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Comparing emotion classification: machine learning algorithms and hybrid model with support vector machines

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ABSTRACT

Recently, the use of artificial intelligence techniques has become widespread, having been adopted in brain-computer interfaces (BCIs) with electroencephalograms (EEGs). BCIs allow direct communication between a person's brain and a computer, and have various uses ranging from assistive technology to neuroscientific study. This paper provides an introductory overview of BCIs and EEG. We adopted the use of machine learning (ML) algorithms, including K-nearest neighbors (KNN), logistic regression, decision trees, random forests, and support vector machine (SVM). Additionally, we proposed a hybrid model of deep learning (DL) and ML by combining convolutional neural networks (CNNs) and SVMs. Our achieved 98% accuracy. The goal is to classify EEG signals into three emotional states: happy, normal, and sad. The study aims to achieve a comprehensive understanding of the effectiveness of these algorithms in accurately classifying emotional states based on EEG data. By comparing the performance of traditional ML methods and the proposed hybrid model, we seek to identify the most robust and accurate approach to sentiment classification.

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1. INTRODUCTION

The principle behind the brain-computer interface (BCI) is to establish a line of communication between the human brain and a computer or other device. The BCI system monitors changes in brain activity and computer screens or other real objects, such as emotions that have been categorised or other external devices. For neurorehabilitation or as a support system for people with a variety of health problems or long-term health effects, BCI has received substantial research in recent years. BCI technology can be effective for idea-only communication [1], [2]. Machine learning (ML) algorithms use input data to achieve goals without explicit programming, replicating human learning from experience [3], [4]. Deep learning (DL) is a ML branch that uses artificial neural networks (ANNs) to create complex neural systems with over 10 layers. It is crucial in medical image processing, disease classification, segmentation, and clinical data recognition [5], [6]. Emotion is a multifaceted condition that reflects human consciousness, and is characterized as a response to stimuli in the environment. Generally, emotions arise in response to thoughts, memories, or events within our surroundings. They play a crucial role in decision-making and interpersonal communication among humans. Decision-making is influenced by emotional states, and the presence of negative emotions can contribute to both psychological and physical issues. Conversely, positive emotions may contribute to improved health, whereas negative emotions could potentially result in a reduced quality of life [7]. In this paper, we discuss a group of studies presented by researchers in the field of identifying emotions using different algorithms and methods.

Djamal and Lodaya [8], emotional therapy, medical rehabilitation, and applications of the BCI all depend on emotional identification. Electroencephalogram (EEG) signals fall into three categories: happy, relaxed, and sad. This research suggests utilising wavelet and learning vector quantization (LVQ) to track human emotion in real-time. Alpha, beta, and theta waves were created in 10 seconds by processing data from 480 sets of data. The method used wavelet extraction and an asymmetric channel to increase accuracy by 72% to 87%. Without losing accuracy, LVQ reduced computation time to under a minute. For the purpose of tracking emotional states in real time, a wireless EEG was integrated into the system. Reolid *et al.* [9] describes an experiment to evaluate the emotional state categorization precision offered by the application programming interface (API) of the emotiv EPOC+ headset. The international affective picture system (IAPS) dataset is used in the study to examine the emotional states using photographs. To determine the classification accuracy, participants' responses are compared to validated values, and ANNs are put to the test. The ANN setup with three hidden layers and 30, 8, and 3 neurons for layers 1, 2, and 3 produces the best results. The emotional states delivered by the headset can be employed in real-time applications based on users' emotional states with high confidence thanks to this configuration's 85% classification accuracy. Additionally, the study shows that multilayer perceptron ANN designs are enough.

Huang *et al.* [10] describes an EEG-based BCI system for emotion identification that uses subject-specific frequency bands to identify happy and melancholy. It was verified in two studies and reached an average online accuracy for two classes of 91.5%, with the gamma band being more closely associated with emotions of happiness and melancholy. Ramdhani *et al*. [11], the BCI system model presented is based on motor imagery and emotion. Eight classes are created from the recovered EEG signals using wavelet transformation: "happy forward," "happy stop," "happy right," "happy left," "neutral forward," "neutral stop," "neutral right," and "neutral left". With AdaMax and VGG16, the model classified the characteristics into eight groups with an accuracy of 90%. Users of this BCI system can control external devices without using their muscles or motor abilities.

Ardito *et al.* [12], BCI allow for machine control using EEG signal processing. EEG signals were used in a study to identify emotional states like valence, arousal, and dominance. The development of a deep neural network to dynamically identify emotions led to the creation of a prototype for an EEG-based emotion recognizer. As a result, the prototype can be used for screening and epidemiological research that require real-time observation of emotional history. With a mean absolute error of 0.08 and an accuracy: R^2 of 0.93, the convolutional neural network (CNN) performed well. The high metrics, however, are based on a limited population sample, necessitating additional validation on a larger test sample. Pandey and Sharma [13], the BCI is a communication device for people with impairments and mental illnesses that translates commands from brain EEG signals. A 96% accurate model for emotion classification developed recently in BCI technology has the potential to enhance device performance.

Wu and Dai [14], the emo-net neural decoding framework, a data-driven method, aims to properly read emotions from neural activity segments for emotional BCI. While DL has great potential, its development has been hampered by the use of non-human primates and noise in training data. This method improves the functionality and decoding skills of basic DL models, enabling the recognition of animal model emotion. DL models are up to 92.02% accurate on a variety of classification and reconstruction tasks. Si *et al.* [15], a DL model for emotion recognition utilising functional near-infrared spectroscopy (fNIRS) and videos is presented in the study. the model achieves 90% outstanding decoding performance. The model also exhibits promise for tasks requiring emotion recognition, although it has drawbacks, including the inability to subdivide emotions and subpar decoding for negative versus neutral emotions.

Researchers who have explored the connection between EEG, BCIs, and emotion have made significant contributions to the field. Their work has focused on investigating how EEG signals can be used to detect and interpret emotional states in individuals using BCIs. These studies have shown promising results in enabling communication and understanding of emotions in individuals with limited motor control. The researchers have employed various methods, such as ML algorithms and pattern recognition techniques, to analyse and classify EEG signals associated with different emotional states. In this research, we present a study where we used some ML algorithms and proposed a hybrid model that combines DL with ML to achieve results with acceptable accuracy and higher than others [8]–[15]. We compared the results of the algorithms we adopted in our study with each other, as well as with the results of other researchers.

2. PROPOSAL MODEL SCHEMA

The proposed model for classifying emotions unfolds across five phases, offering a comprehensive approach to leveraging EEG data. Phase1 of EEG dataset classification: the EEG dataset incorporates three distinct emotional classifications (natural, sad, and happy). This initial stage sets the foundation by defining the emotional categories present in the data. Phase 2 of data processing operations: the processing of EEG data involves a series of operations to ensure its suitability for emotion classification. These operations include data loading, where the dataset is imported, data cleaning to enhance its quality, handling missing values, and finally transforming data. The dataset is then divided into separate groups for training and testing, a critical step in evaluating model performance. Phase 3 of ML algorithms: in the third stage, a group of ML algorithms is employed for emotion classification. The chosen algorithms within this ML group include K-nearest neighbors (KNNs), decision trees (DTs), random forests (RFs), and logistic regression (LR). Each algorithm contributes unique capabilities to discern patterns within the EEG data and classify emotions effectively. Phase 4 of the hybrid DL with ML algorithm: the model introduces a hybrid approach by incorporating a choice between a DL algorithm, CNN, and a traditional ML algorithm, support vector machine (SVM). This hybridization aims to capitalise on the strengths of both paradigms, where CNN excels in feature extraction, and SVM contributes robust classification. The flexibility to choose between DL and ML enhances the model's adaptability to the complexity of EEG data. The final phase involves classification and evaluation, where the model's performance is assessed. This includes employing metrics such as accuracy, precision, recall, and F1-score to gauge the effectiveness of the classification algorithms. Iterative refinement and optimization are conducted based on the evaluation results, ensuring the model's ability to accurately classify emotions from EEG recordings. The proposed model encompasses a holistic approach, integrating diverse algorithms, both traditional ML and advanced DL, to effectively classify emotions from EEG data. The inclusion of a hybrid algorithm enhances the model's adaptability and performance, providing a robust framework for understanding and categorizing emotions in neural signals. As shown in Figure 1.

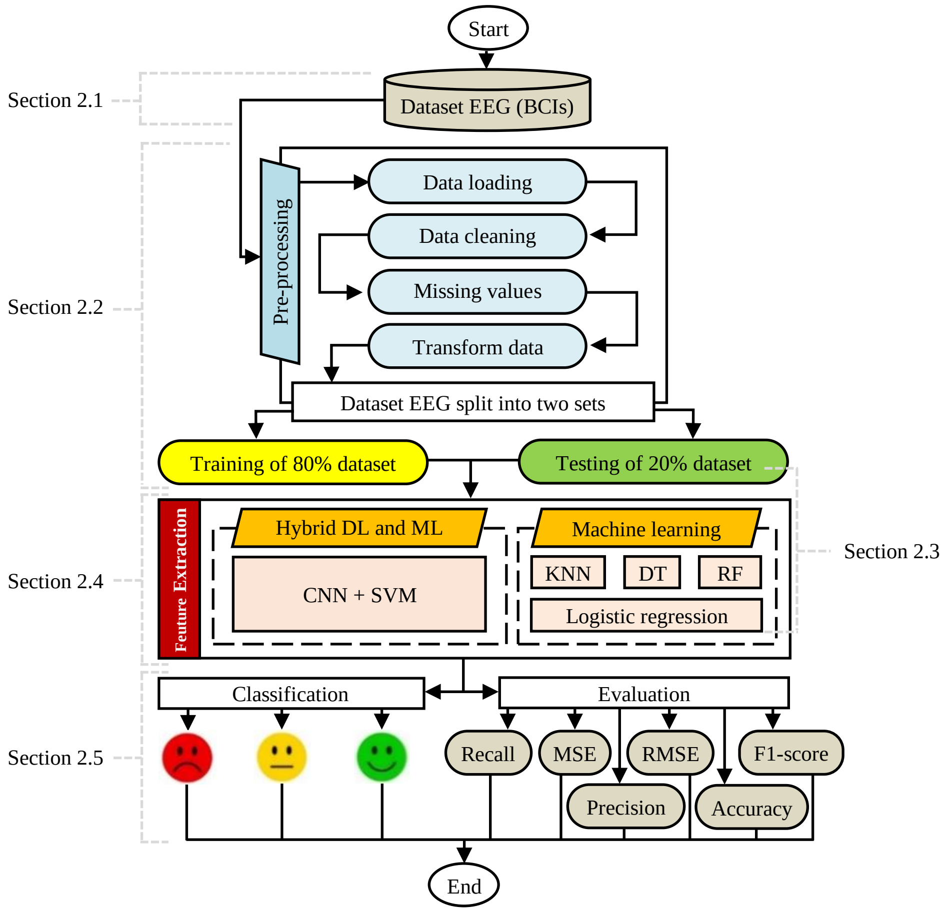


Figure 1. The proposal model schema

2.1. Electroencephalogram

EEG datasets are crucial for exploring and categorizing emotions, providing recordings of brain activity to unveil neural patterns linked to diverse emotional states. The process of emotion classification with

EEG entails extracting significant features from these recordings, which then serve as inputs for ML models. These datasets play a pivotal role in the creation and assessment of a wide range of algorithms, spanning from classical approaches like LR and DT to sophisticated methods such as CNN and hybrid models. This contributes to a deeper comprehension of emotions through neural signals [16].

2.2. Pre-processing

In the preparation phase for emotion classification using EEG datasets, crucial measures are taken to enhance data quality before utilizing ML algorithms. This encompasses addressing missing values, converting labels into numeric form, and choosing pertinent features. Ensuring uniform scaling through standardization or naturalization is key, and the division of data into training and test sets is fundamental. Supplementary techniques, such as feature scaling and transformation, are employed to optimize the performance of ensuing emotion classification algorithms, thereby improving accuracy and dependability in identifying emotional states [17]. Algorithm 1 representation of the steps performed in the code:

Algorithm 1. The phases of pre-processing and dividing the dataset

Input:	Dataset
Output:	Number of Missing Values, Transformed Data (X and Y), Scaled Data, Train-Test Split, Standardized Features
Step 1:	Start
Step 2:	Import necessary libraries: (numpy, pandas, confusion_matrix, matplotlib. pyplot, seaborn, accuracy_score, recall_score, roc_auc_score, classification_report, precision_score, f1_score, mean_squared_error).
Step 3:	Finding Number of Missing Values: a) Apply a function to check for missing values in each column of the dataset. b) Display the shape of the dataset (data), indicating the number of rows and columns.
Step 4:	Transform Data: a) Define a function named 'Transform_data' taking 'data' as input. b) Replace labels ('POSITIVE', 'NEUTRAL', 'NEGATIVE') in the 'label' column with numerical values (2, 0, 1). c) Separate the predictor variables (X) and the target variable (Y). d) Return X and Y.
Step 5:	Call Transformation Function and Split Data: a) Call 'Transform_data(data)' to obtain X and Y. b) Use 'MinMaxScaler' from 'sklearn. preprocessing' to scale the features in the range [0, 1].
Step 6:	Train-Test Split: a) Import 'train_test_split' from 'sklearn. model_selection'. b) Split the dataset into training and test sets (X_train, X_test, Y_train, Y_test) with a testing size of 20% and a training size of 80%.
Step 7:	Standardize Features: a) Import 'StandardScaler' from 'sklearn. preprocessing'. b) Standardize the features using 'fit_transform' for training data and 'transform' for test data.
Step 8:	End

2.3. Machine learning

ML algorithms use input data to achieve goals without explicit programming, replicating human learning from experience. Used to analyze large datasets, perform predictive analytics faster than humans, and use statistical theory to build mathematical models. This branch of artificial intelligence focuses on algorithm development and assessment [18].

2.3.1. K-nearest neighbors

Utilized in emotion classification within EEG datasets, the KNN classifier algorithm determines the emotion class of a data point by assessing the classes of its nearest neighbors. The approach relies on the proximity of instances in feature space, assigning the most prevalent emotion within the KNN [19]. Well-suited for multiclass emotion classification, this method offers a straightforward yet efficient means of identifying emotional states in EEG data, analyzing patterns based on neighboring instances in the dataset [20], [21]. As shown in Figure 2. Algorithm 2 representation of the steps performed in the code:

Algorithm 2. Implementing the K-nearest neighbors algorithm

Input:	Training Data (X_train, Y_train), Test Data (X_test)
Output:	Trained Model, Predictions, Performance Metrics, Confusion Matrix, Classification Report, Error Handling
Step 1:	Start

Step 2: Import necessary libraries: a) Import 'KNeighborsClassifier' from 'sklearn.neighbors'. b) Import 'model_selection' and 'neighbors' from 'sklearn'. c) Import other required libraries such as ("accuracy_score, precision_score, recall_score, f1_score, mean_squared_error, confusion_matrix", classification_report, numpy, matplotlib. pyplot, and seaborn).
Step 3: Create a KNeighborsClassifier: Initialize a KNeighborsClassifier object as 'clf'.
Step 4: Train the classifier: Fit the classifier on the train-ing data (X_train and Y_train) and store the trained model in 'knn_clf'.
Step 5: Predict outcomes for the test set: Use the train-ed classifier to predict outcomes for the test set (`X_test`) and store the predictions in 'Y_pred_test'.
Step 6: Predict outcomes for the training set: Use the trained classifier to predict outcomes for the training set ('X_train') and store the predictions in 'Y_pred_train'.
Step 7: Calculate and print performance metrics for the training and testing set: Calculate and print the ("accuracy, precision, recall, F1-Score, mean squared error, and root mean squared error").
Step 8: Generate and display a confusion matrix for the test set: a) Use 'confusion_matrix' to calculate the confusion matrix for the test set. b) Create a heatmap using 'seaborn' and 'matplotlib.pyplot' to visualize the confusion matrix.
Step 9: Print the classification report for the test set: Generate and print the classification report using 'classification_report' for the test set.
Step 10: End

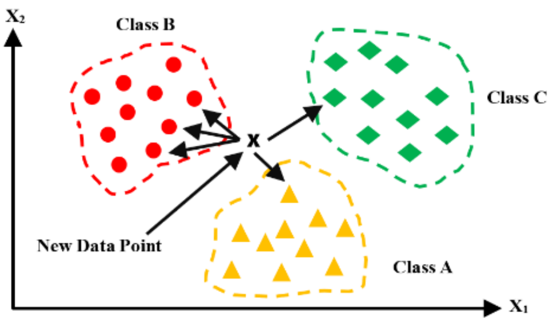


Figure 2. Basic KNN structure

2.3.2. Logistic regression

LR, commonly utilized in emotion classification within EEG datasets, establishes a connection between input features and emotions. It generates probabilities for each emotion class through a logistic function, facilitating the prediction of the most probable emotion. This algorithm proves effective for both binary and multiclass classification, offering valuable insights into discerning emotions from EEG data. Its efficiency and interpretability contribute to a better understanding of the intricate patterns underlying emotional states in EEG recordings [22], [23]. As shown in Figure 3. Algorithm 3 representation of the steps performed in the code:

Algorithm 3. Implementing the logistic regression algorithm
Input: Training Data (X_train, Y_train), Test Data (X_test)
Output: Trained Model, Predictions, Performance Metrics, Confusion Matrix, Classification Report, Error Handling
Step 1: Start
Step 2: Import necessary libraries: a) Import 'LogisticRegression' from 'sklearn. linear_model'. b) Import other required libraries such as ("accuracy_score, precision_score, recall_score, f1_score, mean_squared_error, confusion_matrix", classification_report, numpy, matplotlib. pyplot, and seaborn).
Step 3: Create a Logistic Regression model: Initialize a Logistic Regression model object as 'model'.
Step 4: Train the model: Fit the model on the training data (X_train and Y_train).
Step 5: Predict outcomes for the test set: Use the trained model to predict outcomes for the test set (X_test) and store the predictions in 'y_pred_test'.
Step 6: Predict outcomes for the training set: Use the trained model to predict outcomes for the training set (X_train) and store the predictions in 'Y_pred_train'.

Step 7: Calculate and print performance metrics for the training and testing set: Calculate and print the ("accuracy, precision, recall, F1-Score, mean squared error, and root mean squared error").
Step 8: Generate and display a confusion-matrix for the test set: a) Use 'confusion_matrix' to calculate the confusion-matrix for the test set. b) Create a heatmap using 'seaborn' and 'matplotlib. pyplot' to visualize the confusion matrix.
Step 9: Print the classification report for the test set: Generate and print the classification report using 'classification_report' for the test set.
Step 10: Handle potential errors during the generation of the confusion-matrix for the test set: Use a 'try-except' block to catch any 'ValueError' during the generation of the confusion matrix and print an error message if it occurs.
Step 11: End

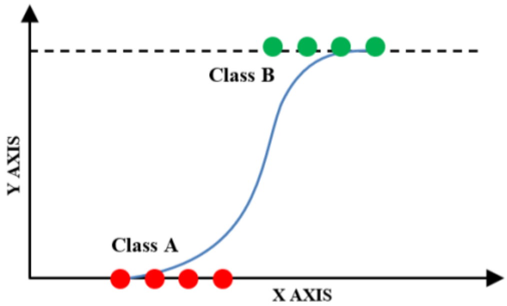


Figure 3. Basic LR structure

2.3.3. Decision tree

Utilized in classifying emotions within EEG datasets, the DT classifier employs a tree-like model to make decisions based on input features, forming a hierarchical structure of nodes [24]. Through recursive partitioning, the dataset branches into nodes that culminate in leaf nodes, each representing specific emotion classes. Particularly effective for multiclass emotion classification in EEG data, DT offer interpretable outcomes by visualizing decision-making processes. They excel at identifying patterns associated with diverse emotional states, contributing to insightful analyses in emotion classification [25]. As shown in Figure 4. Algorithm 4 representation of the steps performed in the code:

Algorithm 4. Implementing the decision tree algorithm
Input: Training Data (X_train, Y_train), Test Data (X_test)
Output: Trained Model, Predictions, Performance Metrics, Confusion Matrix, Classification Report, Error Handling
Step 1: Start
Step 2: Import necessary libraries: a) Import 'DecisionTreeClassifier' from 'sklearn. tree'. b) Import other required libraries such as ("accuracy_score, precision_score, recall_score, f1_score, mean_squared_error, confusion_matrix", classification_report, numpy, matplotlib. pyplot, and seaborn).
Step 3: Create a Decision Tree Classifier: Initialize a Decision Tree Classifier object as 'dtc_clf' with a specified 'random_state'.
Step 4: Train the Decision Tree Classifier: Fit the Decision Tree Classifier on the training data (X_train and Y_train).
Step 5: Predict outcomes for the test set: Use the train-ed Decision Tree Classifier to predict outcomes for the test set (X_test) and store the predictions in 'y_pred_test'.
Step 6: Predict outcomes for the training set: Use the trained Decision Tree Classifier to predict outcomes for the training set (X_train) and store the predictions in 'y_pred_train'.
Step 7: Calculate and print performance metrics for the training and testing set: Calculate and print the ("accuracy, precision, recall, F1-Score, mean squared error, and root mean squared error").
Step 8: Generate and display a confusion-matrix for the test set: a) Use 'confusion_matrix' to calculate the confusion matrix for the test set. b) Create a heatmap using 'seaborn' and 'matplotlib. pyplot' to visualize the confusion matrix.

Step 9: Print the classification report for the test set: Generate and print the classification report using 'classification_report' for the test set.
Step 10: Handle potential errors during the generation of the confusion-matrix for the test set: Use a 'try-except' block to catch any 'ValueError' during the generation of the confusion matrix and print an error message if it occurs.
Step 11: End

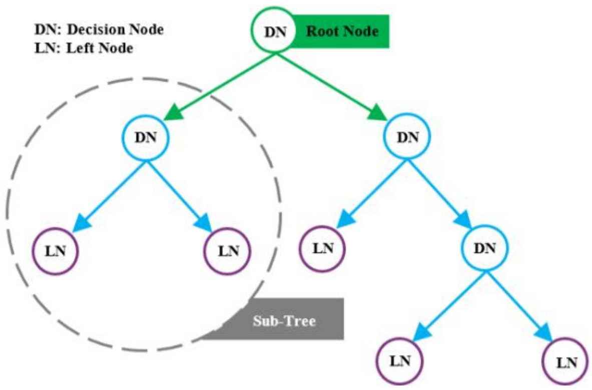


Figure 4. Structure of the DT algorithm

2.3.4. Random forest

The RF classifier plays a vital role in emotion classification within EEG datasets. This ensemble learning technique utilizes multiple DT to improve accuracy and resilience [26]. By consolidating predictions from diverse trees, the RF mitigates overfitting, yielding more dependable outcomes. Particularly adept at capturing intricate patterns in EEG data related to emotions, this algorithm's versatility, capacity for handling multiclass scenarios, and resistance to noise render it an invaluable asset for identifying emotional states in EEG recordings [1]. As shown in Figure 5. Algorithm 5 representation of the steps performed in the code:

Algorithm 5. Implementing the random forest algorithm
Input: Training Data (X_train, Y_train), Test Data (X_test)
Output: Trained Model, Predictions, Performance Metrics, Confusion Matrix, Classification Report, Error Handling
Step 1: Start
Step 2: Import necessary libraries: a) Import 'RandomForestClassifier' from 'sklearn. ensemble'. b) Import other required libraries such as ("accuracy_score, precision_score, recall_score, f1_score, mean_squared_error, confusion_matrix", classification_report, numpy, matplotlib. pyplot, and seaborn).
Step 3: Create a Random Forest Classifier: a) Initialize a Random Forest Classifier object (rmf) with a specified 'random_state'. b) Fit the Random Forest Classifier on the training data (X_train and Y_train) and store the trained model in 'rmf_clf'.
Step 4: Predict outcomes for the test set: Use the trained Random Forest Classifier to predict outcomes for the test set (X_test) and store the predictions in 'y_pred_test'.
Step 5: Predict outcomes for the training set: Use the trained Random Forest Classifier to predict outcomes for the training set (X_train) and store the predictions in 'y_pred_train'.
Step 6: Calculate and print performance metrics for the training and testing set: Calculate and print the ("accuracy, precision, recall, F1-Score, mean squared error, and root mean squared error").
Step 7: Generate and display a confusion matrix for the test set: a) Use 'confusion_matrix' to calculate the confusion matrix for the test set. b) Create a heatmap using 'seaborn' and 'matplotlib. pyplot' to visualize the confusion matrix.
Step 8: Print the classification report for the test set: Generate and print the classification report using 'classification_report' for the test set.
Step 9: Handle potential errors during the generation of the confusion matrix for the test set: Use a 'try-except' block to catch any 'ValueError' during the generation of the confusion matrix and print an error message if it occurs.
Step 10: End

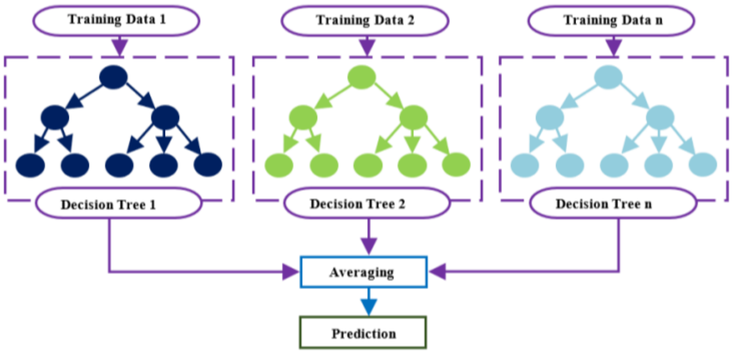


Figure 5. RF algorithm with n DT

2.4. Hybrid deep learning with machine learning

The integration of DL with ML is utilized for emotion classification in EEG datasets [27]. This hybrid model combines DL architectures, including CNNs and SVMs, with traditional ML methods to optimize performance. By synergistically leveraging the strengths of both paradigms, the model proficiently captures spatial and temporal patterns within EEG data, ensuring resilient emotion recognition. This unified approach significantly improves classification accuracy and adaptability, establishing it as a potent tool for deciphering emotions in intricate EEG recordings [18].

2.4.1 Hybrid convolutional neural network with support vector machine

The fusion of a CNN with SVM classifier is utilized to classify emotions in EEG datasets [28]. This hybrid method merges CNN's feature extraction capabilities with SVM's classification strength. CNN extracts spatial features from EEG data, and SVM categorizes these features into emotions. This combined model proficiently captures spatial and temporal patterns, boosting the precision of emotion classification in EEG recordings, particularly in scenarios involving intricate and high-dimensional data [29]. As shown in Figure 6. Algorithm 6 representation of the steps performed in the code:

Algorithm 6. Implementing the hybrid convolutional neural network with support vector machine algorithms

Input: Training and Testing Data (X_train, X_test, Y_train), Original Labels (Y_train), Parameters

Output: Trained Models (CNN, SVM), Predictions (CNN (Y_pred_cnn), SVM (Y_pred_svm)), Performance Metrics (Accuracy, Classification Report, Additional Metrics), Visualizations (Training History Plot, Confusion Matrix Plot)

Step 1: Start

Step 2: Import necessary libraries: a) Import 'pandas' as 'pd'. b) Import 'train_test_split' from 'sklearn. Model _selection'. c) Import 'StandardScaler' from 'sklearn. preprocessing'. d) Import necessary modules from 'keras': "Sequential, Dense, Conv1D, Flatten, and MaxPooling1D". e) Import 'SVC' from 'sklearn.svm'. f) Import 'accuracy_score' and 'classification_report' from 'sklearn. Metrics '. k) Import 'numpy' as 'np'.

Step 3: Reshape data for CNN: a) Reshape the training and testing data for 1D Convolutional Neural Network (CNN) using 'reshape'. b) Assuming it's EEG data, reshape to (number_of_samples, time_steps, 1).

Step 4: One-hot encode the labels: Use 'to_categorical' from 'tensorflow. keras. utils ' to convert the categorical labels (Y_train and Y_test) to one-hot encoded format.

Step 5: Define the 1D CNN model: a) Initialize a sequential model (`cnn_model`). b) Add a 1D convolutional layer with 64 filters, kernel size 3, and ReLU activation. c) Add a 1D MaxPooling layer with pool size 2. d) Flatten the output. e) Add a dense layer with 50 units and ReLU activation. e) Add the output layer with 3 units (for 3 classes) and softmax activation.

Step 6: Compile the model: Compile the model use-ing 'adam' optimizer and 'categorical_crossentropy' loss.

Step 7: Train the model with one-hot encoded labels: a) Train the model on the reshaped training data (X_train_cnn) with one-hot encoded labels (Y_train_one_hot). b) Use 10 epochs and a batch size of 32.

Step 8: Plot training history: a) Create a DataFrame (histdf) from the training history. b) Plot training accuracy and loss using 'matplotlib'.

Step 9: Extract features from the trained CNN: Use the trained CNN model to extract features from the reshaped training and test data.
Step 10: Train an SVM on the extracted features: a) Initialize an SVM model (svm_model) with a linear kernel. b) Fit the SVM model on the extracted features and the original training labels.
Step 11: Make predictions with the SVM: Use the trained SVM model to make predictions on the extracted features from the test set.
Step 12: Evaluate the model: a) Calculate and print accuracy. b) Print classification report.
Step 13: Calculate additional evaluation metrics: a) Calculate and print "precision, recall, f1-score, mean squared error, and root mean squared error". b) Generate and display a confusion matrix using 'confusion_matrix' and 'seaborn'.
Step 14: End

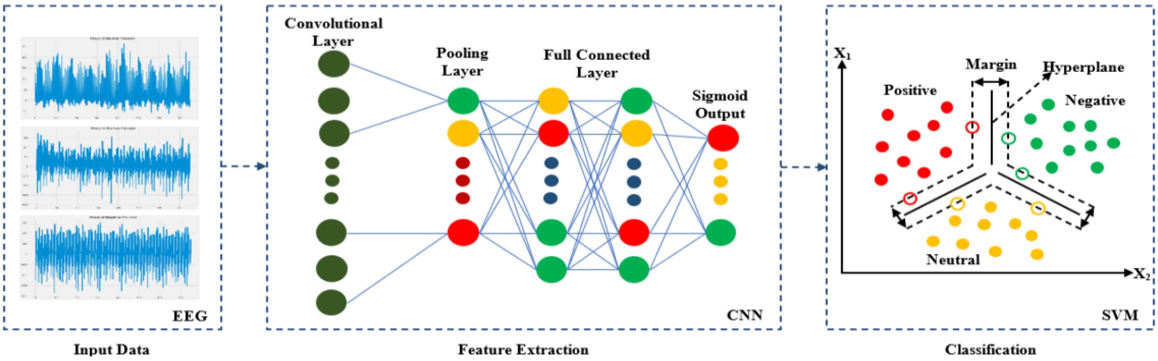


Figure 6. The hybrid CNN with SVM

2.5. Classification and evaluation

In the realm of emotion classification with EEG datasets, the classification and evaluation process entails utilizing diverse ML algorithms to categorize emotional states. Following model training with labeled data, performance assessment utilizes metrics such as accuracy, precision, recall, and F1-score. This iterative approach strives to enhance the model's proficiency in accurately discerning emotions. The incorporation of robust evaluation measures ensures the credibility of emotion classification outcomes, fostering a more profound comprehension of emotional states within EEG recordings [30].

3. RESULTS AND DISCUSSION

The results and discussion section presents the outcomes of the study which employed a combination of algorithms, including ML and DL, to classify emotions using an EEG dataset. The algorithms processed the EEG data, extracting patterns and features relevant to emotional states. ML algorithms were likely employed for their ability to discern complex relationships within the data, while DL models, known for their capacity to automatically learn hierarchical representations, played a crucial role in capturing intricate patterns. The results showcase the effectiveness of the proposed approach in accurately categorizing emotions based on EEG signals. Furthermore, the discussion interprets these findings, highlighting the significance of the chosen algorithms, their performance metrics, and their potential implications for emotion recognition applications. This section contributes to the overall understanding of the methodology's robustness and its implications for advancing emotion classification in EEG-based studies. The following, we discuss several cases involving our findings.

3.1. Case studies of machine learning algorithms

The success of each system depends on its accuracy and performance. In this case, we discuss the results of the ML algorithms for (KNN, LR, DT, and RF). Table 1 shows an explanation of the results we reached in the training and testing phases. In which we used precision, recall, F1-score, mean squared error (MSE), root mean squared error (RMSE), and accuracy to evaluate the models. The work of the proposed system was divided into two phases: the first was training, and the second was testing with a total of 2132 data sets. In the training phase, 80% of the total data was approved, as the algorithms achieved an accuracy of 98%, 88%, 100%, and 100% for each of the KNN, LR, DT, and RF algorithms for a data set of 1705. As for the testing phase, 20% of the total data was used, as the algorithms achieved 94%, 88%, 94%, and 97% accuracy for each of the KNN, LR, DT, and RF algorithms for a data set of 427.

Table 1. The accuracy results of ML algorithms (training and testing)

ML		Precision	Recall	F1-Score	MSE	RMSE	Accuracy	Support
Training	KNN	0.97	0.97	0.97	0.06	0.25	0.98	1705
	LR	0.88	0.88	0.88	0.20	0.45	0.88	
	DT	1.00	1.00	1.00	0.00	0.00	1.00	
	RF	1.00	1.00	1.00	0.00	0.00	1.00	
Testing	KNN	0.94	0.94	0.94	0.11	0.32	0.94	427
	LR	0.88	0.88	0.88	0.17	0.41	0.88	
	DT	0.94	0.94	0.94	0.11	0.33	0.94	
	RF	0.97	0.97	0.97	0.06	0.24	0.97	

A confusion-matrix is a table that shows how well a classificat-ion model performs on a set of test data, where the true labels are known. The rows represent the actual labels, and the columns represent the expected labels. Each cell displays the number of cases that fall into the corresponding category. For example, the cell in the upper left corner shows the number of cases that were correctly classified as natural, the cell in the middle of the diagonal shows the number of cases that were correctly classified as wild, and the cell in the lower right corner shows the number of cases that were correctly classified as happy. Cells outside the diagonal show misclassifications, or instances that were expected to belong to a different category than the actual category [31]. The following is a summary of the values in Figure 7.

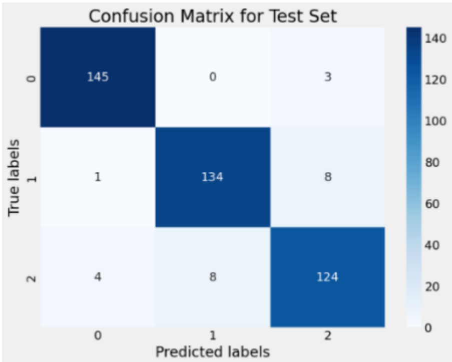
a) Figure 7(a) C-matrix for test of KNN algorithm:
   - The model naturally classified 145 cases as happy, 134 cases as sad, and 124 cases as happy. These are the real positives of each category.
   - The model incorrectly classified one instance as sad, when it was actually natural. This is a false negative for the natural class, and a false positive for the sad class.
   - The model incorrectly classified 4 cases as happy, when they were actually natural. This is a false negative for the natural class, and a false positive for the happy class.
   - The model incorrectly classified 3 states as natural , when they were actually happy. This is a false negative for the happy category, and a false positive for the natural category.
   - The model incorrectly classified 8 cases as sad, when they were actually happy. This is a false negative for the happy category, and a false positive for the sad category.
   - The model incorrectly classified 8 cases as happy, when they were actually sad. This is a false negative for the sad class, and a false positive for the happy class.

b) Figure 7(b) C-matrix for test of LR algorithm:
   - The model naturally classified 146 cases as happy, 123 cases as sad, and 108 cases as happy. These are the real positives of each category.
   - The model incorrectly classified one instance as sad, when it was actually natural. This is a false negative for the natural class, and a false positive for the sad class.
   - The model incorrectly classified 5 cases as happy, when they were actually natural. This is a false negative for the natural class, and a false positive for the happy class.
   - The model incorrectly classified 2 cases as natural, when they were actually happy. This is a false negative for the happy category, and a false positive for the natural category.
   - The model incorrectly classified 19 cases as sad, when they were actually happy. This is a false negative for the happy category, and a false positive for the sad category.
   - The model incorrectly classified 23 cases as happy, when they were actually sad. This is a false negative for the sad class, and a false positive for the happy class.

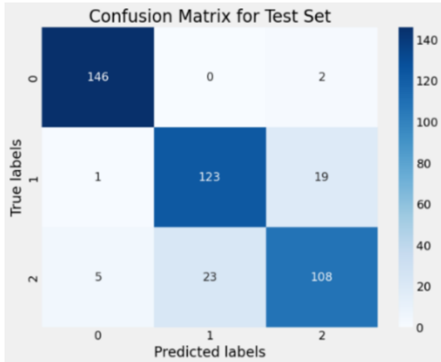
c) Figure 7(c) C-matrix for test of DT algorithm:
   - The model naturally classified 145 cases as happy, 130 cases as sad, and 126 cases as happy. These are the real positives of each category.
   - The model incorrectly classified 4 cases as happy, when they were actually natural. This is a false negative for the natural class, and a false positive for the happy class.
   - The model incorrectly classified 3 states as natural, when they were actually happy. This is a false negative for the happy category, and a false positive for the natural category.
   - The model incorrectly classified 13 cases as sad, when they were actually happy. This is a false negative for the happy category, and a false positive for the sad category.
   - The model incorrectly classified 6 states as happy, when they were actually sad. This is a false negative for the sad class, and a false positive for the happy class.

d) Figure 7(d) C-matrix for test of RF algorithm:
   - The model naturally classified 145 cases as happy, 138 cases as sad, and 132 cases as happy. These are the real positives of each category.

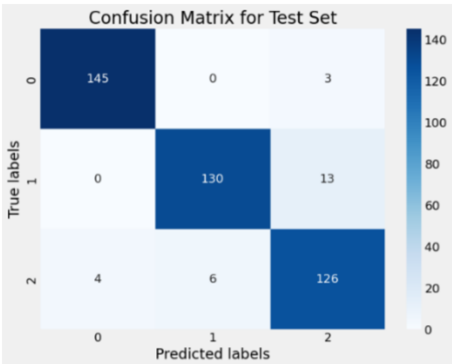
- The model incorrectly classified one instance as sad, when it was actually natural. This is a false negative for the natural class, and a false positive for the sad class.
- The model incorrectly classified one condition as happy, when it was actually natural. This is a false negative for the natural class, and a false positive for the happy class.
- The model incorrectly classified 3 states as natural, when they were actually happy. This is a false negative for the happy category, and a false positive for the natural category.
- The model incorrectly classified 4 situations as sad, when they were actually happy. This is a false negative for the happy category, and a false positive for the sad category.
- The model incorrectly classified 3 states as happy, when they were actually sad. This is a false negative for the sad class, and a false positive for the happy class.



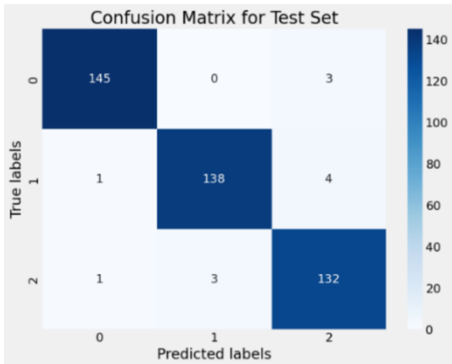
(a)



(b)



(c)



(d)

Figure 7. C-matrix for test of ML algorithms: (a) KNN, (b) LR, (c) DT and (d) RF

Table 2 are the classification results we obtained in the testing phase. The data was classified into several groups. The first group represented whether the feelings were natural (0) with a total of 148 data. The second group represented whether the feelings were sad (1) with a total of 143. The last group represented whether the feelings were happy (2) with a total of 136 for each algorithm (KNN, LR, DT, and RF). To evaluate each rating based on (precision, recall, and F1-score).

Table 2. The results for classifying ML algorthims (testing)

Class	Models	Precision	Recall	F1-Score	Support
Natural (0)	KNN	0.97	0.98	0.97	148
	LR	0.96	0.99	0.97	
	DT	0.97	0.98	0.98	
	RF	0.99	0.98	0.98	
Negative (1)	KNN	0.94	0.94	0.94	143
	LR	0.84	0.86	0.85	
	DT	0.96	0.91	0.93	
	RF	0.98	0.97	0.97	
Positive (2)	KNN	0.84	0.79	0.82	136
	LR	0.89	0.93	0.91	
	DT	0.92	0.91	0.92	
	RF	0.95	0.97	0.96	

3.2. Case studies of hybrid deep learning with machine learning algorithms

In this case, we discuss the results of the hybrid system our proposed. In which the CNN DL algorithm was adopted to train and test the system with the SVM ML algorithm to classify the results into three groups of emotions (natural, sad, and happy). Table 3 and Figure 8 show the training phase where we achieved 100% accuracy and 0% loss. As shown in Figure 8, the loss index, which represents the orange line, decreased and the accuracy index, which represents the blue line, increased after they reached Epoch 10/10.

A confusion matrix serves as a tabular representation for evaluating the performance of a classification model on a specific set of test data with known true labels. It comprises rows representing actual labels and columns indicating expected labels. Each cell indicates the count of cases falling into its corresponding category. Correct classifications are depicted along the diagonal, with misclassifications shown in cells outside the diagonal [31]. The provided summary encapsulates the key values outlined in Figure 9. Figure 9 C-matrix for test of hybrid CNN with SVM algorithm:

– The model naturally classified 141 cases as happy, 146 cases as sad, and 133 cases as happy. These are the real positives of each category.
– The model incorrectly classified 3 cases as happy, when they were actually natural. This is a false negative for the natural class, and a false positive for the happy class.
– The model incorrectly classified 2 states as natural, when they were actually happy. This is a false negative for the happy category, and a false positive for the natural category.
– The model incorrectly classified 2 cases as sad, when they were actually happy. This is a false negative for the happy category, and a false positive for the sad category.

Table 3. The epochs for training the hybrid model

Epochs	Loss	Accuracy
Epoch 1/10	1.0059	0.8194
Epoch 2/10	0.1997	0.9390
Epoch 3/10	0.1460	0.9484
Epoch 4/10	0.0556	0.9865
Epoch 5/10	0.0430	0.9906
Epoch 6/10	0.0291	0.9930
Epoch 7/10	0.0186	0.9988
Epoch 8/10	0.0104	1.0000
Epoch 9/10	0.0078	1.0000
Epoch 10/10	0.0055	1.0000

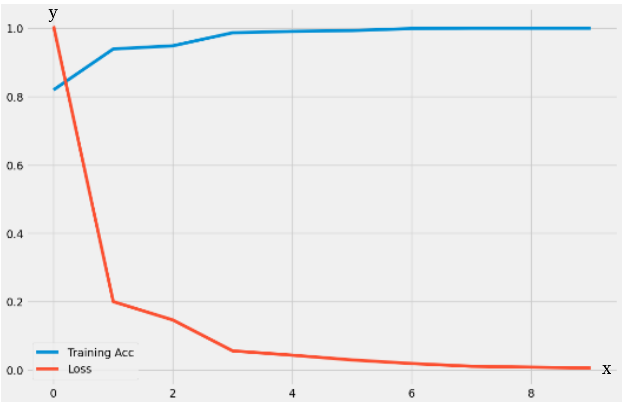


Figure 8. The epochs for training the hybrid model (CNN+SVM)

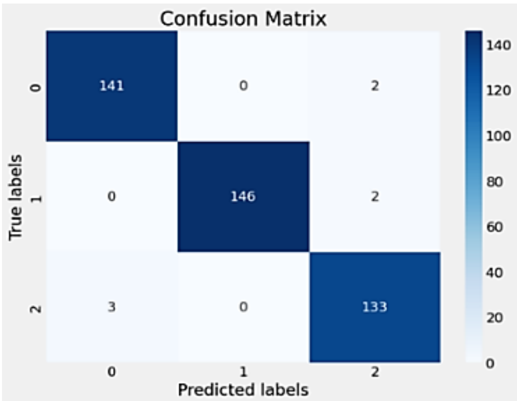


Figure 9. C-Matrix for test of hybrid CNN with SVM algorithm

Table 4 shows the classification results our obtained in the testing phase. The data was classified into several groups. The first group represented if the feelings were natural (0) with a total of 148, the second group represented if the feelings were sad (1) with a total of 143, and the last group represented if the feelings were happy (2) with a total of 136 for the proposed hybrid system in which our adopted the CNN with SVM algorithm. The rating for each classification is calculated based on (precision, recall, F1-score, and accuracy). In which we achieved 98% accuracy.

Table 4. The results for classifying hybrid CNN with SVM algorithms (testing)

DL with ML – Models	Class	Precision	Recall	F1-Score	Support
Hybrid CNN with SVM Algorithm	Natural (0)	0.98	0.99	0.98	148
	Negative (1)	1.00	0.99	0.99	143
	Positive (2)	0.97	0.98	0.97	136
	Accuracy		0.98		427

In Table 5, when comparing the results we achieved in the first case shown in section 3.1 with the results our achieved in the second case in section 3.2, it turns out that the hybrid system is characterized by higher accuracy in achieving results, as shown in Figure 10. Therefore, it is preferable to adopt a hybrid system to achieve high accuracy in emotion classification. Also, in Table 6, we discuss the test results reached by a group of researchers and compare them with the accuracy we achieved in the proposed hybrid system. Table 6, shows the differences that show that the results achieved by our paper are 98% higher than the results achieved by the researchers mentioned in Figure 11.

Table 5. Comparison of results ML with results DL+ML

AI	Models	Accuracy
ML	KNN	94%
	LR	88%
	DT	94%
	RF	97%
DL+ML	CNN + SVM	98%

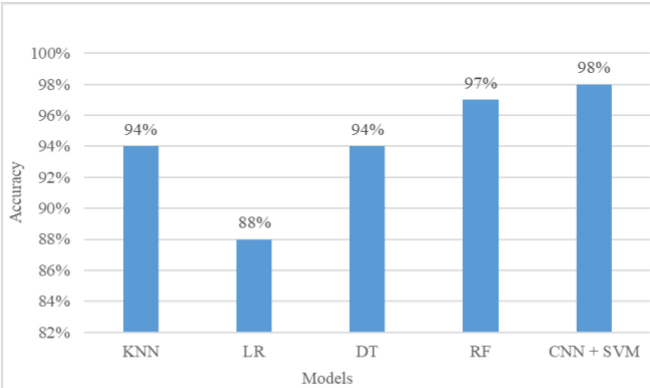


Figure 10. The accuracy chart of our study results

Table 6. Comparison of our results with other researcher's results

Authors	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	Our
Years	2017	2018	2019	2020	2022	2022	2023	2023	2024
Models	Wavelet analysis and LVQ	ANNs	Real-time emotion recognition system	CNN	CNN-1D	LGBM, RFC, DTC	Emo-Net	fNIRS	CNN+SVM
Accuracy	87%	85%	91.5%	90%	93%	96%	92.02%	90%	98%

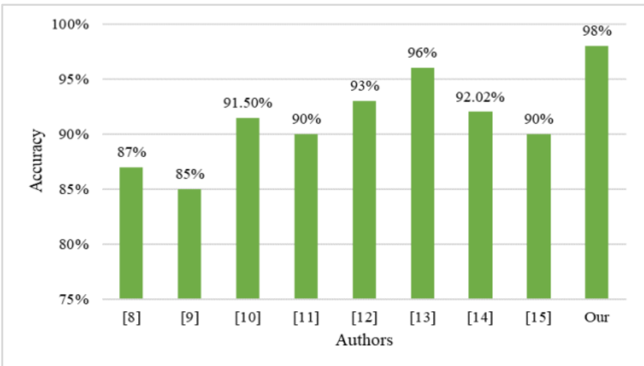


Figure 11. A chart of the accuracy of our study results with the researchers' results

4. CONCLUSION

Our research employed various ML algorithms (KNNs, LR, DT, and RF) for emotion classification (94%, 88%, 94%, and 97%) and introduced a hybrid model combining DL (CNN) with ML (SVM). The proposed hybrid system demonstrated exceptional performance, achieving an impressive 98% accuracy in emotion classification. Comparative analysis against existing research highlighted the superior results of our model, showcasing its efficacy in distinguishing emotions. This underscores the significance of hybrid approaches in enhancing accuracy and reliability in emotion classification systems.

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