Indonesian Journal of Electronics, Electromedical Engineering, and Medical Informatics e-ISSN: 2656-8624
Homepage: https://ijeeemi.org/; Vol. 7, No. 2, pp. 427-437, May 2025

RESEARCH PAPER

OPEN ACCES

EEG-Based Emotion Classification in Response to Humorous, Sad, and Fearful Video Stimuli Using LSTM Networks: A Comparative Study with Classical Machine Learning Models

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ABSTRACT

Emotion recognition based on EEG signals is a critical area within affective computing, with applications in mental health monitoring, human-computer interaction, and neuroadaptive systems. However, accurately classifying emotional states from inherently non-stationary and noisy EEG data remains a major challenge. This study explores the classification of three discrete emotions, Humorous, Sad, and Fearful, elicited through video stimuli, using EEG recordings from six participants acquired via a 19-channel Mitsar amplifier at a 500 Hz sampling rate. Preprocessing steps included bandpass filtering (1–40 Hz), epoch segmentation, and multi-domain feature extraction encompassing statistical measures, spectral features, differential entropy, Hjorth parameters, and hemispheric asymmetry indicators. Data augmentation was applied to balance class distributions, particularly for the underrepresented fear category. The resulting features were normalized and structured to support temporal deep learning and classical machine learning models. The classification performance of Long Short-Term Memory (LSTM) networks was evaluated alongside Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), and Random Forest (RF) classifiers. While LSTM demonstrated competency in capturing temporal dependencies, especially in fear recognition, SVM achieved the highest overall accuracy, 94.12%, outperforming LSTM at 85.16%, RF at 90.00%, and k-NN at 78.01%. These results suggest that when robust and discriminative features are employed, traditional models like SVM can surpass deep learning methods, particularly in small-scale EEG datasets with limited temporal complexity. This study underscores the importance of aligning model architecture with feature representation and contributes a comparative evaluation framework for EEG-based emotion recognition systems.

PAPER HISTORY

Received Feb. 20, 2025
Accepted April 27, 2025
Published May 22, 2025

KEYWORDS

EEG;
LSTM;
SVM;
Machine Learning;
Emotion Recognition;

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1. INTRODUCTION

Electroencephalography (EEG) has gained increasing attention as a non-invasive and temporally precise method for analyzing brain dynamics associated with emotional processing. Emotions play a critical role in human cognition and behavior, and understanding their neural correlates has become essential for the advancement of affective computing, mental health assessment, and human-computer interaction [1], [2]. However, the classification of emotional states using EEG remains a challenging task due to the non-stationary nature of EEG signals, high inter-subject variability, and subtle distinctions between emotional categories[3], [4]. Traditional approaches often rely on shallow classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), or Random Forests, and typically utilize either statistical or spectral features extracted from short EEG segments [5], [6], [7]. While these methods offer reasonable performance, they fall short in modeling temporal dependencies within EEG signals that are crucial for accurately capturing the dynamics of emotional responses [8].

Recent studies have shown that deep learning models, particularly Long Short-Term Memory (LSTM) networks, are well-suited for handling the temporal sequence nature of EEG data, allowing them to learn high-level abstract features from raw or preprocessed input signals [9][10]. LSTM architectures have demonstrated superior performance over traditional methods in various EEG-based affective recognition tasks, especially when trained

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DOI: https://doi.org/10.35882/ijeeemi.v7i2.100
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on time-series inputs that preserve sequential structure [11], [12]. Despite these advances, much of the existing literature remains focused on binary classification problems or relies heavily on valence-arousal models derived from datasets such as DEAP or SEED[13], [14]. These datasets, while popular, often lack ecological validity due to their reliance on controlled laboratory settings and artificial stimuli, which may not fully capture natural emotional responses. Moreover, many studies do not address class imbalance or fail to incorporate features that reflect hemispheric asymmetry an important indicator in emotional EEG research [15].

To address these limitations, the present study proposes a comprehensive framework for classifying three discrete emotional states, humorous, sad, and fearful, elicited by naturalistic video stimuli, using LSTM-based deep learning architecture. The EEG data are preprocessed using a bandpass filter (1–40 Hz) to isolate relevant frequency bands and segmented based on annotated emotional episodes. Each segment undergoes feature extraction across multiple domains, including statistical time-domain measures (mean, variance, skewness), spectral bandpower features (delta to gamma), and hemispheric asymmetry indices derived from frontal and parietal channels [16], [17]. To address the problem of class imbalance particularly the underrepresentation of fear-related responses targeted data augmentation techniques are applied to the "scared" class. All features are normalized, and the resulting dataset is reshaped into sequential format compatible with LSTM input layers. The LSTM model comprises two stacked recurrent layers, dropout regularization, and a dense classification head with class weighting to further mitigate imbalance during training. The model is evaluated using stratified training, validation, and testing splits, with accuracy, confusion matrix, and per-class F1-score as the primary performance metrics [18]. To evaluate the suitability of LSTM in comparison with classical models, we also benchmark its performance against SVM, Random Forest, and k-NN classifiers using the same engineered feature set.

2. MATERIALS AND METHOD

A. Dataset

EEG data were acquired from six healthy adult participants with aged 20–30 years using the Mitsar-EEG 201 amplifier system, a high-resolution neurophysiological recording device compliant with the international 10–20 electrode placement system. A total of 19 channels were recorded, including F7, T3, T5, Fp1, F3, C3, P3, O1, Fz, Cz, Pz, Fp2, F4, C4, P4, O2, F8, T4, and T6, at a sampling frequency of 500 Hz. This spatial configuration enables comprehensive coverage of frontal, central, parietal, temporal, and occipital cortical regions implicated in emotional and cognitive processing [19], [20]. Fig. 1 is the EEG channel used in this study.

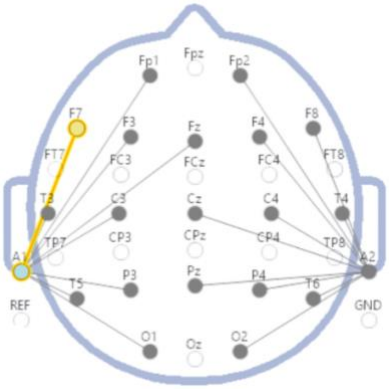

Fig. 1. Electrode in Mitsar-EEG.

B. Scheme of Experiment

Participants were seated comfortably in a sound-attenuated room to minimize environmental noise and artifacts. A 10-minute audiovisual protocol was presented on a 24-inch monitor, structured to evoke three distinct emotional states humorous, sad, and fearful, through a sequence of carefully curated video stimuli as shown in Fig. 2. The protocol was designed as follows: an initial 60-second baseline allowed for physiological stabilization; this was followed by a 2-minute humorous clip to elicit amusement, a 1-minute rest, a 3-minute melancholic video to induce sadness, a second rest period of 1 minute, and finally a 2-minute fear-inducing video. This structured timing ensured temporal separation between emotional stimuli and sufficient stimulus duration for neural entrainment [21],[22].

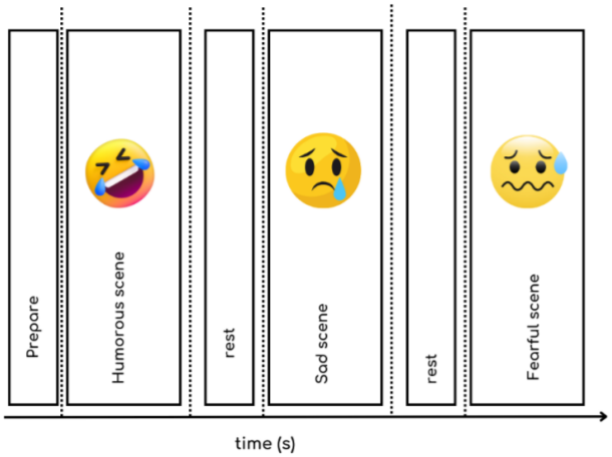

Fig. 2. The Arrangement of display stimuli

C. Data Processing

The overall data processing pipeline for EEG-based emotion classification is illustrated in Fig. 3. Raw EEG signals obtained from a 19-channel system are initially preprocessed to reduce noise and artifact components [23]. A 4th-order Butterworth bandpass filter in the frequency range of 1–40 Hz was applied to retain relevant EEG frequency components while attenuating noise and

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irrelevant artifacts. The transfer function of the Butterworth filter is defined as shown Eq. (1): [24]

$$|H(j\omega)| = \frac{1}{\sqrt{1+\left(\frac{\omega}{\omega_c}\right)^{2n}}} \quad (1)$$

where ω_c is the cutoff frequency and n is the order of the filter. This band was chosen to encompass the delta, theta, alpha, beta, and low gamma bands, which are known to contain discriminative information for emotion-related EEG activity [25], [26]. Subsequently, the filtered EEG data were segmented using a sliding window approach with a window size of 2 seconds and 50% overlap. This segmentation choice balances temporal resolution and redundancy, allowing for a denser sampling of emotional dynamics while avoiding excessive fragmentation of data.

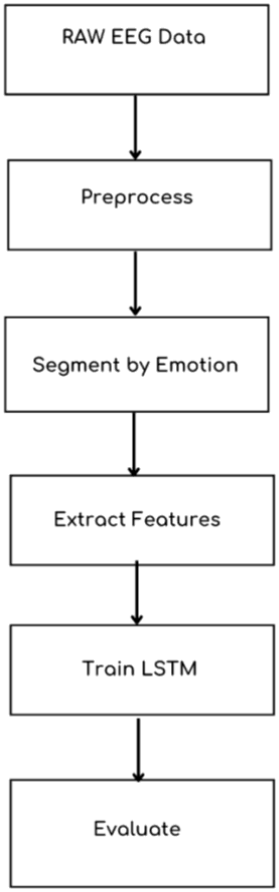

Fig. 3. Flowchart of data processing.

Feature extraction was performed on each window, encompassing statistical features (e.g., mean, variance), spectral features (e.g., power spectral density across delta to gamma bands), and hemispheric asymmetry features. The spectral features were computed using Welch's method, and the hemispheric asymmetry was derived by subtracting the bandpower of symmetrical channels (e.g., F4–F3, P4–P3), based on affect-related EEG asymmetry literature. This resulted in a 114-dimensional feature vector per window. The feature vectors were normalized using z-score normalization across the training set to ensure consistency and comparability between subjects and sessions. To address the class imbalance problem, particularly for the underrepresented "scared" category, we employed data augmentation through segment-wise window shifting and jittering of non-overlapping intervals. Additionally, class weights were assigned during training, computed using Eq. (2) [27]:

$$Weight_i = \frac{N}{C\ x\ n_i} \quad (2)$$

where N is the total number of samples, C is the number of classes, and n_i is the number of samples in class i. These weights ensure that minority classes contribute proportionally during loss computation. Before feeding the data into the LSTM classifier, the sequential structure of EEG dynamics was preserved by reshaping the data into a 3D tensor of shape (N,T,F), where N is the number of instances, T =5 is the sequence length (i.e., number of time steps), and F =114 is the number of features per step. This setup allows the LSTM to learn temporal dependencies across short emotional episodes. The proposed LSTM architecture consists of a single LSTM layer with 128 units and tanh activation, followed by a dropout layer with dropout rate of 0.5, a dense layer with 64 neurons and ReLU activation, and a final softmax output layer for 4-class emotion prediction. The model was trained using the Adam optimizer with earning rate 0.001 and categorical cross-entropy loss. For evaluation, a subject-independent split was implemented, where 70% of subjects were used for training, 15% for validation, and 15% for testing. This ensures that the model generalizes across individuals. Additionally, 5-fold cross-validation was performed within the training set to assess model robustness. Performance metrics reported include accuracy, F1-score, and confusion matrices for comprehensive evaluation. The mathematical formulation of a standard LSTM cell at time step $\boldsymbol{t}$ includes the forget gate $\boldsymbol{f_t}$, input gate $\boldsymbol{i_t}$, candidate memory content $\boldsymbol{\widetilde{C}_t}$, updated cell state $\boldsymbol{C_t}$, and output gate $\boldsymbol{o_t}$, defined as follows in which it mathematically as shown Eq. (3): [28]

$$\begin{aligned} \boldsymbol{f_t} &= \boldsymbol{\sigma}(\boldsymbol{W_f}.[\boldsymbol{h_{t-1}}, \boldsymbol{x_t}] + \boldsymbol{b_f}) \\ \boldsymbol{i_t} &= \boldsymbol{\sigma}(\boldsymbol{W_i}.[\boldsymbol{h_{t-1}}, \boldsymbol{x_t}] + \boldsymbol{b_i}) \\ \boldsymbol{\widetilde{C}_t} &= \boldsymbol{\tan h}\,(\boldsymbol{W_C}.[\boldsymbol{h_{t-1}}, \boldsymbol{x_t}] + \boldsymbol{b_C}) \\ \boldsymbol{C_t} &= \boldsymbol{f_t}.\boldsymbol{C_{t-1}} + \boldsymbol{i_t}.\boldsymbol{\widetilde{C}_t} \\ \boldsymbol{o_t} &= \boldsymbol{\sigma}(\boldsymbol{W_o}.[\boldsymbol{h_{t-1}}, \boldsymbol{x_t}] + \boldsymbol{b_o}) \\ \boldsymbol{h_t} &= \boldsymbol{o_t}.\boldsymbol{\tan h}\,(\boldsymbol{C_t}) \end{aligned} \quad (3)$$

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Here, x_t is the input vector, h_{t-1} is the previous hidden state, C_{t-1} is the previous cell state, and σ and $\tanh$ are the sigmoid and hyperbolic tangent activation functions, respectively. This architecture enables the network to maintain contextual information over long sequences, which is particularly valuable in emotion recognition tasks using EEG data [28], [29]. In Fig. 4 The LSTM model architecture typically includes an input layer reflecting the feature dimensions, one or more LSTM layers, and a dense output layer with softmax activation for multi-class classification. The network is trained using a categorical cross-entropy loss function, optimized via backpropagation through time. The classification performance is assessed through metrics such as accuracy, precision, recall, and F1-score. These are complemented by confusion matrices, which illustrate the classifier's ability to distinguish among emotional categories [29], [30].

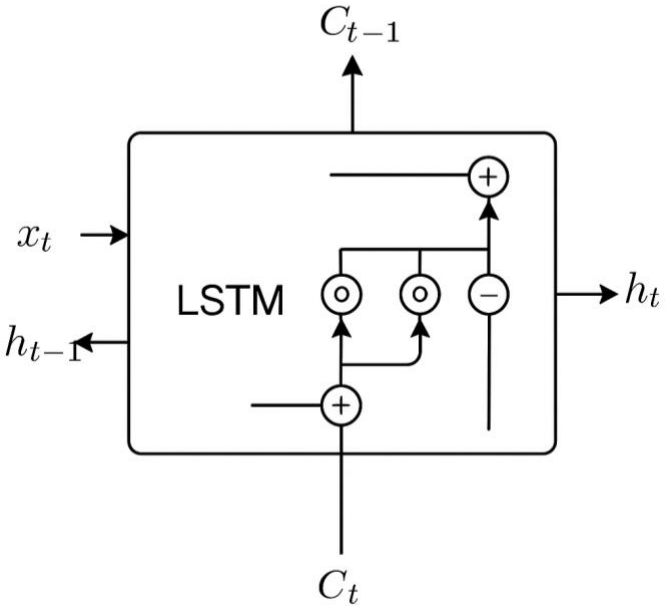

Fig. 4. Basic structure of an LSTM cell showing input, forget, and output gates.

3. RESULTS

A. LSTM Training

The LSTM training results presented in the Table 1 show the performance metrics across six individual subjects based on validation accuracy and validation loss. The average validation accuracy achieved was 83.18%, indicating that the LSTM model effectively captured temporal patterns in EEG signals associated with emotional states. Notably, subject S3 achieved the highest validation accuracy of 98.08% with the lowest loss of 0.06, suggesting a highly accurate and well-generalized model for that individual. In contrast, subject S2 yielded the lowest validation accuracy of 59.62% and the highest loss of 1.34, indicating variability in model performance potentially due to inter-subject differences in EEG patterns or noise levels. The standard deviation (SD) values of 12.46% for accuracy and 0.42 for loss further highlight the degree of variation in classification performance across different subjects. These results underscore the importance of subject-specific modeling and the need for adaptive methods in EEG-based emotion classification using LSTM networks.

Table 1. The result of LSTM Training

Subject	Validation Accuracy (%)	Validation Loss
S1	81.73	0.55
S2	59.62	1.34
S3	98.08	0.06
S4	78.85	0.57
S5	94.23	0.14
S6	86.54	0.39
Mean	83.18	0.51
SD	12.46	0.42

Fig. 5 the LSTM model demonstrates effective learning, achieving high training accuracy and stable validation accuracy for subject 4. However, the divergence between training and validation curves in both loss and accuracy graphs indicates that while the model generalizes well, further regularization (e.g., dropout, early stopping) could enhance performance and reduce overfitting. This subject's results confirm the model's ability to capture temporal patterns in EEG data for emotion classification.

B. Classification Performance of LSTM

The classification performance of the LSTM model for three types of emotional stimuli Humorous, Sad, and Fearful is evaluated using three standard metrics: Precision, Recall, and F1-score. These metrics are particularly relevant in emotion recognition tasks, where the cost of false positives and false negatives may vary depending on the emotional context.

Precision measures the proportion of correctly predicted positive observations to the total predicted positives. High precision indicates that the classifier produces fewer false positives see Eq.(4):

$$\boldsymbol{Precision} = \frac{TP}{TP + FP} \tag{4}$$

Where TP (True Positive) is a correct positive prediction, FP (False Positive) is an incorrect positive prediction, and FN (False Negative) is a missed positive case. Recall, also known as sensitivity or true positive rate, is the proportion of correctly predicted positive observations to all actual positives. High recall indicates that the model is effective at identifying relevant cases (i.e., it misses fewer true cases), see Eq. (5):

$$\boldsymbol{Recall} = \frac{TP}{TP + FN} \tag{5}$$

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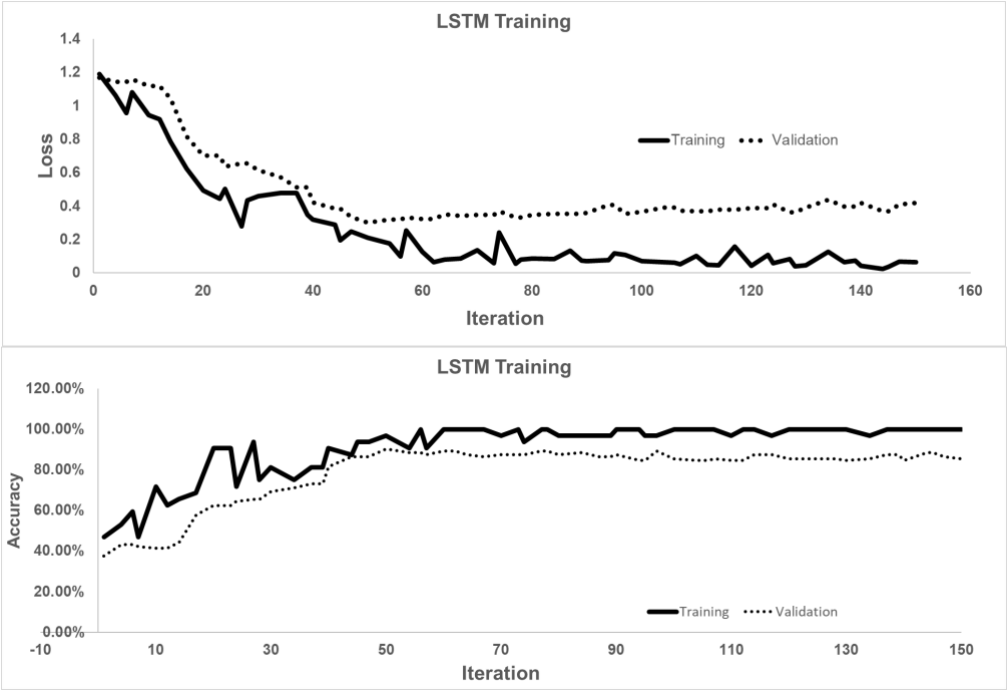

Fig. 5. Training and validation performance of the LSTM model for Subject 4.

F1-score is the harmonic mean of precision and recall. It provides a single score that balances both concerns, especially useful when the class distribution is imbalanced or when both false positives and false negatives carry costs. (see Eq. (6)).

$$\boldsymbol{F1-score} = 2\ x\ \frac{Precision\ x\ Recall}{Precision + Recall} \tag{6}$$

The model achieved a mean precision of 88.50%, recall of 85.51%, and an F1-score of 86.92% as shown in Table 2, indicating that the LSTM was proficient in detecting humor-related EEG patterns. The relatively low standard deviation in F1-score (±11.36) shows moderate inter-subject consistency, although Subject 2 displayed notably low performance (F1-score = 63.64%), possibly due to individual differences in emotional response to humor or EEG signal noise.

Table 2. The result of LSTM Classifier for Humorous Stimuli.

Subject	Humorous (%)		
	Precision	Recall	F1-score
S1	90.48	82.61	86.36
S2	66.67	60.87	63.64
S3	95.24	86.96	90.91
S4	86.96	86.96	86.96
S5	91.67	95.65	93.62
S6	100	100	100
Mean	88.50	85.51	86.92
SD	± 10.57	±12.47	±11.36

Based on Table 3, The average classification results for sad stimuli were slightly lower, with 87.73% precision, 75.24% recall, and 80.28% F1-score. The lower recall, with a standard deviation of approximately ±12.53 suggests that the model sometimes failed to identify true sad responses, potentially due to more subtle or less consistent EEG patterns associated with sadness. This emotional state might elicit less distinct brain activity, or the stimuli may have been less universally evocative across participants.

Table 3. The result of LSTM Classifier for Sad Stimuli.

Subject	Sad (%)		
	Precision	Recall	F1-score
S1	77.78	60.00	67.74
S2	78.57	62.86	69.84
S3	97.14	97.14	97.14
S4	86.21	71.43	78.13
S5	93.55	82.86	87.88
S6	93.10	77.14	84.38
Mean	87.73	75.24	80.85
SD	±7.49	±12.53	±10.23

Table 4 indicates that the LSTM classifier achieved the highest recall of 92.39% and F1-score of 86.99% under the fearful stimulus condition, with a precision of 82.30%. The model's robustness in identifying fear responses is likely due to stronger neural responses associated with high-arousal, threat-related stimuli, which tend to evoke more consistent and distinguishable EEG patterns. Notably, Subject 3 reached near-perfect scores, with a precision of 95.83%, recall of 100%, and an F1-score of 97.87%.

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Table 4. The result of LSTM Classifier for Fearful Stimuli.

Subject	Fearful (%)		
	Precision	Recall	F1-score
S1	71.43	86.96	78.43
S2	65.45	78.26	71.29
S3	95.83	100.00	97.87
S4	84.62	95.65	89.80
S5	91.84	97.83	94.74
S6	84.62	95.65	89.80
Mean	82.30	92.39	86.99
SD	±10.70	±7.50	±9.26

4. DISCUSSION

A. Classifier Analysis

In this study, LSTM networks were employed as the primary deep learning architecture for classifying EEG signals corresponding to different emotional states evoked by video stimuli. LSTM networks are a type of recurrent neural network (RNN) specifically designed to capture temporal dependencies within sequential data. This makes LSTM particularly suitable for EEG signal classification, where time-dependent neural dynamics play a crucial role in encoding cognitive and emotional states. The LSTM model was trained individually for six subjects S1 to S6, and the results were evaluated using validation accuracy and validation loss metrics. As observed in the summary table, the validation accuracy ranged from 59.62% (S2) to 98.08% (S3), with a mean accuracy of 83.18% and a standard deviation (SD) of ±12.46. The corresponding validation loss values varied between 0.06 and 1.34, with a mean of 0.51. The disparity in accuracy and loss between subjects suggests that individual differences in EEG responses, such as noise levels, engagement with the stimuli, or neural variability, substantially influence model performance.

The highest-performing subject (S3) demonstrated near-perfect validation accuracy and minimal loss, indicating a highly learnable and distinguishable pattern in their EEG recordings. In contrast, the lowest performance by S2 may reflect either noisy EEG signals or a weak neural response to the stimuli, leading to reduced model generalizability during validation. Despite this variability, the overall accuracy of over 80% across all subjects affirms the effectiveness of the LSTM model in capturing emotional EEG features when appropriately tuned for each individual. The strong performance of the LSTM network highlights its capability to extract meaningful spatiotemporal representations from EEG data. Its success is likely due to its gating mechanisms, which allow the model to retain relevant features over time and discard noise or irrelevant fluctuations. This architectural advantage is crucial when dealing with EEG data, which is inherently non-stationary and susceptible to artifacts.

B. Emotion Classification Performance based on Confusion Matrices and ROC Curve

To further analyze the effectiveness of the LSTM classifier, we examined its performance across three types of emotional stimuli Humorous, Sad, and Fearful by evaluating precision, recall, and F1-score for each subject and emotion category. These metrics are critical for understanding not just the correctness of predictions but also the model's reliability in handling class imbalances and minimizing false positives or negatives. The classification under humorous video stimuli yielded a mean precision of 88.50%, recall of 85.51%, and F1-score of 86.92%. These high values suggest that the model effectively identified humorous-related EEG responses, with a strong balance between sensitivity and specificity. However, Subject (S2) low performance, indicated by an F1-score of 63.64%, slightly skewed the overall mean and increased the standard deviation, indicating potential variability in subjective humor perception or differential neural engagement. The confusion matrix for this condition would likely reveal some misclassification between humorous and other emotions, particularly for this subject. For sad stimuli, the model showed moderate classification performance, with a mean precision of 87.73%, but a lower recall of 75.24%, resulting in an F1-score of 80.28%. The reduced recall suggests a higher rate of false negatives i.e., actual sad responses that were misclassified as non-sad. This aligns with the known difficulty of detecting sadness from EEG, as sadness often involves low-arousal brain states that may be less distinct than high-arousal emotions like fear. The confusion matrix in this case would reflect more off-diagonal elements, especially in the sad-predicted-as-neutral or sad-predicted-as-fearful cells.

The classifier performed best under fearful stimuli, with the highest recall of 92.39% and an F1-score of 86.99%, despite a slightly lower precision of 82.30%. This pattern suggests that the model rarely misses fear responses but occasionally mislabels non-fear emotions as fearful. Fear-inducing stimuli are typically characterized by heightened physiological and neural responses, which likely generate more robust and consistent EEG patterns. This consistency allows the LSTM model to generalize better across subjects, as also seen in Subject 3's near-perfect classification.

Although the actual confusion matrices are not visualized here, their structure can be inferred from the precision-recall dynamics. A confusion matrix is a square matrix where the diagonal entries represent correct classifications, and off-diagonal entries indicate misclassifications. High precision and recall, as seen in the humorous and fearful conditions, would correspond to strong diagonals, while lower recall in the sad condition implies more dispersed misclassifications. The confusion matrices are essential for identifying emotion pairs that are prone to confusion. For instance, sadness and fear may share overlapping EEG signatures in certain brain regions, leading to classification errors. Similarly, humorous responses might occasionally be mistaken for

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neutral or relaxed states due to the presence of shared low-frequency EEG components.

In addition to the metrics discussed above, a comprehensive evaluation of the classifier's discrimination ability was carried out using ROC curves and the corresponding AUC values for each emotional category and subject, as shown in Fig. 6. The ROC analysis confirms that the model exhibits strong class separation, particularly for humorous and fearful stimuli. Across the six subjects, the AUC values for the "Funny" category consistently exceeded 0.95 in most cases, with Subject 6 even achieving a perfect score of 1.000, indicating exceptional model reliability in detecting humor-related EEG patterns. Conversely, variability was more noticeable in the classification of sadness, where AUC scores ranged between 0.846 and 0.991, reflecting challenges in distinguishing low-arousal emotional states.Subject-wise comparison reveals a high degree of inter-individual variability. Subject 3 achieved nearly perfect classification performance for all emotional categories, with AUCs close to or equal to 1.000, suggesting highly separable EEG patterns and minimal overlap between classes. In contrast, Subject 2 demonstrated the lowest overall AUCs, especially in the "Scared" category with an AUC of 0.808, possibly due to reduced emotional engagement or EEG noise artifacts during data acquisition. Despite these individual differences, the ROC analysis strongly supports the LSTM model's robustness in capturing emotion-specific EEG features, particularly for high-arousal states such as humor and fear, where the neural response tends to be more distinct and temporally structured. This analysis complements the confusion matrix evaluation by offering a threshold-independent view of classifier performance, and underscores the importance of accounting for individual neural variability in EEG-based affective computing.

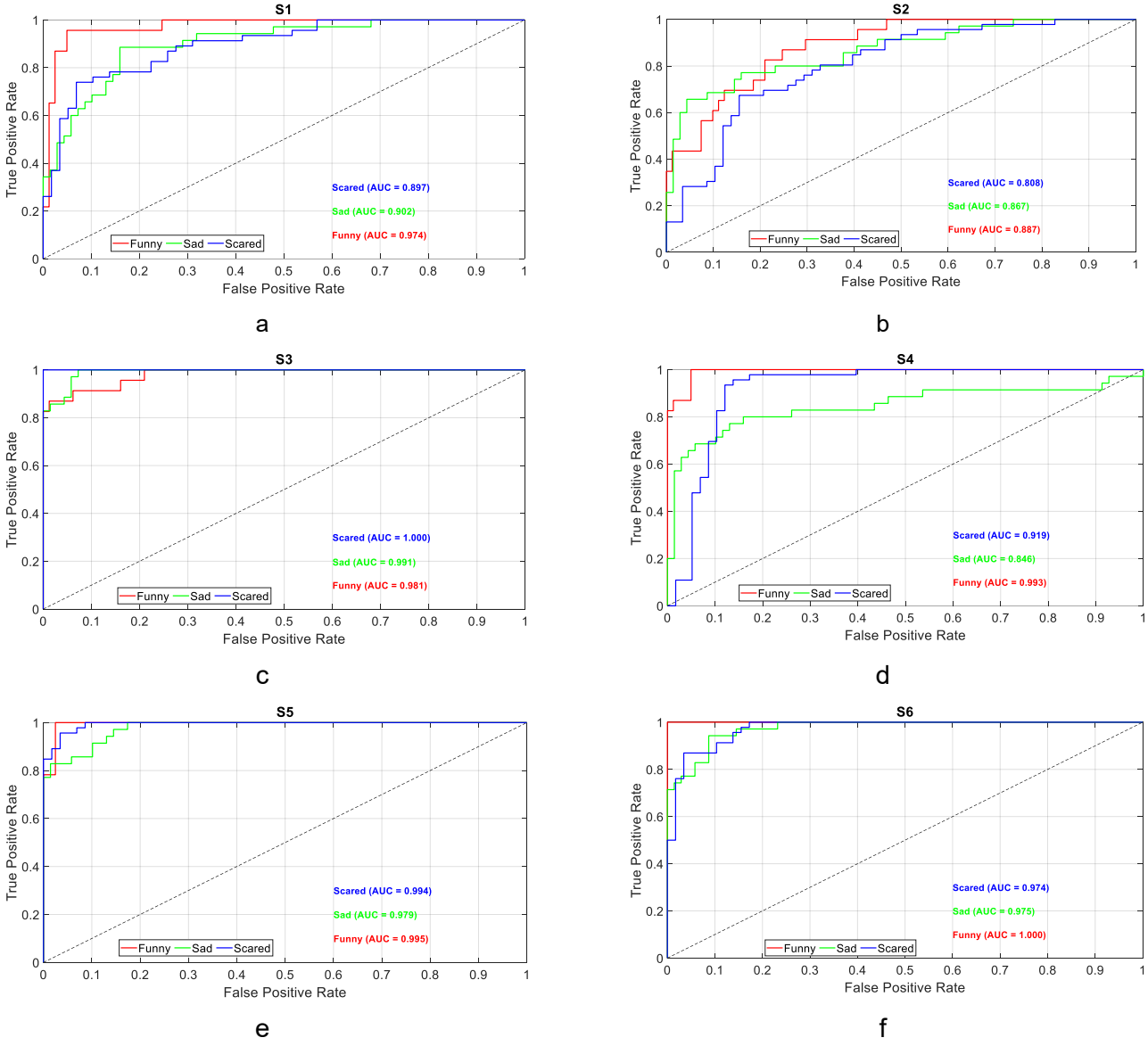

Fig. 6. ROC Curves with AUC Scores for Emotion Classification by Subject

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C. Evaluating the Performance of LSTM and Classical Classifiers

The findings summarized in Table 5 demonstrate that the Support Vector Machine (SVM) classifier outperformed all other models in classifying emotional states based on EEG data, achieving an overall accuracy of 94.12%. LSTM, which was originally hypothesized to be the most suitable model for this task due to its ability to model temporal dependencies, reached an overall accuracy of 85.16%, while Random Forest and KNN achieved 90.00% and 78.01%, respectively. These results invite a deeper reflection on the inherent strengths and limitations of LSTM networks in the context of EEG-based emotion recognition. One of the key advantages of LSTM is its capacity to capture long-range dependencies in time-series data, making it highly effective in tasks where temporal dynamics are strong and meaningful such as speech recognition, language modeling, or video analysis. In EEG applications, this advantage can be significant when emotional states unfold over time or when raw EEG signals are used directly as input.

However, the efficacy of LSTM diminishes when the temporal structure in the data is weak, already summarized by handcrafted features, or when the dataset is relatively small. In this study, the EEG signals were transformed into statistical and frequency-domain features such as Differential Entropy, PSD, Hjorth parameters, and asymmetry which emphasize spatial and spectral characteristics rather than temporal sequences. Consequently, the LSTM was deprived of the kind of raw temporal data it is best suited to process. Furthermore, with limited training data, LSTM models are susceptible to overfitting due to their high number of trainable parameters, especially in the absence of techniques like dropout, early stopping, or sufficient regularization.In contrast, SVM operates effectively in small to medium-sized datasets and excels when the input features are linearly separable or exhibit strong clustering behavior conditions that seem to be satisfied in this case, given the quality of the engineered EEG features. The performance of Random Forest, which also surpassed LSTM, reinforces the notion that simpler, ensemble-based methods may generalize better under constrained data conditions.Nonetheless, the inclusion of LSTM in this study remains valuable. It reflects an important experimental question regarding whether temporal modeling offers added benefits in emotion classification using EEG signals. The answer, as the results indicate, is nuanced: while LSTM holds theoretical advantages, its real-world effectiveness depends heavily on how data is represented, the amount of training data, and the clarity of temporal structure.

This outcome provides a broader implication for future research. In EEG-based affective computing, model selection should be tightly coupled with feature extraction strategy and dataset characteristics. Future work could consider hybrid approaches, such as combining CNNs for spatial feature extraction with LSTMs for temporal modeling, or employing attention mechanisms to focus on the most informative time segments. Additionally, increasing dataset size, utilizing raw EEG time series, or adopting subject-independent evaluation frameworks may further reveal the potential of deep learning models like LSTM in this domain.

D. Comparative Analysis, Limitations, and Implications

The results presented in Table 5 demonstrate that the SVM classifier outperformed all other evaluated models in EEG-based emotion recognition, achieving an overall classification accuracy of 94.12%. Contrary to initial assumptions favoring temporal models, LSTM network achieved a lower accuracy of 85.16%, while Random Forest and KNN recorded accuracies of 90.00% and 78.01%, respectively. These findings are in alignment with several recent studies. Yin et al. [31] developed a hybrid model that integrates Graph Convolutional Neural Networks (GCNNs) with LSTM layers, achieving accuracies of 90.60% for valence and 85.27% for arousal using the DEAP dataset in a subject-independent scenario. Similarly, Salma et al. [32] reported that a multi-layer LSTM framework applied to the DEAP dataset achieved 85.65% for arousal and 85.45% for valence classification. Alibrahim and Kurdi [33] introduced a GRU-based architecture enhanced with attention mechanisms (GANN), reporting a classification accuracy of 94.21%. Other approaches, such as SAE+LSTM and 3D-CNN-based models, have produced results in the range of 72.10% to 81.10%, reinforcing the high performance of the SVM model in the present study, especially when employing well-engineered statistical and spectral EEG features.[31]

Table 5. Comparison of Classification Accuracy for EEG-Based Emotion Recognition between LSTM with SVM, RF and KNN

Classifier	Humorous (%)	Sad (%)	Fearful (%)	**Overall**
LSTM	86.98	81.27	87.23	**85.16**
SVM	96.11	91.64	94.61	**94.12**
KNN	74.78	75.74	83.51	**78.01**
RF	88.43	88.22	93.37	**90.00**

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DOI: https://doi.org/10.35882/ijeeemi.v7i2.100
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Similarly, Liu et al. [34] developed a real-time EEG-based emotion recognition system using standardized movie stimuli to classify eight discrete emotional states. Their multistage SVM-based approach achieved 92.26% accuracy in distinguishing emotional from neutral states and 86.63% in classifying positive versus negative emotions. Furthermore, they classified three positive emotions with 86.43% accuracy and four negative emotions with 65.09% accuracy. This study highlights the effectiveness of SVM models when paired with carefully designed feature extraction and hierarchical classification strategies, reinforcing the strong performance of SVM in EEG-based affective computing.

Despite its high performance, the study has several limitations. The relatively small dataset may reduce the generalizability of the models, especially for deep learning architectures like LSTM, which are sensitive to data size and prone to overfitting without adequate regularization. Moreover, the features used were derived from statistical and frequency-domain transformations, thereby removing temporal dependencies that LSTM models are designed to leverage. The experimental protocol was also conducted under a subject-dependent evaluation, which does not adequately reflect the robustness of the model across different individuals. Although the SVM achieved the highest accuracy, it remains sensitive to hyperparameter tuning and kernel selection, which may affect its replicability on different datasets.

The outcomes of this research underscore the critical need to align model architecture with the nature of input features and dataset characteristics. In future work, hybrid models combining CNNs for spatial feature extraction with LSTM or GRU units for temporal modeling should be considered. Attention mechanisms may further enhance model interpretability and performance by focusing on the most salient EEG segments. Additionally, employing raw EEG signals, increasing dataset size, adopting subject-independent validation frameworks, and incorporating transfer learning or domain adaptation strategies are promising directions to enhance model generalization and applicability in real-world EEG-based affective computing systems.

5. CONCLUSION

Applying Long Short-Term Memory networks in EEG-based emotion classification provides meaningful insight into the potential of temporal modeling for affective brain responses. Designed to capture long-range dependencies in sequential data, LSTM is theoretically well-suited for interpreting EEG signals where emotional states may evolve especially in response to dynamic audiovisual stimuli. In this study, LSTM showed reasonable performance, particuLSTMlarly in identifying fear-related patterns, which often manifest more consistently across subjects. However, the overall accuracy of LSTM was 85.16%, notably lower than that of SVM, which achieved 94.12%, suggesting that in cases where EEG data is represented through handcrafted features such as DE, PSD, Hjorth parameters, and asymmetry measures the advantages of temporal modeling are less pronounced. This discrepancy highlights one of LSTM's primary limitations: its performance depends heavily on the availability of raw temporal data and sufficient training samples. When EEG data is pre-processed into statistical or frequency-domain features that abstract away much of the temporal information, LSTM's strength in sequence learning may not be fully leveraged. Furthermore, with relatively small datasets, LSTM models may underperform due to their high model complexity and tendency to overfit. In contrast, classical machine learning models like SVM are inherently more stable under these conditions, especially when dealing with structured, discriminative features and limited data. The superior performance of SVM in this study underscores its robustness in handling well-engineered EEG features, and the overall result suggests that model selection should consider not only the data type but also the representation and volume of the dataset. Nonetheless, the use of LSTM remains justified as it aligns with the study's core objective to investigate the temporal dimension of EEG signals in emotional processing. Its inclusion allows for a comparative understanding of how temporal architectures fare against classical approaches. These findings also point to promising future directions, such as employing hybrid deep learning models (e.g., CNN-LSTM or attention-based architectures) and using raw time-series EEG data to better exploit LSTM's capabilities. Ultimately, the results advocate for a data-driven alignment between feature representation and model architecture to optimize EEG-based emotion classification. These results highlight that in limited-data contexts, classical machine learning models may outperform deep learning when the temporal aspect of the signal is abstracted away through feature engineering.

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DOI: https://doi.org/10.35882/ijeeemi.v7i2.100
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DOI: https://doi.org/10.35882/ijeeemi.v7i2.100
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DOI: https://doi.org/10.35882/ijeeemi.v7i2.100
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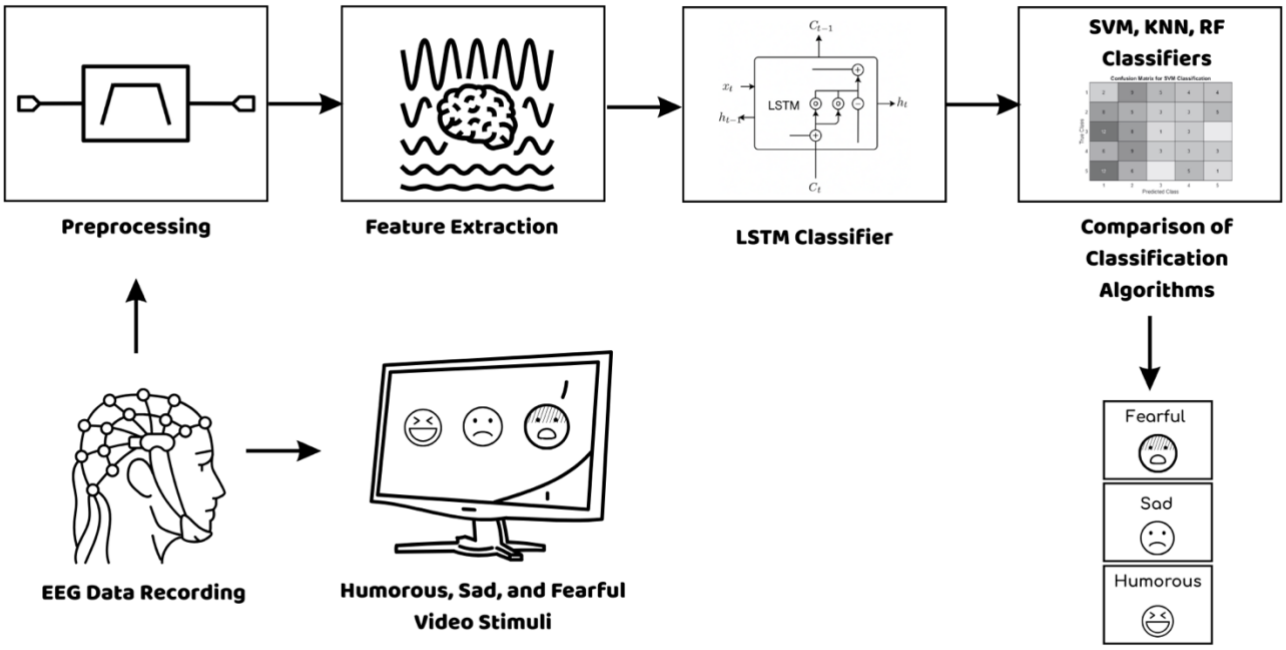

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