity patterns, even though the participant has no prior experience with the stimulus. Meanwhile, the FN cases happen when participants recognize an image, but the model incorrectly classifies it as "unidentified". This result may be caused by weak EEG responses or noise interference during recording. Overall, this confusion matrix helps to understand the model's performance in separating two conditions based on heatmap data, showing that despite some classification errors, the model performs quite well in differentiating between identified and unidentified conditions.

B. Discussion

In general, Table II shows quite good results in distinguishing the recognition of identified and unidentified information using energy wavelet feature values in EEG data. The condition of the brain signal when recognizing unidentified information tends to have a high value. The result is also in line with research [20] where respondent who does not know the information tends to have a higher value using Mean, Mean Absolute Value (MAV), and Standard Deviation (STD) value feature extraction.

The results of the interpreted energy wavelet values show an increase in cognitive activity. When participants attempt to identify an unidentified stimulus, their brains may engage in more complex cognitive processes and make greater efforts to decipher the information received. According to [60], increased cognitive load can lead to increased brain activity as measured through various brain imaging techniques, including wavelet analysis. The research finds that more complex and challenging tasks required more cognitive resources, which are reflected in increased brain wave activity. In addition to increased cognitive activity, greater variability in the unidentified stimulus

TABLE V

COMPARISON OF ELECTROENCEPHALOGRAPHY (EEG) SIGNAL CLASSIFICATION STUDIES BASED ON FEATURES, ALGORITHMS, AND ACCURACY.

Author	Features	Algorithm	Accuracy
[20]	Mean, MAV, STD	K-Nearest Neighbors (KNN)	87.00%
	MAV/STD	Naïve Bayes	50.00%
[14]	P300	Convolutional Neural Network (CNN)	84.44%
[30]	Fisher's LDA, Approximate Entropy (ApEn)	K-Nearest Neighbors (KNN)	85.00%
[44]	PSD	Random Forest	95.40%
[9]	CWT, Hjorth parameters	Support Vector Machine (SVM)	84.37%
[10]	CWT, Hjorth parameters	LDA	72.20%
[1]	FC Features: C, L, Degree	Support Vector Machine (SVM), K-Nearest Neighbors (KNN)	90.58%

Note: MAV= Mean Absolute Value, STD= Standard Deviation, P300= Positive peak at approximately 300 milliseconds, LDA= Linear Discriminant Analysis, PSD= Power Spectral Density, CWT= Continuous Wavelet Transform, FC Features= Functional Connectivity Features, C= Complexity, and L= Lateralization.

condition suggests a wider range of responses among participants. It can be due to individual differences in cognitive and perceptual strategies. For example, some participants may have a better ability to process ambiguous or unclear information, while others may experience greater difficulty, resulting in greater variability in the data. This variability in cognitive abilities can lead to significant differences in brain responses to unidentifiable stimuli [61]. Previous research [62] has used wavelet analysis to identify patterns of brain activity during complex cognitive tasks and found that wavelet analysis is very effective for detecting dynamic changes in brain activity associated with cognitive load.

Furthermore, the use of the MNE library visualization in Python provides deep insight into the significant differences in accuracy in distinguishing identified and unidentified information. In this context, the Gaussian Naïve Bayes algorithm stands out as a method capable of processing EEG data effectively, especially when applied to wavelet energy features. The visualization provided by MNE makes it possible to see directly how this algorithm manages to separate relevant information and produce quite high accuracy values in classification. It shows great potential in applications in the field of neuroimaging data analysis. The result is supported by previous research [63] which recognizes that visualization of heatmap using the MNE Python library helps to understand and validate classification results in a neuroimaging context.

The researchers have compared the research with other studies on EEG. Table V presents a comparison of several studies related to EEG signal classification based on the features used, classification algorithms, and the accuracy achieved. Each study adopts a different approach to feature extraction and model selection to improve classification accuracy. Some studies use statistical-based methods such as MAV, STD, and Power Spectral Density (PSD), while others rely on more complex techniques such as Continuous Wavelet Transform (CWT), Hjorth parameters, and Approximate Entropy (ApEn).

The ability of the Gaussian Naive Bayes algorithm to differentiate between identified and unidentified information, especially in the context of wavelet energy features, shows great potential for further development in this field. This model produces quite good values because just one feature is enough to produce 72% accuracy based on Table III. The value of the findings produces quite high accuracy when compared to previous research [20] which only obtains 50% accuracy on one feature with the same scenario. Additionally, compared to other studies (Table V) that utilize multiple features and more complex algorithms, such as Random Forest with PSD (95.40%) or KNN with Mean, MAV, and STD (87%), this approach with Gaussian Naive Bayes demonstrates that a simpler model with minimal feature extraction can still yield competitive results. This finding gives quite good results because if the researchers use more features, the computing becomes heavier, and the price also becomes more expensive. Moreover, this approach introduces a novel brain heat map visualization, which is absent in previous studies, providing a more intuitive interpretation of brain activity patterns. So, with the research, researchers and other practitioners can optimize the classification process and gain a better understanding of brain activity, paving the way for significant advances in the understanding of brain function and healthrelated development that can be used as a reference for lie detection in the field of investigation.

Compared to traditional polygraph tests, EEG-based lie detection offers more reliable information. Polygraphs rely on physiological responses such as heart rate and blood pressure, which individuals can consciously manipulate. In contrast, EEG measures brain activity, which is much harder to control intentionally, making it a more robust tool for detecting deception. Beyond lie detection, this method has potential applications in various fields. In forensic and crimi-

nal investigations, EEG-based classification can assist in identifying suspects and verifying testimonies. In national security, it may help to detect individuals attempting to conceal critical information. Additionally, in cognitive psychology and neuroscience, it can contribute to research on how humans recognize and recall information.

IV. CONCLUSION

The research proposes the Naïve Bayes method with a Gaussian distribution approach to classify EEG signals according to brain conditions when they can or cannot identify information using brain activities mapping. The channels are T3, T4, T5, T6, O1, and O2 which are then analyzed in the Alpha, Beta, and Gamma subbands. The energy wavelet feature extraction value is used as a visualization parameter for brain activity mapping. Next, the visualization image is classified using the Gaussian Naïve Bayes algorithm. It produces an accuracy of 72% with a scenario of 80% training data and 20% testing data. These results demonstrate a fairly good understanding of brain function and provide strong support for the development of lie detection in investigative contexts. Compared to conventional polygraph methods, which rely on physiological responses that can be consciously controlled, EEG-based lie detection offers a more objective and reliable approach by analyzing neural activity that is difficult to manipulate. The research introduces brain heat mapping as an innovative visualization technique, enhancing interpretability in distinguishing identified and unidentified information. These findings highlight its potential applications in forensic investigations, national security, and cognitive neuroscience research.

The research has limitations in the small sample size and the limited variation of brain activity trigger scenarios. For further research, it is suggested to increase the sample size, carry out more varied scenarios, and try a combination of feature extraction to increase accuracy in distinguishing brain signal conditions to identify or unidentify information via EEG signals. Hence, it can be used as a lie detection development system. The bigger sample size and more diverse participants can increase the generalizability of the findings. The research also suggests performing more varied scenarios that can trigger different brain activities to obtain higher difference scores in the recognition of identifiable and unidentifiable objects in the brain.

AUTHOR CONTRIBUTION

Conceived and designed the analysis, A. D. W; Collected the data, S. D. S. and S. P.; Contributed data or

analysis tools, A. D. W., S. D. S., and S. P.; Performed feature extraction and brain activity mapping using machine learning techniques for EEG signal analysis, A. D. W.; Wrote the paper, A. D. W., S. D. S., and S. P.; Validated the results by comparing heatmaps from different scenarios to improve model accuracy, S. D. S.; and Adapted machine learning algorithms to improve accuracy, S. P.

DATA AVAILABILITY

The participants of the research did not give written consent for their data to be shared publicly. So, due to the sensitive nature of the research, supporting data are not available.



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