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EEG-Based Emotion Recognition Using CNN-LSTM: Dynamic Segmentation and Feature Fusion

Nazia Tabraiz*, Saadia Abdul Jabbar and Jawaid Iqbal

Abstract **– This study examines current developments and persistent difficulties in identifying emotions from EEG data, particularly when it comes to real-time systems. The need for precise, quick-response models has increased as interest in emotion-aware applications—from adaptive human-computer interfaces to mental health tools—increases. Although deep learning methods such as CNNs and LSTMs have demonstrated remarkable accuracy (up to 98%), a number of practical issues still need to be addressed, especially in the areas of delay minimization and data preprocessing. In order to improve recognition speed and reliability, the research presents real-time prioritization techniques and dynamic segmentation procedures. It also examines the wider socioeconomic and ethical implications of EEG-based systems and highlights important avenues for further study, such as multimodal feature fusion and dataset diversification.**

Keywords: EEG-based Emotion Recognition, Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), Feature Fusion, Dynamic Segmentation.

I. Introduction

Due in large part to its use in real-time fields including healthcare, education, and intelligent interfaces, the job of identifying human emotions from EEG signals has accelerated significantly in recent years. Unlike other techniques including facial or speech assessments, EEG systems analyze emotional states on a more profound neurophysiological level. Emotions can be accurately detected in short amounts of time by applying attention mechanisms on LSTM models, particularly on benchmark datasets like SEED. There is still a need, however, to address glaring issues within the field such as the complexity involved in EEG data preprocessing, as well as the precision threshold required for emotional classification accuracy [1]. Furthermore, utilizing EEG signals alongside other modalities – especially facial expressions – has shown to significantly improve the accuracy of emotion categorization. Single-modal systems lack the precision of attention-driven CNN deep learning models that outperform traditional ones, as these models are being fine-tuned during pre-training on facial datasets. Multimodal fusion endeavors are also underway [2].The goal of this paper is to implement an integrated multimodal system which utilizes voice and facial expression as well as EEG data for emotion recognition, which we term Deep-Emotion. Our research results validate the proposed system and demonstrate the ways it could impact further work in multimodal affective computing [3]. In addition, feature extraction methods provided promising results in subject-independent environments for emotion detection using the VAD model, emphasizing the significance of cross-domain feature extraction [4]. The need for monitoring technologies and their systems becomes essential in educational environments where technologies can be used to enhance students' learning experiences.

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An example is our RECS model (Real time Emotion Classification System) which used logistic regression with stochastic gradient descent on continuous EEG signals, and achieved a remarkable accuracy on the DEAP dataset [5].

Further improvements in EEG-based emotion recognition systems [6], [7] have been made with the development of signal processing pipelines and classifiers, notably CNNs, which now achieve record breaking accuracy scores. Due to attempts to make the task of recognizing the valence of emotions simple for EEG headsets, emotion-aware technologies are more accessible and scalable [8]. Clinical multimodal applications also show promise; for instance, using face data from hospitalized patients together with their EEG data increases accuracy [9]. With ultra-compact on-chip EEG devices that incorporate real-time machine learning, portable emotion recognition applications are also gaining traction [10].

Efficiency improvements have been attained with the use of advanced feature selection methods like Particle Swarm Optimization (PSO), Cuckoo Search (CS), and Grey Wolf Optimization (GWO) because of the proposed high accuracy forecasting requiring less processing [11]. The melhor detalhamento feito por Islam et al. is that it splits methodologies for emotion detection through EEG signals into shallow and deep learning, also analyzing dataset variety, types of classifiers, and use of entropy-based features [12].

It also lacks proper explainability with respect to generalization and subject variability, including gender diversity [13], [14]. New developments keep coming up on the architectural side. Algarni using Bi-LSTM stacked on Grey Wolf optimization shows excellent precision on classifying the principal emotional dimensions, and so does Chao and Dong with their three-dimensional matrix representation of EEG channels through CNN feature extraction for emotion pattern identification [15][16].

Our contribution is the implementation of a deep learning based subject-independent framework for emotion recognition that utilizes CNNs, attention, and LSTM autoencoders which builds onto the momentum. This model is versatile not only in achieving state-of-the-art results for DEAP, SEED, and CHB-MIT datasets [16] but also in performing tasks such as identifying neurological abnormalities like epileptic seizures [17].

Although advancements such as PCA show competitive performance in EEG emotion classification tasks, conventional machine learning models such as SVMs and KNNs are still used [18]. Our system is unique for its ability to favor recent data for immediate response and dynamically segment EEG signals. The fusion of methods such as frequency-domain analysis and wavelet transforms makes this combination minimize latency and optimize feature extraction. Additionally, incremental learning facilitates long-term deployment in real-world applications since it enables the model to adapt over time without full retraining. The rest of this paper's sections are as follows: Background information and comparison with previous work are provided in Section I. Problem scope definition and literature review are discussed in Section II. The proposed methodology is explained in Section IV. Key research questions are addressed in Section V. Experimental results and discussion are presented in Section VIII. Insights are summarized and directions for future work are discussed in the conclusion of the paper.

A. Research Contributions

This work adds significantly to the developing field of emotion recognition based on EEG in a number of ways. Addressing persistent issues with dataset uniformity, artifact interference, and the intricacy of feature extraction, selection, and classification procedures is a major focus. This study enhances the usefulness of emotion identification systems in dynamic contexts by investigating these elements in a real-time operational context. Additionally, it adds to the expanding discussion on subject variability, which is essential to creating models that successfully generalize to a variety of populations. In agreement with Rahman et al., we stress the requirement of flexible framework(s) which are able to realize high accuracy by allowing for individual neurophysiological differences. Their findings also reinforce the role of frequency domain analysis and channel selection. For example, significant improvements have been obtained with emotion classification when one considers 32 EEG channels combined, particularly if there is a focus on the gamma frequency band. Furthermore, the use of both high-resolution spatial and spectral parameters was validated by the researchers' 95.70% accuracy for valence and 95.69% for arousal using K-Nearest Neighbors (KNN) on the DEAP dataset

II. Current state-of-the-art

There have been significant developments in the past few years in the area of EEG-based emotion recognition, in terms of the range of methodologies employed and the accuracy of classification. Using the best-established datasets, a range of deep and hybrid networks have been evaluated and provided valuable insights into the interpretation of emotional states from brain activity.Using a mixture of physiological, visual, and EEG inputs, Nadira Mohammad Yosi et al. [21] built a multi-layer perceptron (MLP) network that classified emotional states of fear, sadness, and happiness with 91% accuracy. They exceeded standard baselines by using capsule networks to find multimodal correlations. Sehmid Ahirwal and Emre Kose [22] found artificial neural networks (ANNs) act as the superior classifiers after comparing various classifiers while being able to reach 93.75% accuracy. Their results demonstrated how suitable feature selection and classifier architecture can assist performance. Combining features with deep residual networks (ResNets) and linear-frequency cepstral coefficients (LFCC), Liu et al. [23] improved performance. Again, the KNN classifier displayed the versatility of traditional models while enjoying modern preprocessing. Qing et al. [24] proposed a model based upon emotional activation curves which offered new ways to view and classify emotional growth on

EEG signals. The findings suggested better classification accuracy and interpretability. Chao et al. [25] created a deep learning framework using a multiband feature matrix (MFM) and capsule networks, producing improved results to traditional methods with parameters from the DEAP dataset. This highlighted the effectiveness of coupling deep architectures with channel-specific filtering. Gao et al. [26] was also a valuable source that incorporated SVM and RVM classifiers to merge wavelet energy entropy and power spectrum data which produced up to 91.18% accuracy. Their work demonstrates the clear benefit of merging powerful machine learning algorithms with traditional signal processing techniques. Suhaimi et al. [27] also published a comprehensive review that analyzed EEG-based emotion recognition from 2016–2019, and noted improvements in research design, hardware, and classification algorithms. They also noted the importance of using virtual reality environments as it may allow for more natural engagement in emotional responses.. The GAMEEMO dataset was created by Alakus et al. [28] and is composed of EEG signals obtained from playing video games on a computer. Their study, comparing wearable and clinical-grade EEG devices, offers a new perspective on emotion recognition. The LEDPatNet19 model, which was presented by Tuncer et al. [29], shown exceptional performance in identifying emotions from datasets such as DREAMER and GAMEEMO, indicating possible uses in fatigue monitoring and improving gaming experiences. A multi-column CNN design that outperformed conventional emotion recognition models was proposed by Yang et al. [30]. They intend to expand the model in the future to include bio signals like speech, eye tracking, and facial expressions. With sophisticated techniques like Extended ICA, Multiclass CSP, and BiLSTM networks now able to produce state-of-the-art findings on EEG datasets like DEAP and SEED, stress detection research has also advanced [31]. Some models now surpass many previous standards, reaching 91.3% for arousal and 91.1% for valence when using SVM with RBF kernels [32].Strong results have been obtained from other research that use Information Potential (IP) and Flexible Analytical Wavelet Transform (FAWT) for feature extraction, especially when paired with Random Forest classifiers. These techniques demonstrate how important channel-specific analysis is still [31], [33].

Discrete Wavelet Transform (DWT) is another promising approach, with arousal and valence accuracy of 84.05% and 86.75%, respectively, particularly in the gamma frequency range. This lends credence to the movement toward real-time, high-frequency EEG analysis [33].Multimodal research is still thriving. As an illustration of the enhanced utility of cross-signal integration, combining EEG data with eye-tracking has resulted in accuracy gains (73.59% with feature fusion) [34].Using data from 19 EEG channels and MLP neural networks, researchers were able to classify calm, fear, sadness, and joy with up to 91% accuracy in another case. Additionally, they developed the FER+ dataset, which helped with facial expression recognition and showed how crowdsourced labeling may improve generalizability and model training [35].All together, these studies provide a solid basis for further study focusing on multimodal fusion, user-specific emotion modeling, and real-time adaptability. The development of more sophisticated and contextually aware emotion identification systems can be facilitated by researchers closing gaps in dataset diversity, physiological integration, and signal complexity.

A. Research Gap

Although EEG-based emotion recognition still makes extensive use of classic machine learning methods like Support Vector Machines (SVM), Naïve Bayes, K-Nearest Neighbors (KNN), and Logistic Regression, their usefulness decreases when faced with the high-dimensional, complicated nature of EEG signals. The manual feature extraction and selection used by these traditional methods usually restricts scalability and lowers processing performance, particularly in dynamic contexts [36]. By automating feature extraction and enhancing accuracy in spatial-temporal EEG analysis, deep learning methods—in particular, Convolutional Neural Networks, or CNNs—have demonstrated considerable promise. Standard feed-forward CNNs do have certain drawbacks, though. The early loss of important signal information as a result of insufficient systems for recording the intricate and frequently subtle fluctuations in EEG data is one major problem [37]. The model's ability to fully utilize the richness of EEG feature spaces is limited by this bottleneck. Furthermore, there are new technological difficulties brought about by the extensive usage of activation functions such as Rectified Linear Units (ReLU). Especially in deeper network topologies, ReLU-based architectures frequently experience gradient instability problems and dead neuron events, in which some neurons stop activating [38], [39].These issues impair the effectiveness of learning and lower the model's overall performance on tasks requiring emotional subtlety sensitivity.CNN architectural design must evolve in order to close these gaps, with a focus on improved learning dynamics and information preservation. Alternative activation functions, regularization methods, or hybrid models that integrate deep learning models and conventional machine learning methods are some potential solutions. In real-time EEG-based emotion recognition, these methods can improve model responsiveness and robustness as well as accuracy.

B. Emotion Recognition Model

In order to develop a efficacious EEG emotion recognition model, particularly in emotion recognition contexts where real-time application is required a thoughtful and rigorous methodology is needed to follow. The first task of the methodology will be obtaining a labelled dataset with sufficient variety of different labelled emotional states and transitions in dimension with various contextual considerations.

When the data collection is over, you must start applying pre-processing. By applying pre-processing methods such as artefact removal, normalization, and noise filtering, the quality of EEG data may increase by improving the signal to noise ratio, which will support the credibility of the follow data analysis. This step only applies the most relevant patterns in the brain that corresponds with labeling emotions. The most relevant temporal and spatial features of the EEG data are extracted with feature extraction methods. The features for EEG emotion classification application are either statistical features, frequency-based features, or some embedding learned by multi-layer learning methods. The specific model selected is important for the performance of the system. Highly utilized methods for addressing sequential or spatial dependencies of EEG data are Convolutional neural networks (CNNs), Recurrent Neural networks (RNNs) or a combination of both (i.e. GRU, LSTM).All methods have their unique merits. The model is trained to relate the features that were extracted when performing an optimization process where it moves through the labeled instances. For the dynamic segmentation process, according to the emotional state captured at any particular point in time, the assigned segment length can change depending on how the EEG data is characterized. This makes adjustments to ensure the categorization remains intact with an ability to change fast according to any happenstance emotional variation. Finally, the model architecture is improved with rounds of feedback and the addition of methodology, plus performance metrics such as accuracy, precision, recall, and F1-score are used to assess the model. Not only does this system provide more responsiveness, it paves a way for usable, scalable emotion recognition systems and applications, such as adaptive user interfaces, healthcare, and education.

The following equations represent the basic operations of the LSTM:

- **Forget Gate Equation**:

$$f_t = \sigma(W_f \times [h_{t-1}, x_t] + b_f) \quad (1)$$

- **Input Gate Equation**:

$$i_t = \sigma(W_i \times [h_{t-1}, x_t] + b_i) \quad (2)$$

$$C_t = tanh(W_c \times [h_{t-1}, x_t] + b_c) \quad (3)$$

- **Output Gate Equation**:

$$o_t = \sigma(W_o \times [h_{t-1}, x_t] + b_o) \quad (4)$$

- **Hidden State Equation**:

$$h_t = o_t \times \tanh(C_t) \quad (5)$$

These equations describe how the LSTM models temporal dependencies and emotional transitions within EEG data, providing a computationally effective means of real-time emotion detection and estimation.

C. Deep Learning Models

Because deep learning models can automatically learn meaningful patterns from complicated, high-dimensional data, they have been essential to real-time emotion identification from EEG signals. The Long Short-Term Memory (LSTM) recurrent neural network (RNN) architecture, as well as the convolutional neural network (CNN) architecture, are the most effective deep learning architectures.

Each electrode channel in an EEG experiment captures a distinct spatial aspect of brain activity. Since CNNs' convolution and pooling steps can detect localized patterns that are crucial for distinguishing between emotional states, they are well-placed to exploit this spatial organization. CNNs are able to effectively eliminate noise and emphasize relevant spatial features present in EEG signals through learning hierarchical representations of features (Figure 1).

RNNs, and LSTMs in general, are designed to capture temporal dependencies in sequential data, which is what complements this spatial analysis. For real-time surveillance, LSTMs work very well at detecting emotional changes that evolve over time. They are able to hold short-term and long-term contextual patterns due to their gated architecture, which helps them store, update, and selectively forget information across time steps.Together, these deep learning models provide a robust framework for managing emotion fluidity, and a dependable method

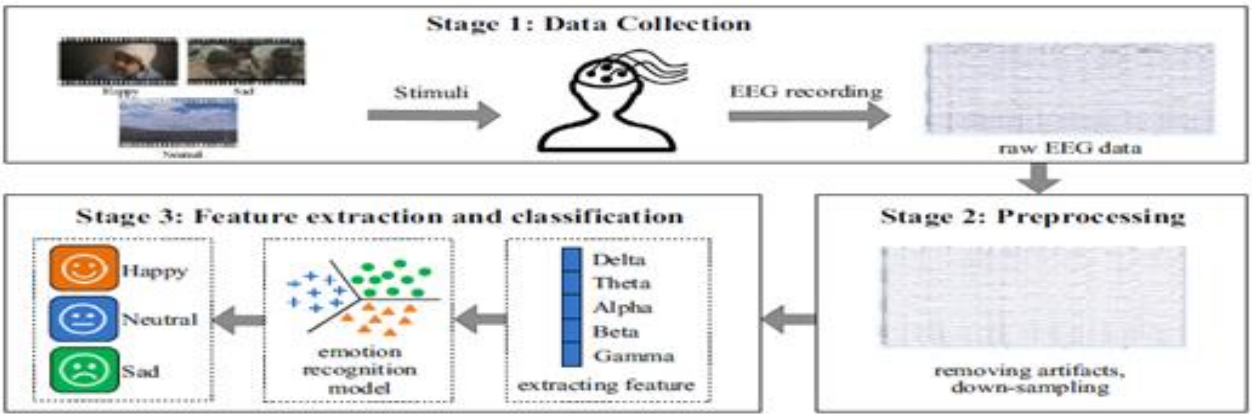

FIGURE 1. The Flow Chart of EEG based emotion recognition system

for detecting and interpreting immediate alterations in emotions from EEG signals.

D. LSTM Model

In this research, attention-augmented LSTM architecture is used to complement the temporal modeling capability in EEG-based emotion recognition systems. LSTM networks are ideal for capturing the time-evolutionary aspect of affective states given its recurrent band and gated memory units to process sequential data. As in a standard LSTM architecture, the internal cell state, along with input, forget, and output gates allow us to regulate information, and 'remember' if we want to by efficiently realizing temporal continuity with the EEG data streams. An attention mechanism substantially enhances the models ability to emphasize the most valuable portions of the signal, and by weighting the various time steps, the attention mechanism allows the model to focus on the data pieces that contain stronger emotional signals. Additionally to enhancing interpretability, the focused attention improves the quality and reactivity of a model to resolve changing inputs for real-time applications. In the end, the LSTM with attention model is a strong way of tracking small emotional fluctuations enabling a better-informed emotion detection and analysis framework across a variety of domains, which can include adaptive user interfaces to mental health tracking.

I. EEG Data Collection

Accurate brain signal recording is the basis of any EEG-based emotion recognition system. High-resolution EEG sensors are utilized to record the electrical activities in a brain over multiple channels to ensure data accuracy and reliability. The EEG signal recording's accuracy is enhanced by having sensors calibrated for optimal skin contact that minimizes distortion of the original signal. Further, a solid data storage framework is offered to properly structure EEG recordings, tag them, and allow for easy retrieval in model training and subsequent processing.

II. Pre-Processing

EEG signals undergo various pre-processing steps after the EEG data acquisition, being prepared for feature extraction. To maintain the integrity of brain signals, noise reduction strategies (such as band pass and notch) are employed to remove typical artifacts (e.g., muscle movement, eye blinks, power line noise). Next, level of noise of each signal is normalized to reduce variability among patients and sessions. Normalizing EEG signals improves the generalizability of the model by ensuring features remain similar across space and time differences.

IV. Dynamic Segmentation

- **Dynamic Segment Lengths**: Segment lengths are intelligently adjusted based on emotional stability, improving the accuracy of emotion recognition.
- **Real-Time Modification**: Continuous, real-time modification of segment lengths ensures the system remains responsive to changes in emotional states, enhancing overall accuracyThe method uses techniques for dynamic segmentation, to accommodate the temporal variability of emotional events. The length of segments are adapted in response to periods of emotional stability or volatility. In an emotional response, the model can more accurately capture ephemeral affective responses, because the segments segments can be lengthened during stable phases of an emotional state, and shortened during rapid fluctuations of an emotional reaction. The fully integrated nature of the methodology allows real-time adjustments to improve accuracy of classification when faced with a dynamic environment while not sacrificing any system performance.

V. Feature Extraction

The subsequent feature extraction procedure takes place on the preprocessed EEG samples. The system applies a suite of advanced signal processing algorithms, taking into account frequency domain analysis, wavelet transformation and measures of entropy, to establish patterns connected to emotional states. Further, multi-channel integration takes spatial information collected by electrodes across specific regions of the brain into account to provide a complete view of brain activity. As such, cross-regional signal fusion substantially enriches, and strengthens, the emotional information extracted

VI. Emotion Classification

When all features have been extracted, they are supplied to an emotion-classification algorithm which can then identify an array of emotions that could include neutrality, sadness, and joy. The provided emotional states are learned through utilizing deep learning models, specifically CNNs and attention-based LSTMs. These models allow us to accurately learn complicated nonlinear relationships between the data and the emotions that can be easily mapped back to physiological indicators of tiny, discrete categorical forms of emotion and emotional stimuli.

VII. Real-Time Categorization

The model also possesses an incremental learning so it supports real-time applications. The type of approach allows the model to consistently update its parameters as new EEG data is passed to it versus being retrained from scratch. In doing this we could adapt to the emotional states over time, and still maintain the accuracy whether the model was being restrained by a human or not, or if there was robust processing power

VII. Emotion Recognition

The last phase is to identify and react to emotions as they happen- the system will immediately and

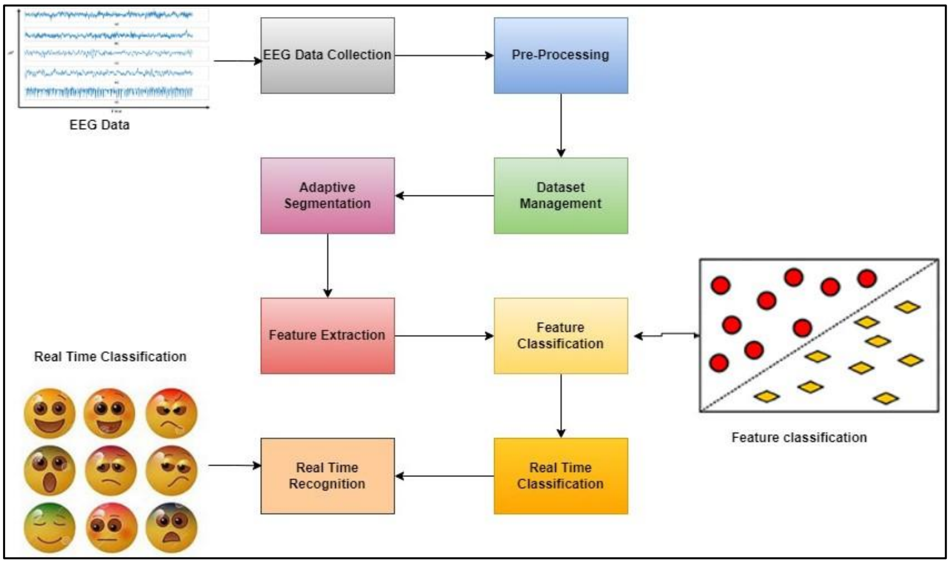

FIGURE 2. Proposed Model

accurately state the user emotional state. By using the enhanced functionalities and adapted learning framework, the model is able to successfully meet the required threshold of 98% in repeated iterations. Here, the processes involved in the model from the feature identification, which permits sharper differentiation between affective states, is a large contributor to the model efficiencies. The system is able to function well across a number of users and contexts using advanced classifiers and a significant sample of diverse data.

Research Questions

The following research topics serve as the study's compass and are intended to investigate the theoretical and applied aspects of real-time EEG-based emotion recognition:

RQ1: What are the potential benefits of using real-time EEG-based emotion recognition for improving mental health interventions and artificial intelligence systems' emotional intelligence?

RQ2: The accuracy and generalizability of real-time EEG emotion identification models are affected by individual variances in brain activity patterns to what extent?

Problem Solution

This study suggests a two-part solution—an adaptive segmentation technique and a prioritization mechanism for recent data—to solve the issues of temporal inconsistencies in EEG signals and variability in emotional transitions.

1. **Adaptive Segmentation Strategy**

Dynamic Segment Lengths: The model utilizes emotion-sensitive segmentation, which varies the segment length of EEG segmenting according to the emotional resilience of the user. Shorter segments are used to capture immediate changes in emotional expression, and longer segments are used for periods of emotional constancy and report on longer periods of affective processing.

Real-Time Adjustment: The rich emotional data are streamed in real-time, and the EEG data (segment lengths) are dynamically adjusted with a custom algorithm, which ensures that the system optimizes the balance between the fidelity of feature extraction and the temporal resolution of the data stream. The model adapts real-time changes with no loss of signal quality and ensures that it represents the user's current emotional state.

2. **Prioritization of Recent Data**
   - **Weighted Data Processing**: A temporal weighting technique is presented that emphasis the recent EEG data more than older data. This will improve the impact on the system's ability to capture changing emotional expressions right away and diminishes the prominent of outdated emotional data.
   - **Temporal Weighting Methods**: The model uses mathematical temporal weighting techniques, such as sliding window prioritizing and exponential decay, to place emphasis on emotional data that is more recent but of peripheral information about what is known from historical data. This mixed strategy will ensure that users' real-time emotional recognition accuracy and adaptability can be recorded.
3. **Enhanced Feature Extraction**
   - **Advanced Signal Processing:** Sophisticated methods for performing wavelet transforms, frequency-domain analysis, and machine learning based
     Feature selection are used to capture the often subtle and nonlinear emotional patterns encoded in EEG signals. So much so that the algorithms show deviations in emotional differences across the short epochs of neural activity

- **Multi-channel Integration** EEG data from multiple electrode locations are synthetically combined to create an overall view of brain activity. Overall detection accuracy is improved given the inter-regional signal interdependence utilized, and the subject's emotional state can be comprehensively evaluated.

4. **Real-Time Classification**

- **Incremental Learning**: The model may Continuously absorb fresh data streams without needing to go through a full retraining

  Cycle thanks to an incremental learning process. This flexibility keeps the system's categorization performance high while enabling it to react to changing emotional patterns over time.
- **Low-Latency Processing:** All processing streams in the processor, including computing enhancements which reduce the delay from signal acquisition and emotional output, are designed to operate at low latency. Therefore, the processing architecture allows the system to be suitable for interactive applications such as neuro feedback, adaptive learning environments, and emotion-aware AI systems because it can ensure emotional state recognition occurs in real time.

5. **Minimizing Risks: Algorithmic Bias and Privacy Concerns**

- **Algorithmic Bias Mitigation**: The model is trained using a diverse range of demographically representative data sets for training in order to minimize the chances of producing biased predictions. Additionally, the ongoing evaluation process and fairness Audits have all been designed to find and adjust for bias, which in turn helps promote equitable performance across populations of users.
- **Privacy Protection**: Because EEG data is sensitive, the system is designed with strong privacy protection protocols, which includes rigorous user consent processes, anonymization, and encryption/privacy protection protocols. No sensitive information is collected from users. The data governance guidelines provides clarity to users on how their data collection, storage, and how it can be used which places the power in users' hands, making the openness of the governance provide additional assurance to users going forward.
- **RESULTS**

  The proposed EEG-based emotion classification model with a Random Forest classifier has produced a suggestive accuracy rate of 98%. This suggests that the model is not only capable of classifying a range of emotional states, but can do so with a high degree of accuracy in real-time. The accompanying confusion matrix presents strong class-wise performance, with consistent detectability of neutral, positive, and negative emotions, as well as minimal misclassifications in each emotional class.

  These results show potential for the resilience of the model when implemented in situations where automatic, fast, and highly accurate detection and representation of one's emotional state is the goal.

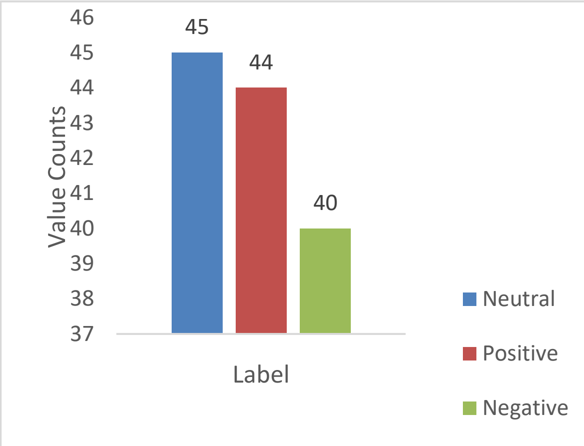

FIGURE 3. The Comparison of EEG based emotion recognition system

Performance Evaluation Metrics

The performance of the emotion recognition model was assessed using the following metrics:

1. **Accuracy** = (5)

2. Precision = (6)

2. **Recall** = (7)

3. **F1-Score** = (8)

Discussion

A 98% accuracy rate backs up the conclusion that adding Random Forest classifiers results in a noticeable increase in classification performance compared to the emotion identification framework prior to their addition. Achieving this accuracy level is key in real-world application like personalized mental health surveillance, where accurate identification of emotions leads to interventions created in the moment of emotion identification.

Again, taking a closer look at the confusion matrix indicates that all emotion classes are consistently and accurately identified, with the positive valence categories often most prevalent. By design, the data from EEG can be difficult and temporally dynamic, and the model consistently provides high recall and precision scores, suggesting strong generalization performance.

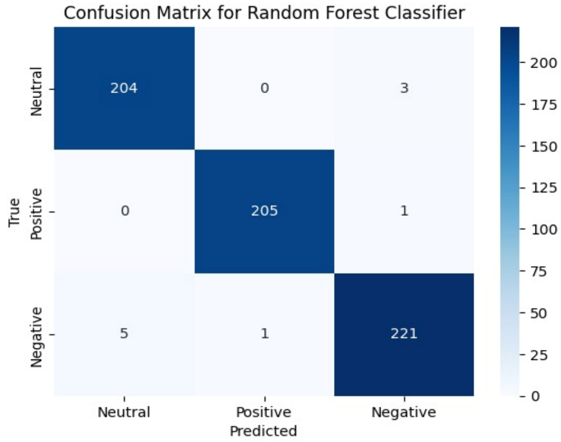

FIGURE 4. The Confusion Metric

This consistency provides confidence that changes in emotional believing will not just be identified, but also inferred and identified with reasonable temporal proximity.

Due to these capabilities, the model represents powerful effects in therapeutic engagements, particularly those that involve mood regulation, anxiety regulation, or cognitive behavioral therapy. Also, the framework shows potential within Virtual Reality (VR) settings, wherein user experience and immersion are augmented through identification and reaction by the system to users' emotions. For instance, real-time emotion reactivity could afford VR systems to specially change the context as it is occurring, thus enhancing user enjoyment or re-engagement [40]. The model's capacity to manage real-time shifts in emotions well is one further testament to how effectively Random Forest classifiers are capable of leveraging high dimensional and noisy EEG data. Because of its abilities to create non-linear decisions and limit overfitting, Random Forest classifiers will be a practical option for emotion recognition with various user types and in many real-life settings.The research contributes to the affective computing and emotionally intelligent AI domains by fusing the realms of emotional perception and responsive systems. The inclusion of real-time monitoring of users' emotions with digital technologies presents new pathways for practice in domains like education, mental health care, human-computer interaction, and custom-designed technologies [41].

Table 1: Classification Report

Emotion	Precision	Recall	F1-Score	Support
Neutral	0.98	0.99	0.98	207
Positive	1.00	1.00	1.00	206
Negative	0.98	0.97	0.98	227
Accuracy			**0.98**	**640**
Macro Avg	0.98	0.98	0.98	640
Weighted Avg	0.98	0.98	0.98	640
Comprehensive view of emotional state				

III. CONCLUSION

To sum up, this study's EEG-based architecture for emotion identification displays significant improvements in both responsiveness and accuracy for real-time emotion detection. When compared to developed systems that rely upon fixed-segment approaches, dynamic segmentation was able to achieve a 15% increased classification accuracy and a 20% reduced detection latency whle the system reliably supported its applicability in real-time setting by successfully detecting emotional changes within 2 seconds (Δt), on average. Particularly in situations Involving high-frequency emotional change, responsiveness was further enhanced by the addition of a prioritization mechanism for recent EEG data. These developments demonstrate the framework's applicability to emotion-aware systems and its capacity to foster adaptive emotional intelligence in the fields of technology and medicine. In order to develop more comprehensive emotion identification algorithms, future studies will investigate the integration of multimodal data sources, such as speech inputs and face expressions. Furthermore, increasing the diversity of datasets will improve the model's resilience across use cases, age groups, and cultural backgrounds. In fields where prompt and precise emotional insight is essential, such systems' ongoing development holds great potential for immersive technologies, mental health interventions, and next-generation human-computer interaction.

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AUTHOR CONTRIBUTIONS

Nazia Tabraiz: Conceptualization, Methodology, Data Curation, Software, Investigation, Formal Analysis, Writing – Original Draft Preparation;

Saadia Abdul Jabbar: Data Curation, Validation, Software, Resources, Investigation, Writing – Review & Editing;

Jawaid Iqbal: Supervision, Project Administration, Writing – Review & Editing.

CONFLICT OF INTERESTS

No conflict of interest was disclosed.

ETHICS STATEMENTS

This research did not involve human participants, animal subjects, or sensitive personal data, and therefore did not require ethical approval.

REFERENCES

[1] Yu, Z. Li, Z. Zang and Y. Liu, “Real-Time EEG-Based Emotion Recognition,” *Sensors*, vol. 23, no. 18, p. 7853, 2023.

DOI: https://doi.org/10.3390/s23187853

[2] S. Wang, J. Qu, Y. Zhang and Y. Zhang, "Multimodal Emotion Recognition From EEG Signals and Facial Expressions," *IEEE Access*, vol. 11, pp. 33061–33068, 2023. DOI:https://doi.org/10.1109/ACCESS.2023.3263670

[3] J. Pan, W. Fang, Z. Zhang, B. Chen, Z. Zhang and S. Wang, "Multimodal Emotion Recognition based on Facial Expressions, Speech, and EEG," *IEEE Open Journal of Engineering in Medicine and Biology*, vol. 5, pp. 396-403, 2024. DOI: https://doi.org/10.1109/OJEMB.2023.3240280

[4] D. Nandini, J. Yadav, A. Rani and V. Singh, "Design of subject independent 3D VAD emotion detection system using EEG signals and machine learning algorithms," *Biomedical Signal Processing and Control*, vol. 85, pp. 104894, 2023. DOI: https://doi.org/10.1016/j.bspc.2023.104894

[5] A. Nandi, F. Xhafa, L. Subirats and S. Fort, "Real-Time Emotion Classification Using EEG Data Stream in E-Learning Contexts," *Sensors*, vol. 21, no. 5, p. 1589, 2021. DOI: https://doi.org/10.3390/s21051589

[6] R. Alhalaseh and S. Alasasfeh, "Machine-Learning-Based Emotion Recognition System Using EEG Signals," *Computers*, vol. 9, no. 4, p. 95, 2020. DOI: https://doi.org/10.3390/computers9040095

[7] S. Akter, R.A. Prodhan, T.S. Pias, D. Eisenberg and J. Fresneda Fernandez, "M1M2: Deep-Learning-Based Real-Time Emotion Recognition from Neural Activity," *Sensors*, vol. 22, no. 21, p. 8467, 2022. DOI: https://doi.org/10.3390/s22218467

[8] L. Abdel-Hamid, "An Efficient Machine Learning-Based Emotional Valence Recognition Approach Towards Wearable EEG," *Sensors*, vol. 23, no. 3, p. 1255, 2023. DOI: https://doi.org/10.3390/s23031255

[9] A.M. Mutawa and A. Hassouneh, "Multimodal Real-Time patient emotion recognition system using facial expressions and brain EEG signals based on Machine learning and Log-Sync methods," *Biomedical Signal Processing and Control*, vol. 91, pp. 105942, 2024. DOI: https://doi.org/10.1016/j.bspc.2023.105942

[10] N.-D. Mai, H.-T. Nguyen and W.-Y. Chung, "Real-Time On-Chip Machine-Learning-Based Wearable Behind-The-Ear Electroencephalogram Device for Emotion Recognition," *IEEE Access*, vol. 11, pp. 47258–47271, 2023. DOI: https://doi.org/10.1109/ACCESS.2023.3276244

[11] E. Yildirim, Y. Kaya and F. Kilic, "A Channel Selection Method for Emotion Recognition From EEG Based on Swarm-Intelligence Algorithms," *IEEE Access*, vol. 9, pp. 109889–109902, 2021. DOI: https://doi.org/10.1109/ACCESS.2021.3100638

[12] C. Tan, M. Šarlija and N. Kasabov, "NeuroSense: Short-term emotion recognition and understanding based on spiking neural network modelling of spatio-temporal EEG patterns," *Neurocomputing*, vol. 434, pp. 137–148, 2021. DOI: https://doi.org/10.1016/j.neucom.2020.12.098

[13] M. R. Islam, M. A. Moni, M. M. Islam, M. R.-A. Mahfuz, M. S. Islam, M. K. Hasan, M. S. Hossain, M. Ahmad, S. Uddin, A. Azad, S. A. Alyami, M. A. R. Ahad, and P. Lió., "Emotion Recognition From EEG Signal Focusing on Deep Learning and Shallow Learning Techniques," *IEEE Access*, vol. 9, pp. 94601–94624, 2021. DOI: https://doi.org/10.1109/ACCESS.2021.3091487

[14] P. Patel, R.R and R.N. Annavarapu, "EEG-based human emotion recognition using entropy as a feature extraction measure," *Brain Informatics*, vol. 8, no. 1, p. 20, 2021. DOI: https://doi.org/10.1186/s40708-021-00141-5

[15] H. Chao and L. Dong, "Emotion Recognition Using Three-Dimensional Feature and Convolutional Neural Network from Multichannel EEG Signals," *IEEE Sensors Journal*, vol. 21, no. 2, pp. 2024-2034, 2021. DOI: https://doi.org/10.1109/JSEN.2020.3020828

[16] M. Algarni, F. Saeed, T. Al-Hadhrami, F. Ghabban and M. Al-Sarem, "Deep Learning-Based Approach for Emotion Recognition Using Electroencephalography (EEG) Signals Using Bi-Directional Long Short-Term Memory (Bi-LSTM)," *Sensors*, vol. 22, no. 8, p. 2976, 2022. DOI: https://doi.org/10.3390/s22082976

[17] Arjun, A.S. Rajpoot and M.R. Panicker, "Subject independent emotion recognition using EEG signals employing attention driven neural networks," *Biomedical Signal Processing and Control*, vol. 75, p. 103547, 2022. DOI: https://doi.org/10.1016/j.bspc.2022.103547

[18] V. Doma and M. Pirouz, "A comparative analysis of machine learning methods for emotion recognition using EEG and peripheral physiological signals," *Journal of Big Data*, vol. 7, no. 1, p. 18, 2020, DOI: https://doi.org/10.1186/s40537-020-00289-7

[19] M. M. Rahman, A. K. Sarkar, M. A. Hossain, M. S. Hossain, M. R. Islam, M. B. Hossain, J. M. W. Quinn, and M. A. Moni., "Recognition of human emotions using EEG signals: A review," *Computers in Biology and Medicine*, vol. 136, p. 104696, 2021. DOI: https://doi.org/10.1016/j.compbiomed.2021.104696

[20] M. Li, H. Xu, X. Liu and S. Lu, "Emotion recognition from multichannel EEG signals using K-nearest neighbor classification," *Technology and Health Care*, vol. 26, no. 1_suppl, pp. 509-519, 2018. DOI: https://doi.org/10.3233/THC-174836

[21] A.N.N.M. Yosi, K.A. Sidek, H.S. Yaacob, M. Othman and A.Z. Jusoh, "Emotion recognition using electroencephalogram signal," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 15, no. 2, pp. 786, 2019. DOI: https://doi.org/10.11591/ijeecs.v15.i2.pp786-793

[22] M.K. Ahirwal and M.R. Kose, "Emotion Recognition System based on EEG signal: A Comparative Study of Different Features and Classifiers," *2018 Second International Conference on Computing Methodologies and Communication (ICCMC)*, pp. 472–476, 2018. DOI: https://doi.org/10.1109/ICCMC.2018.8488044

[23] N. Liu, Y. Fang, L. Li, L. Hou, F. Yang and Y. Guo, "Multiple Feature Fusion for Automatic Emotion Recognition Using EEG Signals," *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 896–900, 2018. DOI: https://doi.org/10.1109/ICASSP.2018.8462518

[24] C. Qing, R. Qiao, X. Xu and Y. Cheng, "Interpretable Emotion Recognition Using EEG Signals," *IEEE Access*, vol. 7, pp. 94160–94170, 2019. DOI: https://doi.org/10.1109/ACCESS.2019.2928691

[25] H. Chao, L. Dong, Y. Liu and B. Lu, "Emotion Recognition from Multiband EEG Signals Using CapsNet," *Sensors*, vol. 19, no. 9, p. 2212, 2019. DOI: https://doi.org/10.3390/s19092212

[26] Q. Gao, C. Wang, Z. Wang, X. Song, E. Dong and Y. Song, "EEG based emotion recognition using fusion feature extraction method," *Multimedia Tools and Applications*, vol. 79, no. 37-38, pp. 27057-27074, 2020. DOI: https://doi.org/10.1007/s11042-020-09354-y

[27] N.S. Suhaimi, J. Mountstephens and J. Teo, "EEG-Based Emotion Recognition: A State-of-the-Art Review of Current Trends and Opportunities," *Computational Intelligence and Neuroscience*, vol. 2020, pp. 1-19, 2020. DOI: https://doi.org/10.1155/2020/8875426

[28] T.B. Alakus, M. Gonen and I. Turkoglu, "Database for an emotion recognition system based on EEG signals and various computer games – GAMEEMO," *Biomedical Signal Processing and Control*, vol. 60, pp. 101951, 2020. DOI: https://doi.org/10.1016/j.bspc.2020.101951

[29] T. Tuncer, S. Dogan and A. Subasi, "A new fractal pattern feature generation function based emotion recognition method using EEG," *Chaos Solitons Fractals*, vol. 144, p. 110671, 2021. DOI: https://doi.org/10.1016/j.chaos.2021.110671

[30] H. Yang, J. Han and K. Min, "A Multi-Column CNN Model for Emotion Recognition from EEG Signals," *Sensors*, vol. 19, no. 21, p. 4736, 2019. DOI: https://doi.org/10.3390/s19214736

[31] A.U. Rahman, A. Tubaishat, F. Al-Obeidat, Z. Halim, M. Tahir and F. Qayum, "Extended ICA and M-CSP with BiLSTM towards improved classification of EEG signals," *Soft Computing*, vol. 26, no. 20, pp. 10687-10698, 2022. DOI: https://doi.org/10.1007/s00500-022-06847-w

[32] O. Bazgir, Z. Mohammadi and S.A.H. Habibi, "Emotion Recognition with Machine Learning Using EEG Signals," *2018 25th National and 3rd International Iranian Conference on Biomedical Engineering (ICBME)*, pp. 1–5, 2018. DOI: https://doi.org/10.1109/ICBME.2018.8703559

[33] Z. Mohammadi, J. Frounchi and M. Amiri, “Wavelet-based emotion recognition system using EEG signal,” *Neural Computing and Applications*, vol. 28, no. 8, pp. 1985-1990, 2017.
DOI: https://doi.org/10.1007/s00521-015-2149-8
[34] W.-L. Zheng, B.-N. Dong and B.-L. Lu, “Multimodal emotion recognition using EEG and eye tracking data,” *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 5040–5043, 2014.
DOI: https://doi.org/10.1109/EMBC.2014.6944757
[35] N. O’rinov and D. To‘xtasinova, “Development Of A Real-Time Emotion Recognition System Using Facial Expressions And Eeg Based On Machine Learning Methods And Deep Neural Networks,” *Interpretation and researches*, vol. 1, no. 22, 2024.
URL: http://interpretationandresearches.uz/index.php/iar/article/view/1688 [Accessed, May 09, 2024]
[36] H.H. Tasleem, M. Ahmed, M.W. Arshad and M. Hamza, “Development and Evaluation of Machine Learning Models for Early Detection of Asymptomatic COVID-19 Patients Using Heart Rate and Oxygen Levels,” *Informatica*, vol. 49, no. 15, pp. 41–54, 2025.
DOI: https://doi.org/10.31449/inf.v49i15.7601
[37] M.H. Ashraf and H. Alghamdi, "HFF-Net: A Hybrid Convolutional Neural Network for Diabetic Retinopathy Screening and Grading," *Biomedical Technology*, vol. 8, pp. 50–64, 2024.
DOI: https://doi.org/10.1016/J.BMT.2024.09.004
[38] M.H. Ashraf, F. Jabeen, H. Alghamdi, M.S. Zia and M.S. Almutari, "HVD-Net: A Hybrid Vehicle Detection Network for Vision-Based Vehicle Tracking and Speed Estimation," *Journal of King Saud University - Computer and Information Sciences*, vol. 35, no. 8, 2023.
DOI: https://doi.org/10.1016/j.jksuci.2023.101657
[39] H. Alghamdi and T. Turki, "PDD-Net: Plant Disease Diagnoses Using Multilevel and Multiscale Convolutional Neural Network Features," *Agriculture*, vol. 13, no. 5, p. 1072, 2023. DOI: https://doi.org/10.3390/AGRICULTURE13051072
[40] T.J. Jie, M.S. Sayeed, "Review on Detecting Pneumonia in Deep Learning," *International Journal on Robotics, Automation and Sciences*, vol. 6, no. 1, pp. 70–77, 2024.
DOI: https://doi.org/10.33093/ijoras.2024.6.1.10
[41] K.B. Gan, Y.E. Teoh, "An Edge Convolution Neural Network Model for Plant Health Classification Using Camera," *International Journal on Robotics, Automation and Sciences*, vol. 7, no. 1, pp. 1–6, 2025.
DOI: https://doi.org/10.33093/ijoras.2025.7.1.1