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Performance Evaluation of Machine Learning Models for Emotion Recognition

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Emotion recognition is a part of artificial intelligence that detects human emotions using machine learning (ML) techniques, thus analysing inputs like facial expressions, voice tone and physiological signals. Individuals with Autism Spectrum Disorder (ASD) experience difficulties in social interaction and communication and exhibit repetitive behaviours. ML has greatly helped autistic people by analysing their behavioural data to detect and comprehend slight emotional indicators. This paper explores the abilities of ML-based systems to recognize and understand these emotional cues, which are of great importance for improving communication and intervention methods. We employed datasets of EEG signals and applied principal component analysis (PCA) and uniform manifold approximation and projection (UMAP) for dimension reduction. We used ML models such as Random Forest (RF), Support Vector Machines (SVM), Logistic Regression, Long Short-Term Memory (LSTM) and 1D Convolutional Neural Network (1D-CNN) on the datasets. The evaluation of the models relied on metrics like accuracy, precision, recall and F1-score to determine their ability to recognize emotions in EEG signals. The RF model achieved 95% accuracy on the original dataset and maintained robustness with PCA (88%) and UMAP (85%), outperforming other models in classification accuracy and stability. Future research should concentrate on broadening the datasets to include a more varied group of participants and combining multimodal data, using advanced deep learning methods to increase the accuracy and the feasibility of emotion recognition systems for personalized ASD therapies.

1. Introduction

Emotion recognition, a rapidly growing area within AI and affective computing, has a great deal of prospects across different domains such as healthcare, human-computer interaction and assistive technology. It includes the computer-aided analysis of human feelings, which is based on different modalities like facial expressions, physiological signals, speech and gestures [1]. Machine learning (ML) has enabled the development of advanced algorithms that effectively handle the high variability in human emotional expression and individual differences, thereby improving emotion recognition accuracy [2].

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The advancement of ML or AI has led to the development of sophisticated algorithms that address the challenges posed by human emotional expressions and other interpersonal variability, thus optimizing the accuracy of emotion recognition. These advancements provide an opportunity for the development of more advanced systems for recognition of emotions. For example, Tong *et al.,* [2], have attempted to combine ML and DL with EEG-based emotion recognition.

The electroencephalogram (EEG) is a non-invasive method of recording electrical activity of the brain and forms the basis of emotion recognition through ML. Although EEG signals provide the most direct information about the neural correlates of emotions, the use of additional modalities such as facial expressions, speech and other physiological signals improve accuracy [3]. Analysing time series EEG data, ML models are able to detect patterns in brain behaviour, which enables the design of more accurate and interpretable systems for recognition of emotions.

Autism spectrum disorder (ASD) involves difficulty in recognizing emotions and expressing them which disrupts social interactions and affects one's quality of life. Emotion detection and identification of autism using machine-learning techniques is a step in a different direction. Recent researches by Farooq *et al.,* [4], Manoj *et al.,* [5] and Kamble *et al.,* [6] has analysed emotions held by individuals with ASD in both single and multiple modalities and noted higher classification accuracy and lower time-to-detection values. Models based on ML can enable early diagnosis and treatment of ASD by recognizing subtle features characteristic of the disorder from facial expressions, physiological signals or voice features. The integration of emotion recognition using EEGs, artificial intelligence and autism research offers fresh insights into emotional processing gaps in people living with ASD [5]. An emotion recognition captive system based on ML and AI has the potential of offering an objective view of the autistic person's emotional experience, especially in cases of severe articulation difficulties [1].

Most techniques [7-10] that currently employ EEG data for emotion recognition do not have a standard pre-processing pipeline, leading to inconsistent methods. The lack of standardization around feature engineering is problematic for interoperability. While models [11,12] show high accuracy, the absence of unified evaluation metrics complicates benchmarking and validation. In this study, the main objective is to improve EEG-based emotion recognition using ML models, specifically for detecting ASD traits. The paper aims to achieve this by exploring different ML models in processing EEG signals. Therefore, the paper focuses on developing an emotion recognition system that is not only accurate and reliable but also capable of handling the unique challenges of ASD diagnosis. This research aims to combine interdisciplinary approaches and recent advancements in ML to enhance the understanding of emotional processing in individuals with ASD and lay the groundwork for personalized diagnostic and support strategies.

The structure of this paper is as follows:

i. Section 1.1 provides a literature review on recent advancements in emotion recognition using ML, emphasizing improvements over previous models.
ii. Section 2 covers the techniques applied in the research, including data preprocessing, feature extraction, model development and evaluation, highlighting novel contributions.
iii. Section 3 presents the experimental results and discussions and summarizes the paper with implications, limitations and future research directions based on identified gaps.

1.1 Literature Review

The field of emotion recognition in ML techniques has been improving lately, particularly in analysing physiological signals like the EEG and facial expressions. The goal is to emphasize current state-of-the-art methods and provide recommendations on areas needing improvement in a rapidly developing field.

1.1.1 EEG signals

Researchers actively study emotion recognition in EEG signals, viewing it as an efficient tool in many fields. Pratiwi *et al.,* [3] examined the feasibility of EEG-based emotion classification using LSTM and biLSTM models. Their research focused on distinguishing between happy and sad emotions, achieving classification accuracy over time with time-domain factors [3]. Manoj *et al.,* [5] showed the usefulness of feature selection in ML algorithms of emotion recognition by integrating bigger ASD datasets to enhance the efficiency of the models. Such research provides room for developing ML techniques in emotion recognition where the conditions of technical constraints, biases, ethical issues and in-depth investigation of model effectiveness and verification in several data sets are necessary [5]. Wei *et al.,* [13] have developed an emotion recognition system in real-time using EEG and heart rate variability (HRV) signals. The authors suggested a DE feature extraction method and a DNN model training approach, which proved the excellent performance of emotion classification [13]. The following steps should be in the research. Furthermore, it examines the techniques to address the non-stationary effect, improving the system's workability in the dynamic environment. Du *et al.,* [11] built an EEG-based emotion recognition model named ATtention-based LSTM with Domain Discriminator (ATDD-LSTM). Their study focused on attention mechanisms and domain adaptation techniques, which achieved state-of-the-art performance in emotion recognition X [11].

1.1.2 Classification models

The authors discussed the application of EEG and ML for emotion recognition, especially in autism. They underline the possibility of EEG and ML to help in the early detection and understanding of emotional processing differences in people with autism [14]. Thus, Mutawa *et al.,* [15] made a multimodal emotion recognition system based on facial expressions and EEG signals, allowing real-time patient emotion recognition. They implemented the log-sync tagging algorithm and they used cross-validation to make sure that their emotion recognition system was accurate and they concentrated on the stability of the system to the changes in data [15]. The goal of this method can be further raised by adding other feature selection approaches to the research to create a more interpretable model that can be generalized to various datasets. Zhang *et al.,* [7] discussed the advantages of using wavelet transform for EEG signals, where it can capture both slow and fast changes in EEG components and serve as valuable features for subsequent analysis and classification.

Rahman *et al.,* [8] proposed a new way: combining the principal component analysis (PCA) and t-statistical approach for feature extraction from the multichannel EEG signatures. They based their model on the SJTU Emotion EEG Dataset (SEED). They showed that their method could achieve results with the high accuracy of classification [8]. Furthermore, the research conducted by Chowanda *et al.,* [16] focused on using KNN, ANN and LSTM in DL algorithms for emotion recognition in speech signals. Uddin *et al.,* [17] delved into the importance of early detection of ASD and the use of convolutional neural networks (CNNs), LSTM networks and CNN-LSTM architectures for feature extraction and classification. It also leverages MRI features extracted from various atlases and time series data of regions of interest (ROIs) to analyse ASD, providing valuable insights into the neurological roots of autism [17].

However, the study of Klibi *et al.,* [18] emphasized the emotion classification from EEG signals based on ML algorithms like RF and InfoGain, demonstrating the efficiency of these approaches.

Tahseen *et al.,* [19] proposed EEG-based emotion recognition and applied various methods: feature extraction or model building. They did not, however, seem to generalize or do robust validation through various datasets [19]. Qiao *et al.,* [9] proposed a new approach to human behaviour recognition based on the PCA-LSTM algorithm that was applied to the EMG signals; the proposed method showed better recognition rate and efficiency performance than the traditional algorithms. Hasib *et al.,* [20] also presented that EEG, ML and emotion recognition are interconnected through the analysis of brain activity to understand emotional states and these techniques have implications for understanding conditions such as autism spectrum disorder. Kang *et al.,* [21] proposed a method combining spectrograms to detect emotional patterns in EEG signals across time and frequency domains. It involves ICA for signal decomposition, evolutionary algorithms for data augmentation and ensemble CNNs with LSTM for feature extraction, thus solving the problems of limited training data and the changeability of EEG signals in emotion recognition. A study leveraging pre-trained CNN architectures (VGG16, InceptionV3 and MobileNetV2) for classification in the OASIS MRI dataset demonstrated the effectiveness of transfer learning in medical image classification. The VGG16 model, fine-tuned by replacing fully connected layers with custom dense layers and trained using the Adam optimizer (learning rate 0.0001, 50 epochs + 20 fine-tuning epochs), achieved 98.56% training accuracy and 90.24% validation accuracy, showcasing CNNs' efficiency in feature extraction for medical imaging [22].

Several classification methods that may be employed are the one that involve emotion recognition with the EEG signals being used to identify features for a precise classification of emotional states. Tong *et al.,* [2] examined EEG-based emotion recognition using ML and DL algorithms as their tools. The study compared the performance of CNN, RF and SVM models on EEG data while focusing on the importance of feature extraction and critical frequency for emotion recognition [2]. On the other hand, Farooq *et al.,* [4] applied Federated Learning (FL) for ASD detection in children and adults and compared the performance of models like SVM, LR and KNN. Nath *et al.,* [23] presented a mechanism distinguishing emotion from LSTM networks. The researchers reached a top classification accuracy (a good agreement between EEG data and LSTM models), thus proving the successful use of LSTM models for detecting temporal patterns in EEG data [23]. Pamungkas *et al.,* [12], considered the emotion EEG classification algorithm using RNN, LSTM and Bi-LSTM and obtained reasonable accuracy rates for the classification of emotions.

Alam *et al.,* [24] implemented a formal study into automated human emotion recognition through physiological measurements, including EEG signals that are typical for ML algorithms like RF, Support Vector Machine (SVM) and k-nearest neighbours (k-NN). Garg *et al.,* [25] conducted an overview of ML techniques for the diagnosis of ASD without thoroughly analysing the drawbacks and biases of the ML-based ASD diagnosis. Using KNN and the RF model, Bhatlawande *et al.,* [26] fused physiological and facial expressions for emotion recognition using signal fusion and facial recognition.

The reviewed research presents a variety of classification models for emotion recognition, each with its strengths and weaknesses. This research suggests that there is a need for extensive validation and benchmarking on diverse datasets. While models like LSTM, Nath *et al.,* [23] have demonstrated high accuracy in classification, their performance may not be consistent across datasets and demographics. Furthermore, the absence of standardized evaluation metrics and benchmarks makes it difficult to compare the performance of various models objectively. Furthermore, some of the research, similar to Bhatlawande *et al.,* [26], emphasizes the integration of multiple modalities for emotion recognition, which could lead to data preprocessing and feature fusion complexities. Awan *et al.,* [10] suggested implementing facial expression recognition technology that will include preprocessing and classification models. It developed a high level of accuracy as well. Apart from that, it is essential to investigate methods that could be used to mitigate bias, which might stem from facial expression datasets. Such a mechanism could contribute to the fact that the system was not biased and was inclusive.

1.1.3 Dimensionality reduction and feature engineering

In dimensionality reduction for EEG-based classification, Deng *et al.,* [27] compared UMAP with PCA and t-SNE, showing that UMAP improved classification accuracy by 11% and Macro-F1 score by 20%. Its ability to preserve global and local structures makes it a superior EEG feature extraction and clustering tool. However, integrating UMAP with DL models such as CNNs, LSTMs or transformers could further optimize EEG-based sleep classification (UMAP for EEG) [28]. A performance evaluation of UMAP and t-SNE for high-dimensional datasets found that UMAP preserves global structure better, making it more effective for clustering-based tasks and anomaly detection. PCA pre-processing improved accuracy by reducing the average prediction error from 16.28% to 15.11%. However, further research should explore UMAP's integration with DL architectures for applications like EEG-based emotion recognition. Lastly, a comparative analysis of UMAP and t-SNE [29] found that UMAP offers superior scalability and computational efficiency in handling large datasets. In contrast, t-SNE is better at cluster separation for small-scale datasets. A significant limitation is the lack of integration with DL models, which could improve performance in EEG emotion recognition tasks.

1.1.4 Deep learning models

Deep learning has significantly improved emotion recognition, mainly through CNNs and multimodal approaches. A Neuro-Fuzzy model (ANFIS) trained using MATLAB's fuzzy clustering method (Sugeno model) with Particle Swarm Optimization (PSO) for parameter tuning achieved a mean absolute error (MAE) of 0.0004, highlighting its high predictive accuracy. However, real-world deployment of ANFIS for industrial applications remains unexplored (Health Index). In speech emotion recognition (SER), a study proposed a 1D CNN model that bypasses attention mechanisms, opting for efficient feature extraction using MFCC, Mel-Spectrograms and Log-Mel Spectrograms. The model outperformed baseline CNN and RNN architectures, demonstrating higher accuracy across multiple speech-emotion datasets [30]. For EEG-based emotion recognition [31], the MSDCGTNet model combined a Multi-Scale Dynamic 1D CNN and a Gated Transformer Encoder for end-to-end EEG signal processing. The Temporal Convolution Network (TCN) extracted sequential dependencies, significantly improving feature extraction. On the DEAP, SEED and SEED_IV datasets, the model achieved 99.66, 98.85 and 99.67% accuracy, outperforming conventional approaches. For facial emotion detection, a deep CNN model was trained using batch normalization, max pooling and dropout layers to prevent overfitting. The model was integrated with OpenCV's Haar Cascade method for real-time facial detection, demonstrating robust performance in real-time applications [32]. In the end, existing research has made significant advancements in EEG-based emotion recognition, with deep learning models showing notable improvements in classification accuracy and generalization.

Table 1
Summary of EEG signals used and techniques implemented

Study	Dataset Type	Techniques Implemented
[1]	EEG signals	Support Vector Machines, Random Forest, CNN
[2]	EEG signals	CNN, Random Forest, SVM feature extraction and frequency analysis
[3]	EEG signals	EEG-based emotion classification with LSTM and bLSTM models, time-domain factors
[8]	EEG signals	PCA and t-statistical approach for feature extraction, classification accuracy measures
[11]	EEG signals	ATDD-LSTM model with attention mechanisms and domain adaptation
[12]	EEG signals	RNN, LSTM, Bi-LSTM for emotion EEG classification algorithm
[13]	EEG signals, HRV signals	DE feature extraction, DNN model training, real-time emotion classification
[18]	EEG signals	Machine learning algorithms (Random Forest, InfoGain)
[19]	EEG signals	EEG-based emotion recognition, various feature extraction and model building approaches
[20]	EEG signals	Time-domain methods, frequency-domain methods and advanced approaches like independent component analysis and adaptive filtering algorithms
[22]	EEG signals	Transformer-based feature extraction, self-attention models, multimodal fusion
[23]	EEG signals	Distinction of emotion from LSTM networks, detection of temporal patterns
[24]	EEG signals	Random Forest, SVM, k-NN
[26]	EEG signals	Random Forest models
[27]	EEG signals	Hybrid CNN-LSTM model, feature engineering using wavelet transforms
[28]	EEG signals	Dimensionality reduction with UMAP, t-SNE and PCA for classification tasks
[29]	EEG signals	Attention-based Transformer for EEG signal processing, fine-tuned with domain adaptation
[30]	EEG signals	Real-time EEG emotion classification with 1D-CNN model
[33]	EEG signals	Explainable AI (XAI) methods for EEG classification, SHAP & Grad-CAM visualization

EEG-based emotion recognition faces several critical research gaps that must be addressed to enhance model performance, generalizability and real-world applicability. One major challenge is the need for advanced feature engineering and dimensionality reduction, as traditional methods like PCA and ICA often fail to capture the most discriminative features in EEG signals. While DL-based feature extraction techniques, such as CNN autoencoders and attention-based transformers, show promise, they remain underexplored and their integration with dimensionality reduction techniques like UMAP and t-SNE is still limited. Additionally, transformer-based models for EEG emotion recognition are underdeveloped compared to their success in NLP and vision tasks. There is a lack of trained transformer architectures specifically for EEG signals and existing models struggle with computational efficiency, making them impractical for real-time applications. Another critical limitation is the black-box nature of DL models, which hinders explainability and interpretability in EEG-based emotion classification. Without proper visualization and interpretation techniques like SHAP, LIME or Grad-CAM, it remains challenging to understand how EEG signals influence model decisions, limiting trust and adoption in clinical and neurophysiological studies. Lastly, EEG datasets for emotion recognition are limited and often imbalanced, leading to overfitting in DL models. There is a strong need for data augmentation techniques to generate synthetic EEG signals, improve model robustness and enhance generalization across different datasets and demographic variations. Addressing these research gaps by integrating transformer-based architectures, advanced feature selection, explainability methods and data augmentation will significantly improve the accuracy, reliability and real-world applicability of EEG-based emotion recognition systems.

2. Methodology

The proposed research employs ML models that process EEG signals and classify them based on emotions. The paradigm encompasses segmentation and variety of classifications. Steps of methodology include data engineering and feature engineering phases, data splitting, classifier modelling and performance evaluation. An overview of the methodology is illustrated in Figure 1.

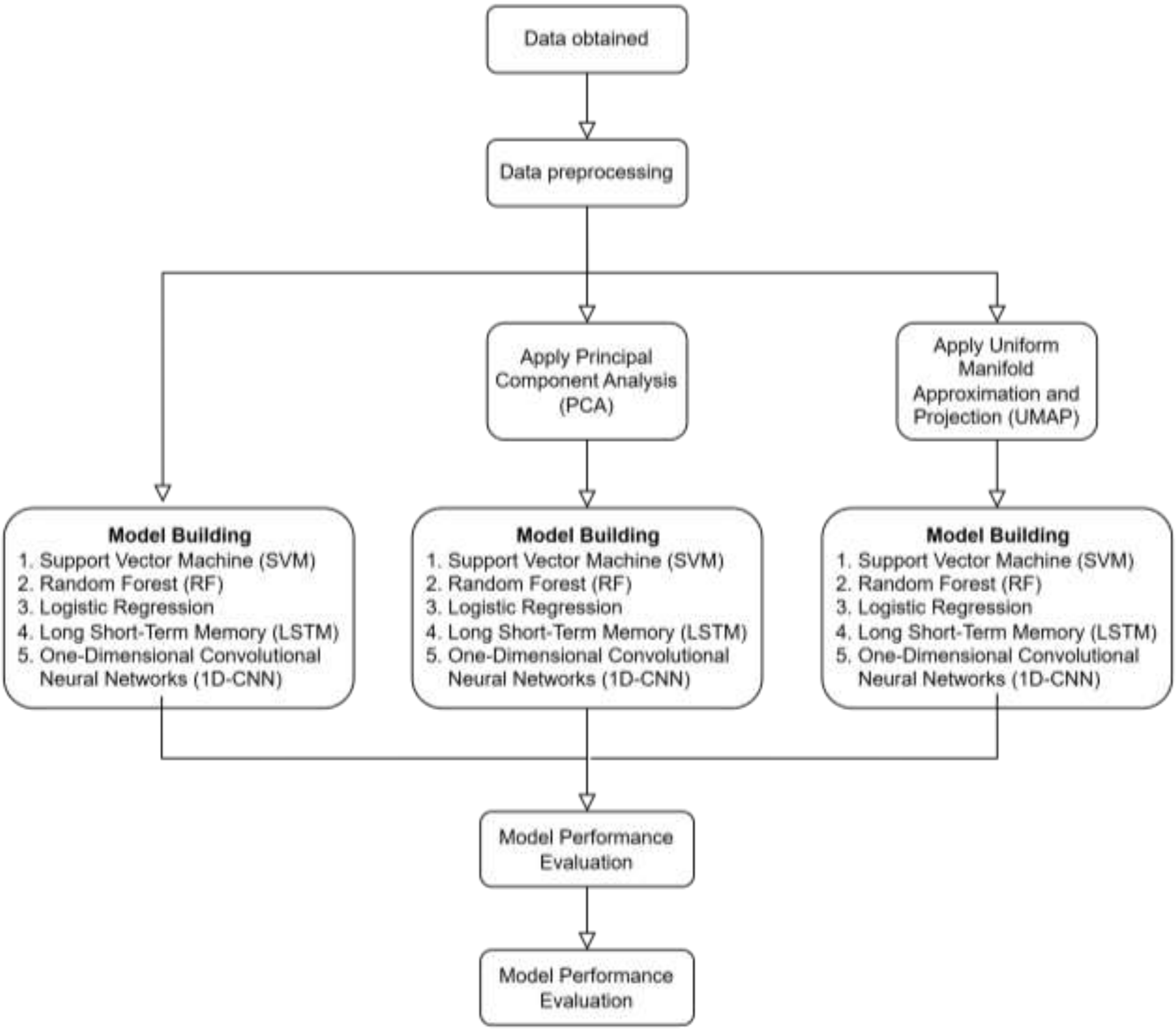


Fig. 1. Overview of the methodology

2.1 Data Obtained and Pre-processing

The dataset [31] is from Kaggle and is named 'mental-state.csv'. The dataset consists of gender-specific patterns in EEG readings across different mental states. The dataset comprises four people (2 males and 2 females) for 60 seconds per state - relaxed, concentrating and neutral. The dataset consists of 2480 rows and 989 columns. The dataset's final column is the EEG signals' emotion label.

Data pre-processing involves handling missing values using 'SimpleImputer' followed by feature scaling using 'StandardScaler' to ensure uniform contribution of all features. Employing SimpleImputer preserves the spectral features by suppressing the influence of outliers and maintaining the temporal continuity of the EEG signals. Standard scaling using StandardScaler ensures the normalization of EEG features. It enables ML models to take all frequency bands equally into account. It improves the chances of capturing hidden emotional states in the EEG signals using the patterns.

2.2 Feature Engineering Phase

In this phase, it is crucial to identify patterns correlating with different emotions. Therefore, two-dimensionality reduction techniques, PCA and Uniform Manifold Approximation and Projection (UMAP) were applied in this study. PCA identifies linear combinations of features that account for the highest variance, helping distinguish emotional states effectively by retaining the most informative attributes while simplifying the dataset's complexity. On the other hand, UMAP preserves non-linear relationships within the data, enhancing the representation of complex emotional patterns not easily captured by PCA.

2.3 Model Building

During the Modelling Phase, ML models RF, SVM, Logistic Regression, LSTM and 1D-CNN were constructed and trained on three dataset variations: PCA-transformed, UMAP-transformed and original datasets. Each model was trained on the respective dataset splits, enabling comparisons in performance and highlighting the impact of dimensionality reduction techniques. Table 2 illustrates the classifier designs used for each of these models. Each model fits the training data to learn from the features.

Table 2
Model performance comparison on datasets

Dataset	Models
Original Dataset	Random Forest
	Support Vector Machine (SVM)
	Logistic Regression
	Long Short-Term Memory (LSTM)
	One-Dimensional Convolutional Neural Networks (1D-CNN)
PCA-applied	Random Forest
	Support Vector Machine (SVM)
	Logistic Regression
	Long Short-Term Memory (LSTM)
	One-Dimensional Convolutional Neural Networks (1D-CNN)
UMAP-applied	Random Forest
	Support Vector Machine (SVM)
	Logistic Regression
	Long Short-Term Memory (LSTM)
	One-Dimensional Convolutional Neural Networks (1D-CNN)

Various libraries and frameworks were employed in this study for traditional ML classifiers such as RF, SVM and Logistic Regression. The primary libraries were Scikit-learn, Pandas and NumPy, essential for data handling, numerical operations and preparing data through processes like filtering, splitting and transforming into suitable formats. DL models, including LSTM and 1D-CNN, relied heavily on TensorFlow and Keras, enabling efficient handling of sequential data, capturing temporal patterns and learning complex features from EEG signals.

2.3.1 Random Forest

In the proposed method, the RF algorithm was a key point for discerning EEG signal patterns. This model enhances accuracy and robustness by averaging multiple deep decision trees trained on different splits of the training set. However, this approach helps to address the problem of overfitting, which is usually observed with highly complex EEG signals, making it especially suitable for discriminating against the EEG signal features of individuals with autism from their neurotypical counterparts.

2.3.2 Support vector machine (SVM)

The SVM wrapper was crucial to the proposed method since it can deal with the high-dimensional space that EEG data has. A linear discriminant that maximally separates the classes of data (autistic vs. neurotypical) and distinguishes them based on complex and delicate signals was obtained by the SVM. It turned out to be an excellent choice, considering the variety of shades on the EEG signal displays among the patients with the autism spectrum.

2.3.3 Logistic regression

Using logistic regression is beneficial due to its effectiveness in modelling the probability of a relationship between EEG features and emotional states. Using the pre-processed EEG data, I employed polynomial feature augmentation logistic regression as a baseline emotion classification model to evaluate the classification accuracy benchmark. In addition to the model's class probability outputs, performance evaluation metrics provide meaningful information concerning the model's capability to differentiate between various emotions.

2.3.4 Long short-term memory (LSTM)

The principal library used in designing and training the LSTM structures for the EEG emotion recognition system was “Keras”. During the data pre-processing stage, the EEG data was reshaped into a three-dimensional format to match the input requirements of LSTM networks. The LSTM model was built using multiple layers, including LSTM layers from Keras, which are specifically designed to handle sequence-based learning tasks by maintaining past data dependencies over time. Since EEG data is time-series, LSTM networks were employed to capture temporal dependencies and dynamic variations in brain signals. The model consisted of two LSTM layers, each with 64 units, with the first layer returning sequences to allow deeper feature extraction. Dropout layers with a high dropout rate (0.7) were integrated after each LSTM layer to mitigate over-fitting and improve generalization. Finally, a Dense layer with a SoftMax activation function was included to produce probability distributions for emotion classification. This architecture was designed to recognize complex temporal patterns in EEG signals, which is crucial for understanding emotional states and their neural representations.

2.3.5 One-dimensional convolutional neural networks (1D-CNN)

The primary library used for building and training the 1D-CNN models for the EEG emotion recognition system was “Keras”. Before training, the EEG data was reshaped into a 3D format to match the input requirements of CNNs. The 1D-CNN model was designed to extract spatial and temporal patterns from the EEG signals using 1D convolutional layers. Gaussian noise was added at the input layer to improve generalization and robustness against noise in EEG data.

The model architecture starts with a Conv1D layer (256 filters, kernel size = 7), followed by Batch Normalization and LeakyReLU activation to stabilize training and prevent gradient issues. A residual connection was introduced using another Conv1D layer (128 filters, kernel size = 5), enabling the model to learn hierarchical features effectively. The output was then passed through another Conv1D layer (64 filters, kernel size = 3), followed by MaxPooling1D for dimensionality reduction and Dropout (0.5) to prevent over-fitting.

After feature extraction, the flattened layer converted the output into a 1D vector, passing through a Dense layer (128 neurons, ReLU activation) for further feature transformation. A final Dropout layer (0.5) was used before the SoftMax output layer, which produced the probability distribution for emotion classification. The AdamW optimizer with weight decay and a learning rate scheduler were used to optimize model convergence.

The model was trained on three datasets: Original, PCA-transformed and UMAP-transformed EEG data, using an early stopping mechanism and learning rate reduction on the plateau to prevent over-fitting and enhance training efficiency.

2.3.6 Model performance evaluation

Finally, in the training and evaluation phase, the trained models are evaluated against the test dataset to assess their performance and generalisation ability. Metrics such as accuracy, precision, recall and F1-score are calculated to quantify the effectiveness of the models in recognising emotions in individuals with ASD. The formula for performance metrics is as follows:

i. Accuracy: measures the proportion of correct predictions (Eq. (1)),

$$A_c = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

ii. Precision: calculates the accuracy of positive predictions (Eq. (2)),

$$P_c = \frac{TP}{TP+FP} \tag{2}$$

iii. Recall/Sensitivity assesses the ability to correctly identify positive instances (Eq. (3)),

$$R_c = \frac{TP}{TP+FN} \tag{3}$$

iv. F1 score: provides a balance between precision and recall (Eq. (4)),

$$F1 = 2 \times \frac{P_c \times R_c}{P_c + R_c} \tag{4}$$

The results are also visualized using plots like confusion matrices, ROC (Receiver Operating Characteristic) curves and plots of accuracy and loss over epochs. Confusion matrices for each classifier model visualize the classification performance across different classes, while ROC curves evaluate the trade-off between sensitivity and specificity.

3. Results

For this project, we trained and evaluated the methods and algorithms with a pre-processed dataset. We used classifiers such as RF, SVM, Logistic Regression, LSTM and 1D-CNN. At first, we applied these classifiers over the pre-processed dataset. We subsequently ran the classifiers on the dataset that had dimensionality reduction performed on it. We applied PCA and UMAP for these methods. For evaluation of the classification performance, we computed accuracy, precision, recall and F1 score metrics for each classification within these datasets. Additionally, we computed the performance measures per class emotional states as Relaxed (0), Concentrating (1) and Neutral (2).

3.1 Classifiers on Dataset

The performance of different ML models with the pre-processed Kaggle dataset, with no dimensionality reduction, is captured in Table 3.

Table 3
Comparative analysis of model's performance metrics on original datasets

Model	Accuracy (%)	Class	Precision	Recall	F1-Score
Random Forest	95	0	0.98	0.93	0.96
		1	0.94	0.91	0.92
		2	0.93	1.00	0.96
SVM	81	0	0.72	0.90	0.80
		1	0.82	0.55	0.66
		2	0.91	0.97	0.94
Logistic Regression	93	0	0.90	0.93	0.91
		1	0.92	0.87	0.89
		2	0.96	0.99	0.89
LSTM	82	0	0.84	0.78	0.81
		1	0.73	0.78	0.75
		2	0.90	0.90	0.90
1D-CNN	90	0	0.83	0.92	0.87
		1	0.90	0.78	0.84
		2	0.96	0.98	0.97

Figure 2 shows the confusion matrices for all models, which captures the classification performance accuracy for all the classes.

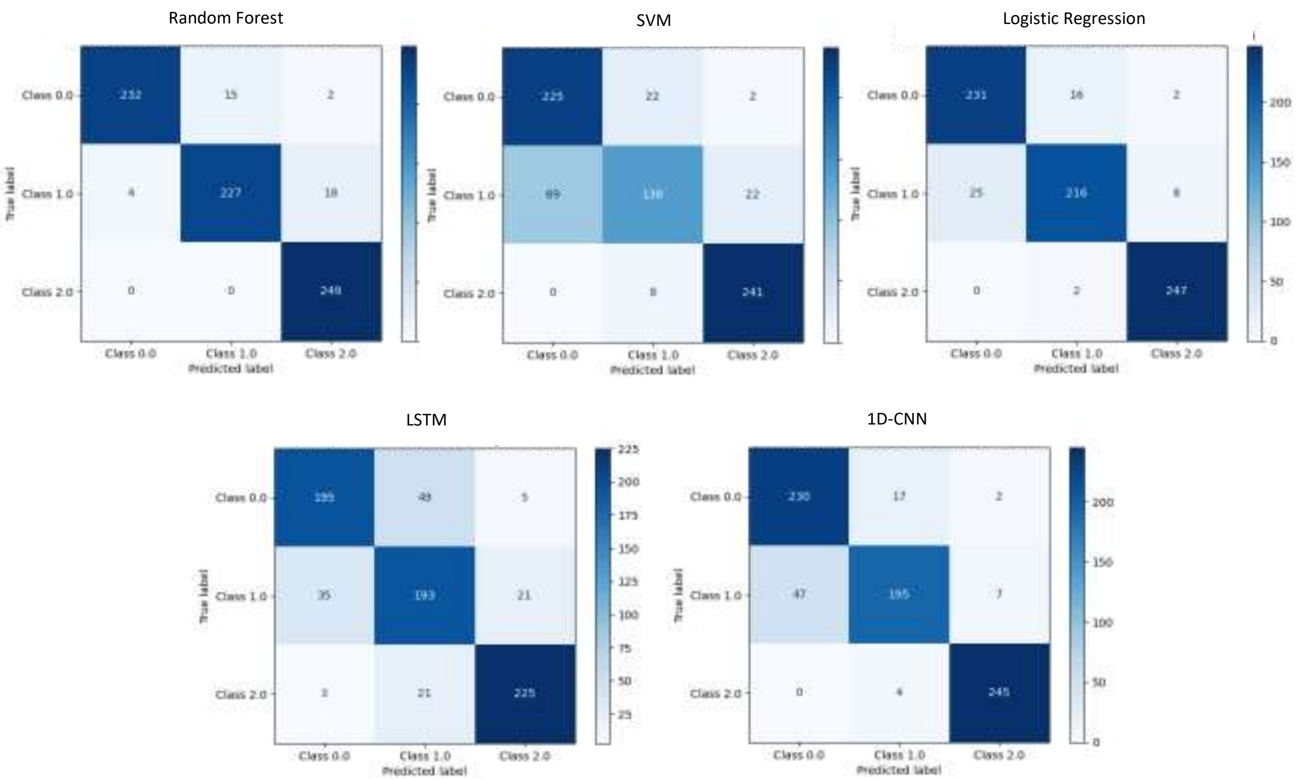
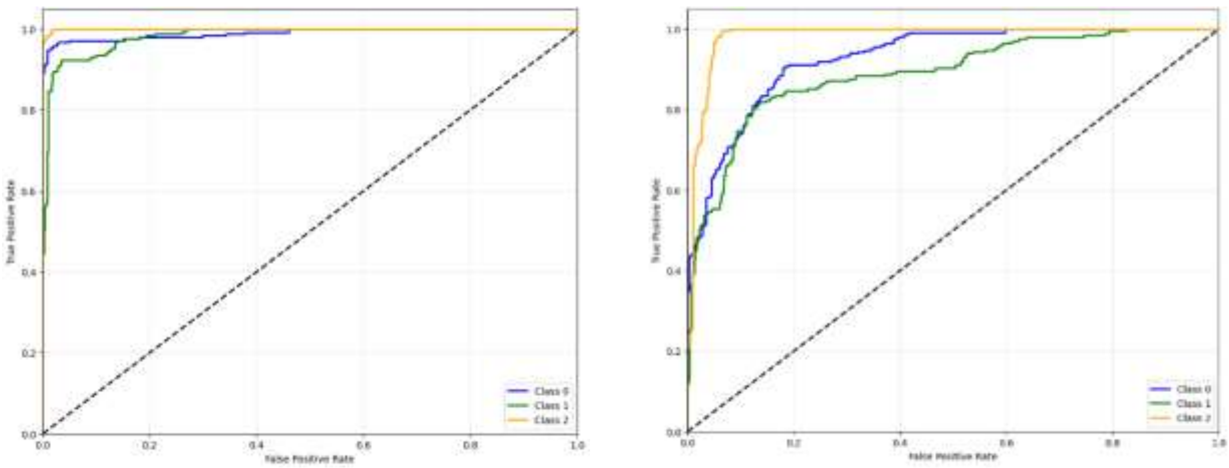
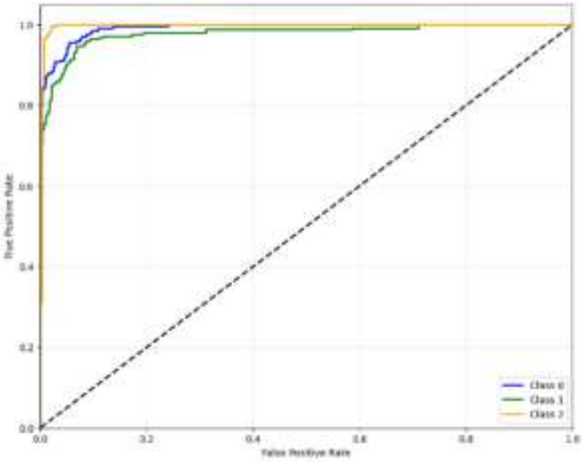


Fig. 2. Confusion matrices for all models on the original dataset

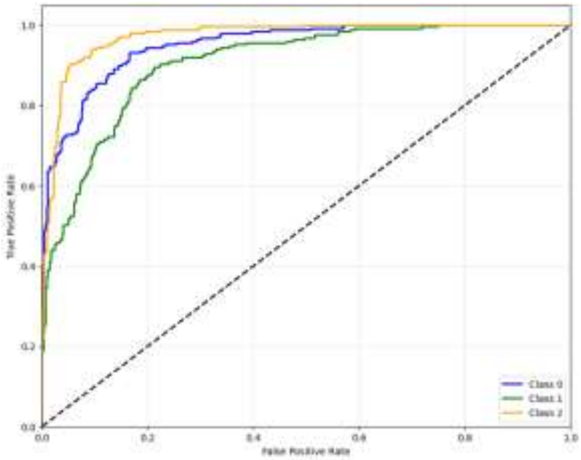
In contrast, Figure 3 shows the ROC curves for all models depicting the relationship between true positive and false positive rates.

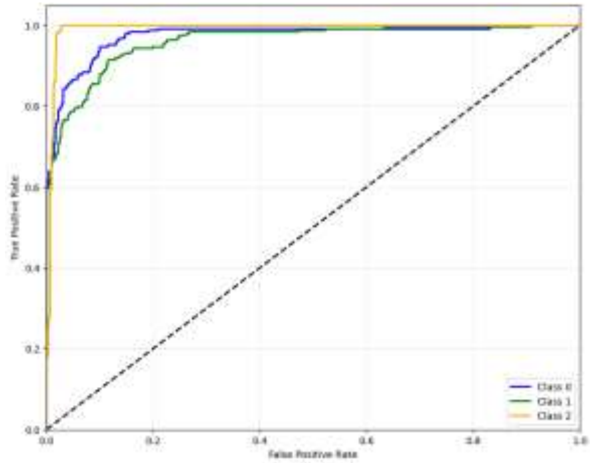


(a) (b)



(c)





(d) (e)

Fig. 3. ROC Curves (a) RF (b) SVM (c) Logistic regression (d) LSTM (e) 1D-CNN

As illustrated in Figure 3 and Table 3, RF outperforms all other models with an overall accuracy of 95%. The classifier performs better recall and F1 scores across all three classes, associated with a Class 2 recall score of 1 and F1 score of 0.96, suggest a more substantial capacity to identify positive instances correctly. This Indicates that RF can grasp the underlying patterns in the high dimensionality EEG data, thus achieving better classifications than the other models. The prediction using decision tree ensembles increases robustness, aiding in the positive generalization of the unseen data.

SVM indicators show the lowest overall accuracy at (81%). In particular, it has an extremely poor recall for Class 0 (0.72) and F1-score (0.80), which suggests that it does not perform well in classifying this class. This imbalance in classification contributes to SVM's inferior overall grade. Although capable of modelling complex non-linear interactions, the kernel may fall short of being finely tuned to the specific demands of this EEG dataset. The accuracy of Logistic Regression is equal to 93%. Also, its precision for class 0 is 0.90, while recall and F1 are 0.93 and 0.91, respectively. Class 1's precision is 0.92, with a recall of 0.87 and F1 of 0.89. Class 2 captures precision equal to 0.96, recall of 0.99 and F1 score of 0.98.

With an accuracy of 82%, the LSTM model shows the lowest performance. It demonstrates average results at class balanced classification for EEG Dataset with high precision, recall and F1 score. The efficiency of LSTM is modest compared to RF and 1D-CNN, as the data is not time-dependent (one dimension). The 1D-CNN model performs competently, likely due to its capacity to acquire local and global patterns about emotional state classification from the raw EEG signals.

Convolutional layers serve the purpose of feature extraction; therefore, they detect salient features without an alternative to feature engineering.

3.2 Models with PCA-Applied Data

PCA is applied to the EEG data to reduce dimensionality, filter out noise and retain the most relevant features, making the subsequent classification models accurate and precise. This section discusses how effectively the classifiers recognize emotions through EEG signals obtained from the results. Table 4 presents the performance metrics for models trained on the PCA-applied dataset.

Table 4
Comparative analysis of model's performance metrics on PCA applied dataset

Model	Accuracy (%)	Class	Precision	Recall	F1-Score
PCA+Random Forest	88	0	0.88	0.82	0.85
		1	0.83	0.82	0.82
		2	0.92	1	0.96
PCA+SVM	81	0	0.74	0.89	0.81
		1	0.85	0.55	0.67
		2	0.87	1	0.93
PCA+Logistic Regression	89	0	0.88	0.88	0.88
		1	0.86	0.82	0.84
		2	0.94	0.98	0.96
PCA+LSTM	80	0	0.72	0.85	0.78
		1	0.76	0.61	0.68
		2	0.94	0.96	0.95
PCA+1D-CNN	86	0	0.82	0.87	0.85
		1	0.82	0.76	0.79
		2	0.94	0.96	0.95

Figure 4 shows the Confusion matrices, which clearly illustrate how correct predictions based on different emotion classes are, alongside which predictions are made incorrectly.

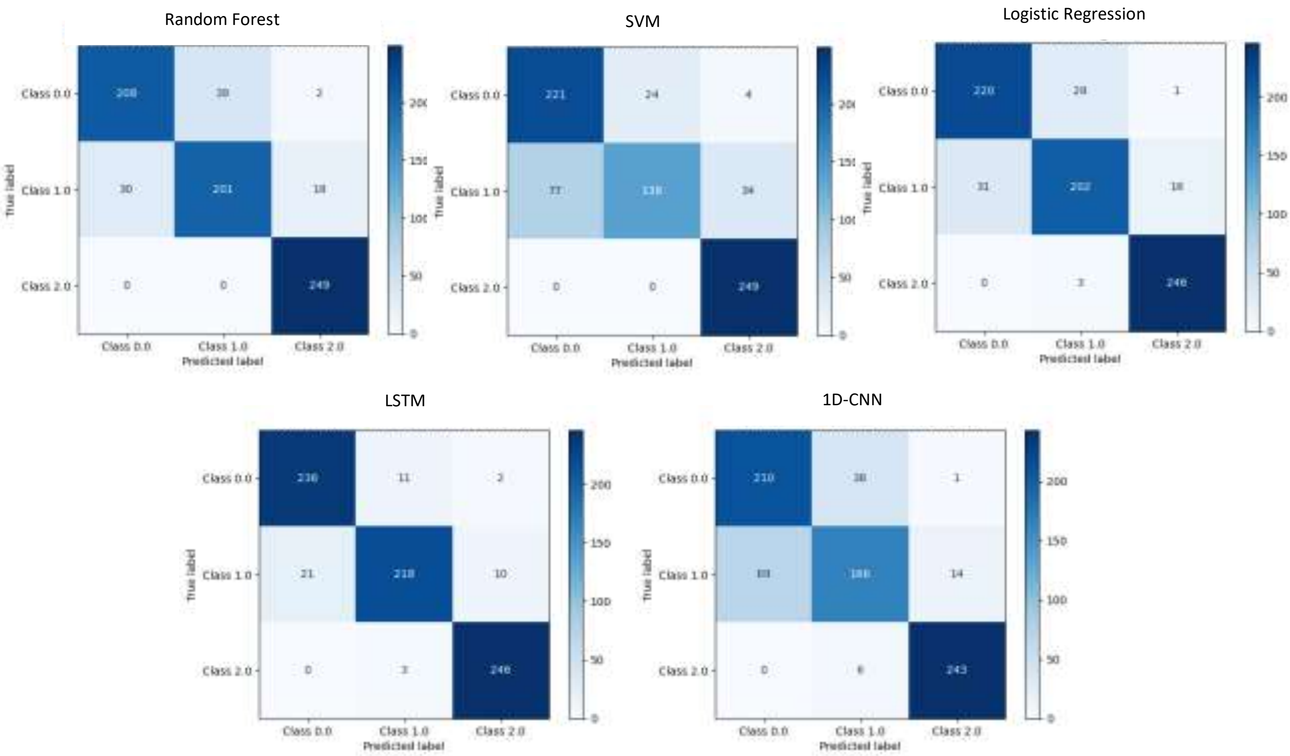
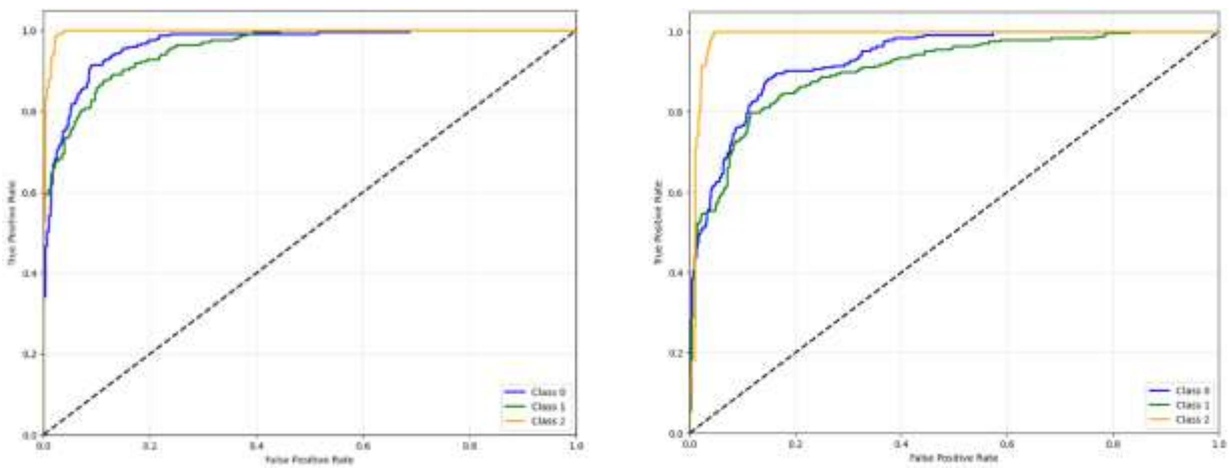
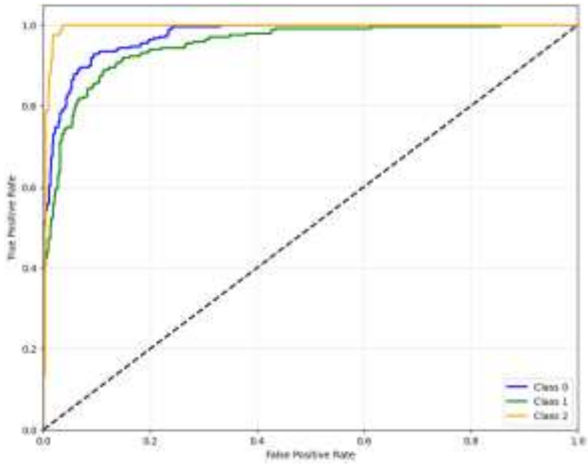


Fig. 4. Confusion matrices for all models on the PCA applied dataset

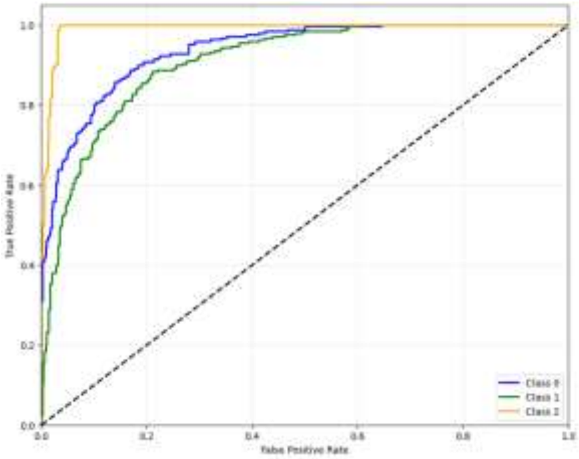
Figure 5 shows the ROC curve. Among the models, RF achieved the best-balanced accuracy, surpassing SVM and Logistic Regression with high precision and recall values, indicating that the class instances were correctly identified. For Class 0, RF was comparatively the least misclassifying model. RF also had robust recall and F1 scores for Class 1 and Class 2, demonstrating good generalization capability. It is plausible that RF's superior performance was due to its ensemble nature, which combines numerous decisions trees and captures complex EEG data patterns.

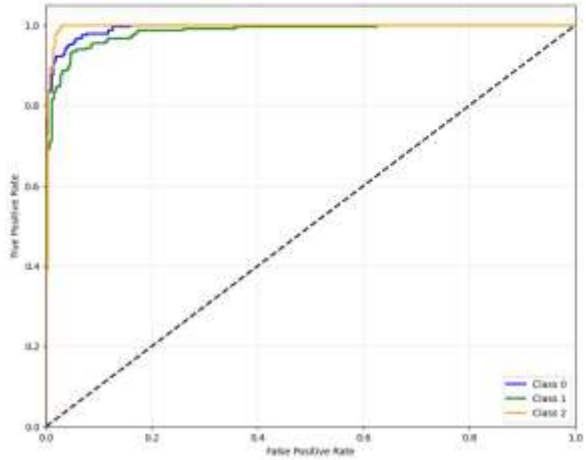


(a) (b)



(c)





(d) (e)

Fig. 5. ROC Curves (a) RF (b) SVM (c) Logistic regression (d) LSTM (e) 1D-CNN on PCA applied dataset

Contrarily, SVM appeared as the least favourable option, affecting Class 0 the most, especially regarding recall, which rendered it susceptible to higher rates of false negatives. Such a shortcoming might arise due to issues concerning the lowered dimension after conducting PCA. Logistic regression performed reasonably well, but the linear boundary restricted its effectiveness, as it could not capture the non-linear interrelationships present in the EEG data.

Among the LSTM and 1D-CNN models, the 1D-CNN was one of the better performers because it can capture local features of the EEG signals. The model could withstand more signal variability due to the inclusion of Gaussian noise at the input layer. Nonetheless, the lower dimensionality of the PCA-transformed data still constrained the model's performance. The LSTM model was not as good as CNN and RF and performed worse than expected. While LSTM takes advantage of the temporal dependencies with bidirectional layers and attention, it most probably failed because of too little temporal information in the PCA-reduced data.

As shown in Figure 6, ROC curves illustrate the trade-off of the true positive rate against the false positive rate. The AUC scores assigned to these curves give a quantifiable measure of the model's proficiency in differentiating between emotion classes. RF model provides better predictions than SVM and PLR models, meaning that RFs give better predictions of emotional states prevalent in the EEG data. The SVM models presented low AUC values for the test set, which points towards a likely misconfiguration of the model.

As stated earlier, RF stands out from other algorithms' effectiveness for emotion recognition through EEG signals, as it overcomes non-linear interactions and over-fitting problems. PCA showed improved efficiency but may have overlooked some key characteristics vital for distinguishing emotional states.

3.3 Models with UMAP-Applied Data

Applying UMAP to the dataset reduces its dimensions while maintaining the data structure, which often remains hidden due to non-linearity and can enhance the classification results. Table 5 shows the performance metrics for models trained on the UMAP-applied dataset. After applying UMAP dimensionality reduction, the performance of the RF model was comparatively more accurate in balanced accuracy assessment than the SVM and Logistic Regression models. The high precision and recall in all three classes indicate that the system correctly identified the class instances in the cases. RF achieved the lowest classification error of Class 0 while possessing good generalization, as demonstrated by the strong recall and F1-scores of Classes 1 and 2. This result is likely due to the ensemble nature of RF, which uses multiple decision trees to capture complicated patterns in the EEG dataset.

Table 5
Comparative analysis of model's performance metrics on UMAP-applied dataset

Model	Accuracy (%)	Class	Precision	Recall	F1-Score
UMAP+Random Forest	85	0	0.80	0.86	0.83
		1	0.81	0.72	0.76
		2	0.94	0.96	0.95
UMAP+SVM	69	0	0.56	0.88	0.68
		1	0.72	0.39	0.51
		2	0.93	0.80	0.86
UMAP+Logistic Regression	78	0	0.68	0.78	0.73
		1	0.72	0.57	0.63
		2	0.93	0.99	0.96
UMAP+LSTM	61	0	0.48	0.98	0.65
		1	0.74	0.14	0.23
		2	0.92	0.71	0.81
UMAP+1D-CNN	86	0	0.82	0.87	0.85
		1	0.82	0.76	0.79
		2	0.94	0.96	0.95

Conversely, SVM demonstrated poor performance, especially in class 0, due to a high rate of false negatives. It could result from some issues with the dimensional reduction that follows UMAP. Logistic regression performed well to some extent, but the simple linear boundary created by the model could address the non-linear aspects of the EEG data only to a certain extent.

Compared to the LSTM model, the 1D-CNN model performed surprisingly well due to its ability to retrieve local features from EEG signals while withstanding signal variability from Gaussian noise at the input layer, although the data still limited it. The LSTM model initially outperformed 1D-CNN and RF due to using bidirectional layers and attention mechanisms to leverage temporal dependencies, but this did not last long. The less preserved temporal information in the UMAP reduced data could explain why the LSTM model faced issues, demonstrating the downside to dimensionality reduction.

Figure 6 shows the confusion matrices for all the models. Classification reports delineate correct and incorrect predictions concerning the different classes of emotions. Differences in performance for classes 0, 1 and 2, in particular, are remarkable.

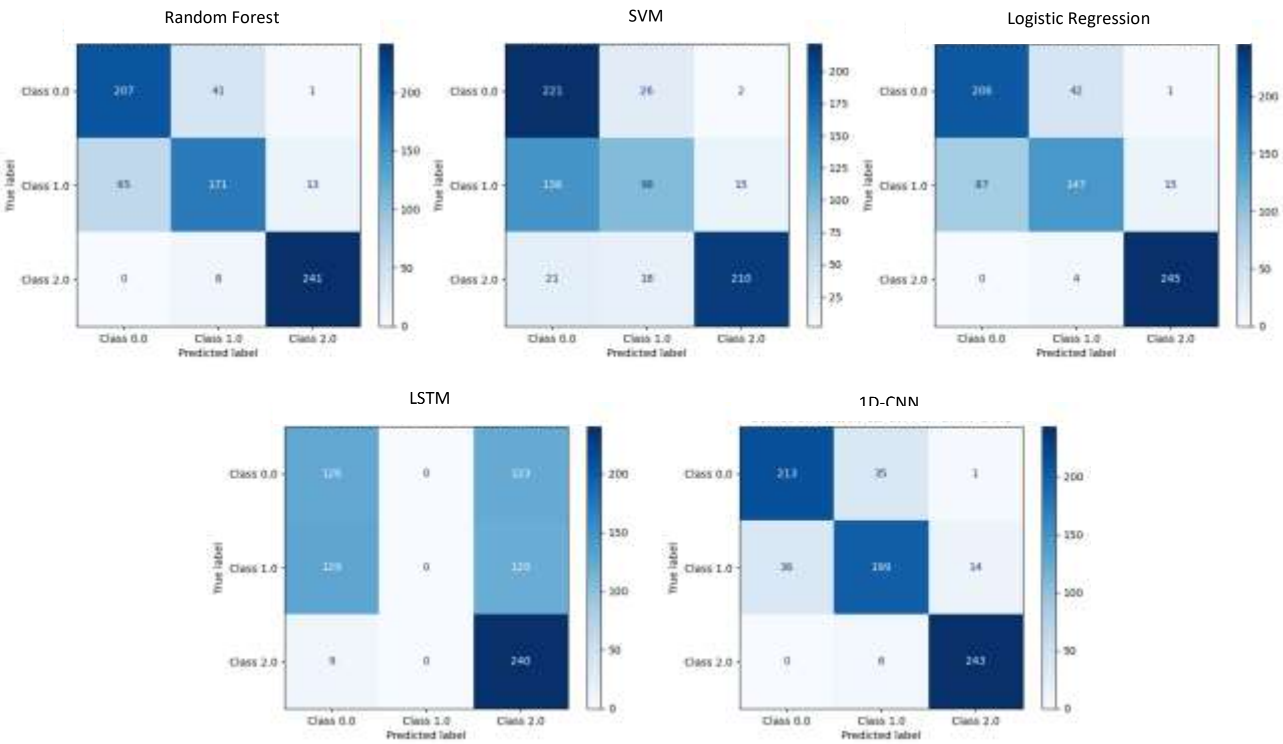
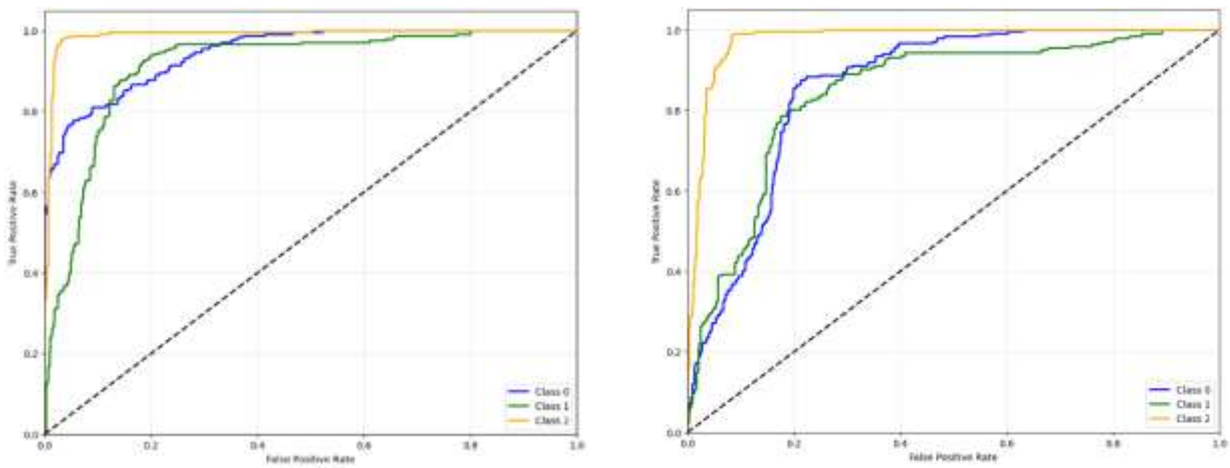
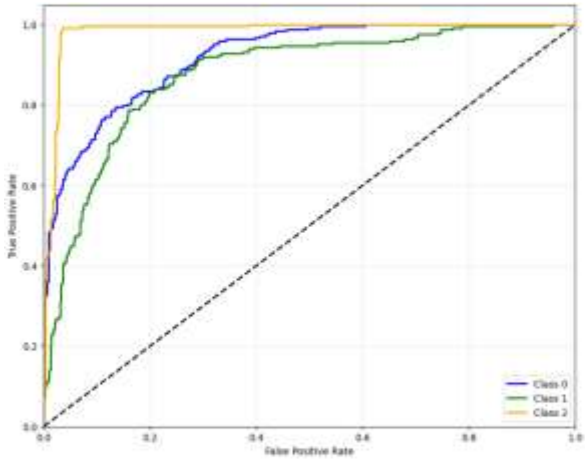


Fig. 6. Confusion matrices for all models on the UMAP-applied dataset

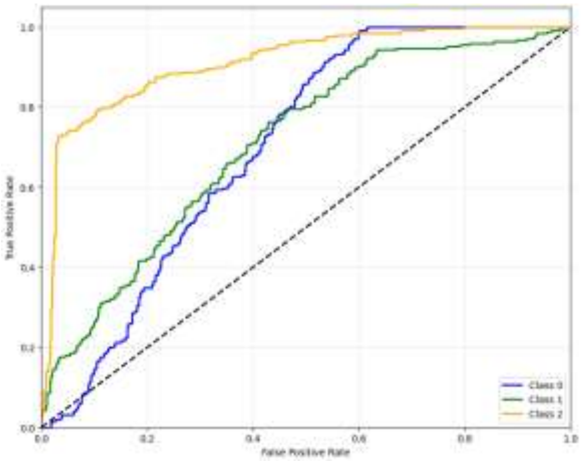
Figure 7 shows the ROC curve for all the models on UMAP- the UMAP-applied dataset. We have observed that RF predicts emotional states in the EEG data better than SVM and LR models. In SVM, low AUC values for the test set suggest possible misconfiguration of the model. These results underscore the efficacy of RF in emotion recognition from EEG signals by accounting for non-linear relationships and overfitting. While UMAP performed more efficiently, it may have contributed to losing critical distinguishing features of the emotional states.



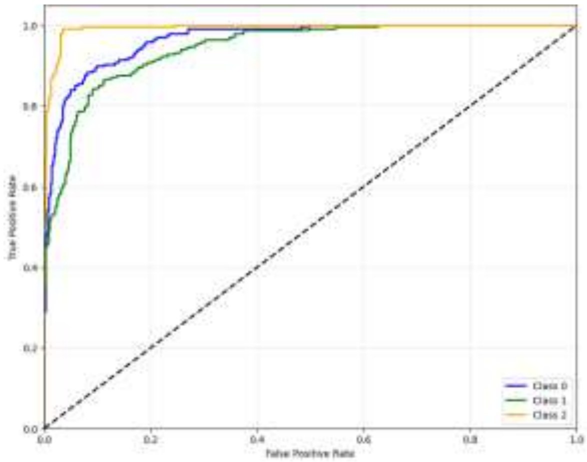
(a) (b)



(c)



(d)



(e)

Fig. 7. ROC Curves (a) RF, (b) SVM, (c) Logistic regression, (d) LSTM (e) 1D-CNN on UMAP- applied dataset

3.4 Discussion

This paper examines the performance of ML models for emotion recognition via EEG signals, specifically regarding feature engineering interventions such as PCA and UMAP. Table 6 and Figure 8 present the results, which advance our understanding of the impact of various preprocessing approaches on model performance, demonstrating that feature engineering is critical in maximizing classification accuracy and other evaluated metrics.

Table 6
Model accuracies comparison

Model	Original	PCA	UMAP
Random Forest	95	88	85
SVM	81	81	69
Logistic Regression	93	89	78
LSTM	82	80	61
1D-CNN	90	93	86

The findings show that RF leads in accuracy within each dataset, significantly surpassing the others by reaching an accuracy of 95% on the original dataset. This model's accuracy is robust even with the application of PCA (88%) and UMAP (85%), demonstrating its robustness across feature reduction techniques. On the other hand, SVM are not as robust, as the accuracy drops from 81% on the original and PCA datasets to 69% with UMAP. Logistic Regression follows a similar pattern, starting with a higher accuracy of 93% on the original dataset, then with PCA and UMAP, it achieves only 89% and 78%, respectively. Interestingly, DL models like LSTM and 1D-CNN respond distinctly to feature engineering. While the accuracy of LSTM suffers tremendously with UMAP at 61%, 1D-CNN performs better with PCA at 93% compared to the baseline of 90%, suggesting that convolutional architectures may benefit more.

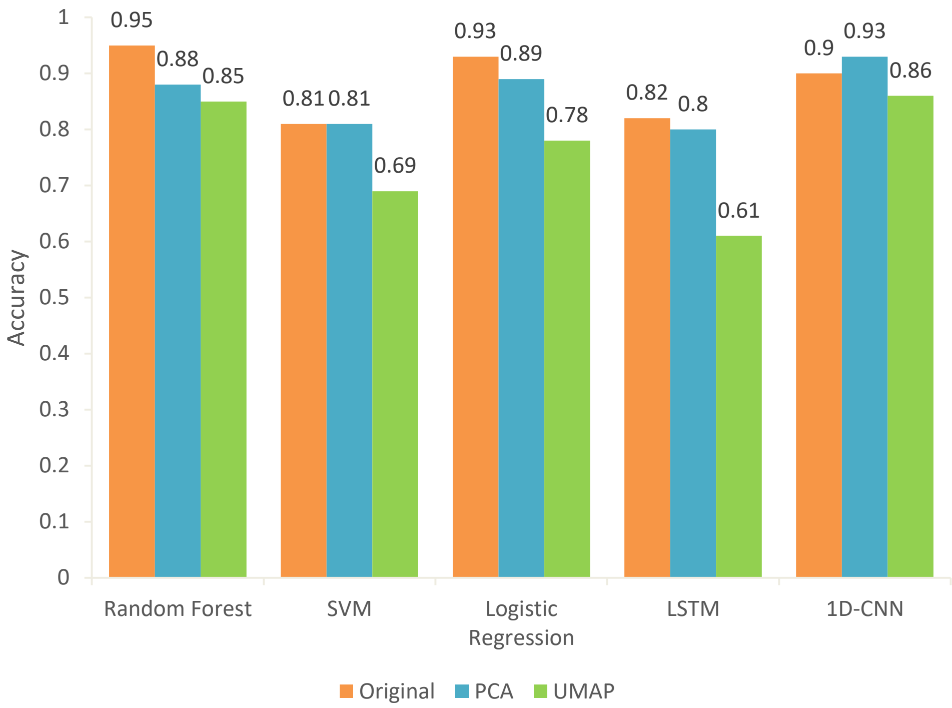


Fig. 8. Model comparison

A thorough study of precision, recall and F1 score provides additional insights into the specific strengths and weaknesses of each model. RF scores high on divisional precision and recall for all classes in the original dataset and does particularly well in classifying class 2 emotions, achieving a perfect recall of 1.00. Its performance does drop slightly relative to other models when feature engineering is applied, but it is still competitive. Logistic Regression, on the other hand, shows an aggregation of precision-recall balance dominance across all other pre-processing methods but excels most on PCA-applied datasets. SVM suffers the most from class imbalance, particularly for class 1, where recall is very low through PCA and UMAP transformations.

We utilized SHapley Additive Explanations (SHAP) to explain how and why our models predicted specific outcomes. We computed SHAP values based on PCA and UMAP analysis using RF models. Figure 9 shows that, for the UMAP transformed data, the components derived from the averages of previous data points (lag1_mean_1, lag1_mean_2 and lag1_mean_0) hold the most importance across UMAP components. These findings imply that 'lag' features, which encapsulate patterns over time, are essential for the simplified representation of the data. Similarly, the most crucial component for the PCA transformed data was PCA Component 0, which demonstrates the lagged relationships among the data points (it is driven by lag1_logcovM_2_2). Also important is PCA Component 1, which captures the frequencies present in the data (freq_649_1). These results reinforce the understanding of the usefulness of the models, the identified features and the effectiveness of the model's dimensionality reduction technique.

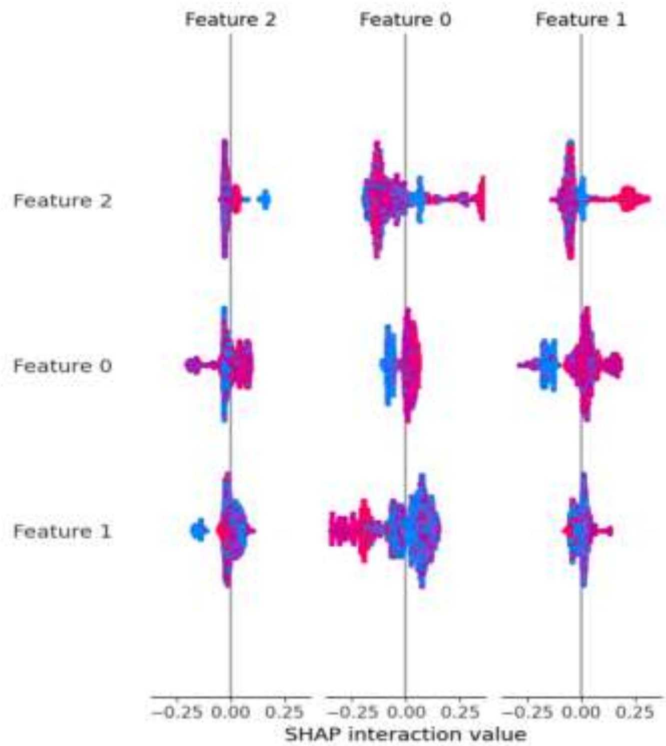


Fig. 9. SHAP

This research also highlights the limitations of UMAP when used as a feature reduction method for the recognition of emotions. Although it works moderately well with RF and 1D-CNN, it is still less favourable in overall performance compared to PCA. For example, UMAP significantly lowers the accuracy of LSTM by a large margin (82% to 61%), suggesting that this approach may not be appropriate for sequential models that depend on time.

The results of this research are crucial for systems that use EEG to detect emotions. The RF technique's best result signifies that ensemble methods are appropriate for this area, as they tend to perform well for high dimensional data. The disparities observed in LSTM and 1D-CNN models highlight the varied performance of these approaches. Additionally, the controversies surrounding PCA and UMAP analyses indicate that, in this scenario, PCA is less informative but more dependable for dimensionality reduction.

This study emphasizes assessing ML frameworks for emotion detection in ASD, yet we acknowledge the need to connect principles with practice. There is potential for future research to attempt the integration of these models into therapeutic approaches, such as real-time emotion feedback mechanisms for social skills training or other assistive tools like wearable sensors providing context-sensitive emotional aid. For example, the temporal and frequency domain features identified (for example, lag-based metrics and PSD components) could lead to adaptive interventions that give feedback depending on the person's emotional state. These examples go beyond showing the impact of emotion recognition systems in real life; they also help stimulate interdisciplinary action to deal with the translational issues of care for people with ASD.

4. Conclusion

This research illustrates the effectiveness of implementing ML in recognizing emotions by robotic mechanisms using EEG signals. People experiencing ASD have difficulties with social interactions and communication along with stereotypic activity. In contrast, ML incarnations facilitate the recognition of emotional states by examining behavioural data in detail. This research evaluates the scope of ML-based systems to automate the processes of recognizing and interpreting emotional markers, which are crucial in the development of communication and intervention tactics. We performed PCA and UMAP dimensionality reduction on the analysed EEG datasets and then evaluated RF, SVM, Logistic Regression, LSTM and 1D CNN over these datasets. The effectiveness of the models was measured by comparing the achieved results in accuracy, precision, recall and F1 scoring, which quantify recognition capabilities of emotions in functional EEG signals by a mannequin. The RF model proved decisive in this task, achieving an accuracy of 95% when working with the original dataset and showing robustness when using PCA (88%) and UMAP (85%), unlike other models, which suffered significantly in classification accuracy and stability. An ultimate aim of further studies should be to reflect the larger picture of the phenomenon by including a more varied range of sample participants, incorporating multi-modal multimedia data and battering DL methodologies for realizing systems of emotion recognition aimed at individual therapies of children with ASD.

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