Optimizing Emotion Recognition in EEG Data: A Genetic Algorithm Approach with XAI Insights

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Abstract—Emotion recognition using electroencephalogram data presents a burgeoning area of research, yet navigates through intricate optimization hurdles, alongside the persistent challenge of rendering results interpretable. In this study, we employed a combination of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks and utilized a Genetic Algorithm (GA) for optimization and enhancing the model's performance and robustness in deciphering emotional states from EEG signals. Our methodology encompasses data pre-processing techniques, including Short-Time Fourier Transform (STFT) analysis, applied to EEG data for feature extraction and GA-driven hyperparameter optimization to identify an optimal neural network architecture. This architecture, consisting of Convolutional and Recurrent layers with dropout regularization, is adept at extracting temporal and spatial features from EEG signals while mitigating overfitting. Furthermore, we investigate explainable AI (XAI) strategies to get insight into the decision-making process of our GA-based optimized model. Additionally, rigorous cross-validation ensures the generalization performance of the optimized model across diverse datasets. Empirical results demonstrate the effectiveness of our approach, with the optimized CNN-LSTM hybrid model achieving an accuracy of 93.28% in classifying 24 different emotions. This study enhances our understanding of emotion recognition systems by examining the intricate interplay between EEG data analysis, CNN-LSTM networks, and Genetic Algorithm optimization. Additionally, it provides practical insights into the optimization of such systems, potentially influencing future advancements in affective computing technologies.

Index Terms—CNN-LSTM, Genetic Algorithm (GA), Explainable AI, EEG, Emotions Recognition, Optimization

I. INTRODUCTION

The human brain, an intricate organ harboring millions of neurons, orchestrates a diverse range of reactions and responses. The endeavor to unravel the complexities of the human mind has given rise to an array of techniques, all aimed at augmenting sectors such as healthcare [1], education [2], and Human-Computer Interaction (HCI) [3]. A notable subset of these endeavors is the classification of human emotions, a task that necessitates the study of brain activity.

Brain activity can be examined through two primary categories of methods: invasive and non-invasive [4]. Invasive methods, presents potential risks and ethical considerations that must be carefully managed. Conversely, non-invasive methods offer safer alternatives for studying brain activity [5]. One such method, Electroencephalography (EEG), have gained significant traction in neuroscience research due to its non-intrusive nature.

There has been significant advancement in the field of emotion recognition; studies such as [6]–[9] which aim to categorize emotions using EEG data with high accuracy and reliability. Although [10] indicates that these research have successfully recognized intense emotions, identifying and classifying more subtle, unsaturated emotions remains a difficulty. These feelings necessitate an acute differentiation in the received signal. This paper presents our research, which attempts to accurately and precisely anticipate these nuanced emotions.

In addressing these challenges and maintaining the accuracy and generalizability of previous approaches [11]–[13], we have employed a CNN-LSTM hybrid deep learning model. CNN layers are able to extract spatial information, while LSTM specializes in capturing temporal information.

Although deep neural networks are superior to classical

methods, as indicated in [14], [15], the performance of our model heavily relies on the selection and optimization of their numerous parameters. Traditional optimization techniques often struggle to effectively navigate the vast parameter space of CNN-LSTM, leading to suboptimal solutions. In this regard, Genetic Algorithms (GAs) offer a promising alternative [16]. GAs leverage principles inspired by biological evolution to efficiently explore and exploit the parameter space, making them well-suited for optimizing complex and high-dimensional models like CNN-LSTM networks.

However, to truly comprehend the exceptional predictive capabilities of our model and to identify the specific frequencies that influence the output for a particular emotion, a more thorough analysis is necessary. Currently, the CNN-LSTM model functions as a "black box," providing little insight into its decision-making process. To address this, our paper proposes the use of Explainable Artificial Intelligence (XAI) [17] techniques. We specifically employ the SHAP (SHapley Additive exPlanations) method to trace back the root causes of the model's predictions, thereby enhancing our understanding of its decision-making process. By incorporating GA and XAI, researchers can not only improve the accuracy of deep learning models for tasks such as emotion recognition but also ensure their interpretability and trustworthiness, thereby advancing the capabilities of deep learning techniques.

II. LITERATURE SURVEY AND CHALLENGES

The ability to recognize emotions is essential for comprehending human behavior and the dynamics of interaction [18]. Electroencephalography (EEG) presents a promising avenue for deciphering emotional states due to its capacity to capture brain acitivities [19]. Previous research has demonstrated notable success in classifying emotions across various emotional states. For instance, in a study by [12], Regularized Graph Neural Network (RNN) was employed, achieving an accuracy of 79.37% in discerning between Sad, Fear, and Happy emotions. In [20], researchers leveraged Temporal or Spectral Features alongside ZTW-based epoch selection (ZTWBES) methodology, coupled with recurrent neural networks. This approach yielded an impressive accuracy of 89.33% in distinguishing among nine distinct emotional states. In Furthermore, in another study documented by [21], Support Vector Machine and Particle Swarm Optimization (PSO) were utilized, achieving a notable accuracy of 80.625% in classifying three primary emotions. In [22] researchers detected emotion stress using GA based feature selection and attain an classification accuracy of 71.76%. In [23], researchers used electroencephalogram data and Local Interpretable Model-Agnostic Explanations (LIME) to identify human activity patterns.

While previous research has made significant strides in this domain, there remain opportunities for enhancing the accuracy and efficiency of emotion recognition systems. Building upon these foundations, our proposed approach integrates advanced deep learning techniques, such as CNN-LSTM architectures optimized using Genetic Algorithms, and incorporates principles of Explainable AI (XAI) to further improve the classi-

fication accuracy, interpretability, and robustness of emotion recognition models. By leveraging the strengths of both deep learning, optimization methodologies, and XAI techniques, our project aims to help advance affective computing technologies, with potential applications in healthcare, human-computer interaction, and psychology.

III. METHODOLOGY

A. Dataset Description

There are numerous emotion-related EEG datasets available [24]–[27]. We have utilized the DENS dataset [28] because it contain details about the participants' emotional states at different times. It recorded high-density EEG on 128 channels. EEG recordings from 40 individuals (average age: 23.3 ± 1.25 years), are present in the collection. Participants were exposed to emotionally charged film stimuli while data was being collected. There were a total of 24 unique categorized emotions as a consequence of the participants' promptings to either choose emotions from a predetermined list or indicate emotional categories that most accurately captured their experiences. Every participant clicked at least once, and a total of 465 emotional events were collected. To improve its quality and usability for analysis, the dataset underwent preprocessing steps. Independent Component Analysis (ICA) was used in conjunction with a bandpass filter that had frequencies between 1 and 40 Hz. EEG recordings lasting seven seconds at a sampling rate of 125 Hz are used to represent each emotional event in the dataset. Moreover, the EEG data includes signals captured from 128 channels, offering a thorough understanding of participants' brain activity during emotional events.
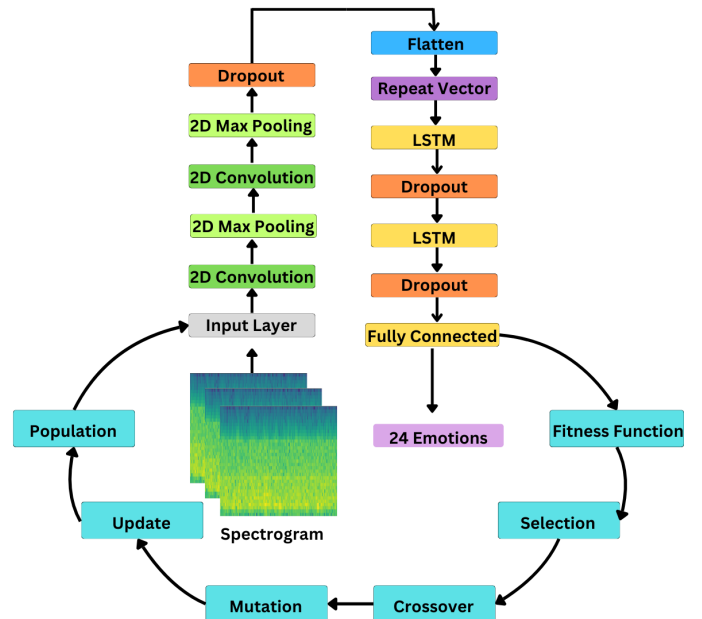
B. Proposed Model

Fig. 1. Mutation and crossover

In our study we propose a GA-based CNN-LSTM hybrid architecture, as illustrated in Figure 1 for the classification of 24 emotions on DENS dataset. Our model leverages a ensemble of CNN and LSTM.

1) Convolutional Layers: The initial layers of our model consist of two-dimensional convolutional layers followed by max-pooling operations. These layers serve as feature extractors to capture spatial patterns within the EEG data. The first convolutional layer comprises 32 filters with a kernel size of 5×55×5 and employs the Exponential Linear Unit (ELU) activation function. The feature maps are then downsampled using max-pooling with a 2×22×2 window size and a stride of 2. The second convolutional layer consists of 64 filters with a 3×33×3 kernel size, utilizing the hyperbolic tangent (tanh) activation function, followed by another max-pooling operation.

2) LSTM Layers: Following the convolutional layers, the model incorporates LSTM layers to capture temporal long range dependencies within the EEG signals of subjects. To reduce overfitting, a 0.3-rate dropout layer is implemented. To keep sequential information, the LSTM layer is set to return sequences and has 512 units. Following this LSTM layer, a 0.4-rate dropout layer is applied. To further regularize the model, another 512-unit LSTM layer is added, followed by a dropout layer with the same rate.

After the LSTM layers, the feature representations are flattened and passed through fully connected layers for classification. A dense layer with 64 neurons and rectified linear unit (ReLU) activation is introduced, followed by dropout regularization with a rate of 0.2. Finally, a dense layer with 24 neurons and softmax activation is utilized to output the probability distribution over the different emotion classes.

3) Model Compilation: The Nadam optimizer, a variation of Adam that combines adaptive moment estimation with Nesterov accelerated gradient, is used to construct the model. The loss function in our 24 class (emotion) classification tasks is categorical cross-entropy. Accuracy metrics are also tracked during training, and class imbalances are taken into consideration by calculating weighted accuracy.

IV. GENETIC ALGORITHM IMPLEMENTATION FOR MODEL OPTIMIZATION

A. Initialization of Population:

The method starts with the construction of an initial population of 60 individuals made up of chromosomes are given in Algorithm 1, which are potential solutions. In our context, each chromosome represents a candidate set of hyperparameters governing the architecture and configuration of our CNN-LSTM model. These hyperparameters encompass architectural elements such as convolutional layer units, activation functions, kernel size dropout rates, LSTM units, optimizer selection, and epoch count.

B. Fitness Evaluation:

Following population initialization, each chromosome undergoes fitness evaluation as described in Algorithm 1, during which it is translated into our concrete CNN-LSTM model configuration. This model is then trained, and its performance is quantified on validation dataset using a predefined fitness metric—in our case, we utilized classification accuracy. The accuracy serves as a surrogate fitness function guiding the evolutionary process, with higher values indicating superior model performance.

C. Selection Mechanism:

After fitness evaluation the accuracy values of all the individuals are normalized in Algorithm 2. The probabilities of selection are calculated by dividing each individual's fitness score (accuracy) by the total fitness score of the population and multiplying by 100 to convert them into percentages. This normalization ensures that the sum of probabilities equals 1, making it akin to a probability distribution. I have utilized Roulette Wheel selection process where the wheel is essentially a list where each individual's index appears a number of times proportional to its selection probability. When spinning the wheel, individuals with larger segments (higher probabilities) are more likely to be selected as parents.
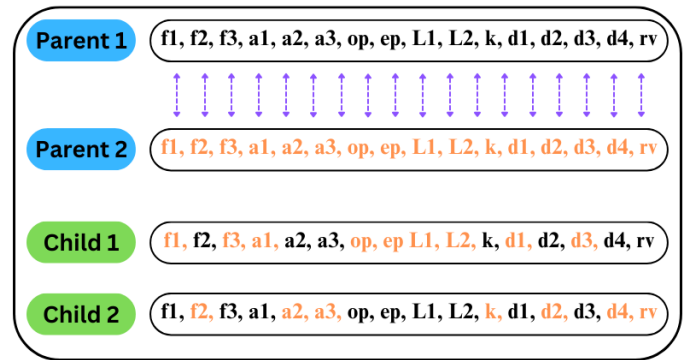
D. Crossover Operation:

Fig. 2. Mutation and crossover

In our study, we employ uniform crossover, decribed in Algorithm 3, a genetic operator where each hyperparameter in the child chromosome inherits values from either parent with equal probability. This inclusive process encompasses key hyperparameters such as convolutional filter sizes, kernel size, activation functions, dropout rates, LSTM units, optimizer, and the number of epochs. By facilitating genetic material exchange, uniform crossover promotes diversity in the offspring population, allowing for the inheritance of beneficial traits from both parents.

E. Mutation:

In our research, we implement a mutation strategy focused on adaptive adjustment of the number of epochs in offspring chromosomes within the genetic algorithm framework in Algorithm 4. With a mutation probability of 50%, each chromosome has an equal chance of undergoing mutation during each generation. When mutation occurs, the number

of epochs randomly increases or decreases by a small integer value. This dynamic mutation process promotes exploration of neighboring solutions while maintaining convergence towards optimal configurations, enhancing the algorithm's ability to discover high-performing neural network architecture

F. Population Update:

In our approach, population update is driven by a roulette wheel selection method, ensuring that individuals with higher fitness scores are more likely to contribute genetic material to the next generation. Through uniform crossover, offspring inherit hyperparameter values from both parents, fostering diversity in the population and enabling exploration of varied solution configurations. Additionally, our mutation strategy targets adaptive adjustment of the number of epochs in off-spring chromosomes, introducing variability into the population and facilitating exploration of novel solution spaces.

G. Termination Criteria:

The genetic algorithm iterates through 20 generations, with each generation representing a cycle of selection, crossover, mutation, and population update. Termination occurs when the desired accuracy threshold, set at 99%, is met or exceeded, or when computational resources are depleted. This decision-making process ensures that the optimization process concludes in a timely manner while achieving satisfactory results.

Algorithm 1 Genetic Algorithm for Hyperparameter Optimization

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Require: $num\_population$, $generations$, $threshold$

1: Initialize population with random hyperparameters:
2: f_1, f_2, f_3, k, a_1, a_2, a_3, d_1, d_2, d_3, d_4, L_1, L_2, op, ep, rv
3: **for** $generation \leftarrow 1$ to $generations$ **do**
4:    **for** each individual in the population **do**
5:       Train model with hyperparameters of the individual
6:       Evaluate fitness of the individual by measuring classification accuracy on test data: $Accuracy = \frac{Correct\ Predictions}{Total\ Predictions}$
7:    **end for**
8:    Select parents for crossover using selection method
9:    Perform crossover and mutation to create offspring
10:    **for** each offspring **do**
11:       Train model with hyperparameters of the offspring
12:       Repeat step 5 for offspring
13:    **end for**
14:    Replace least fit individuals in the population with offspring
15:    **if** Maximum fitness meets or exceeds $threshold$ **then**
16:       Terminate algorithm
17:    **end if**
18: **end for**
19: **return** Best individual from final population

Algorithm 2 Selection

Require: Population size: num_pop, Fitness distribution: $[fitness_1, fitness_2, ..., fitness_{num\_pop}]$

1: Compute selection probabilities based on fitness
2: $Selection\ Probability_i = \frac{fitness_i}{\sum_{j=1}^{num\_pop} fitness_j} \times 100$
3: Select parents using roulette wheel selection method
4: **return** Index of selected parents

Algorithm 3 Crossover

Require: Parent chromosomes $parent1$, $parent2$

1: Initialize empty child chromosomes $child1$, $child2$
2: **for** each attribute $attr$ in $parent1$ and $parent2$ **do**
3:    Randomly select value for $attr$ from $parent1$ or $parent2$ and assign it to $child1$
4:    Randomly select value for $attr$ from $parent1$ or $parent2$ and assign it to $child2$
5: **end for**
6: **return** Children chromosomes $child1$, $child2$

Algorithm 4 Mutation

Require: Chromosome representing hyperparameters
Ensure: Mutated chromosome

1: Let $chromosome$ be the input chromosome representing hyperparameters
2: Generate a random integer $flag$ between 0 and 40
3: **if** $flag \leq 20$ **then**
4:    Perform mutation operation
5:    Randomly select one hyperparameter for mutation
6:    Let $param$ be the selected hyperparameter
7:    Determine the type of $param$ (e.g., number of epochs, filter size, activation function)
8:    **if** $param$ is the number of epochs (ep) **then**
9:       Mutate the number of epochs
10:       Increase ep by a random integer between 0 and 10
11:    **else if** $param$ is another hyperparameter **then**
12:       Mutate the selected hyperparameter
13:       **Example**: For filter size (f), randomly choose a new value from the available options
14:    **end if**
15: **end if**
16: **return** Mutated chromosome

V. RESULTS AND EXPERIMETATION

Our experimental setup focuses on optimizing the CNN-LSTM model for emotion recognition using Genetic Algorithm (GA). This approach aims to enhance both model performance and interpretability. Optimization with GA fine-tunes model parameters, while the integration of Explainable AI techniques provides insights into model decisions, fostering trust and understanding. In the following segments, we will examine the findings of our experiment, emphasizing the efficacy of this method.

A. Optimization of CNN-LSTM Network using Genetic Algorithm

After conducting extensive experimentation and optimization using a Genetic Algorithm (GA), the optimal hyperparameters for our CNN-LSTM architecture were identified. This process was crucial for enhancing the performance and efficiency of our model. The hyperparater of our best-performing model, achieved through genetic algorithm-driven optimization, is outlined in Table 1 with parameters considered for optimization and their ranges:

TABLE I
PARAMETERS CONSIDERED FOR OPTIMIZATION, THEIR RANGES, AND OPTIMIZED VALUES

Parameter	Range	Optimal Value
Filter (f1)	32, 64	32
Filter (f2)	64, 128	64
Filter (f3)	64, 128, 256	64
Repeat Vector (rv)	3, 4, 6	3
Kernel Size (k)	3, 5	5
Activation Function (a1)	relu, selu, elu, tanh	elu
Activation Function (a2)	relu, selu, elu, tanh	tanh
Activation Function (a3)	relu, selu, elu, tanh	relu
Dropout (d1)	0.1 - 0.5	0.3
Dropout (d2)	0.1 - 0.5	0.4
Dropout (d3)	0.1 - 0.5	0.4
Dropout (d4)	0.1 - 0.5	0.2
LSTM Units (L1)	128, 256, 512	512
LSTM Units (L2)	128, 256, 512	512
Optimizer (op)	Adam, rmsprop, adamax, nadam, sgd	nadam
Epochs (ep)	50 - 100	90

B. Explainable AI (XAI) Integration

In the emotion classification process, a spectrogram is passed into the SHAP Deep Explainer. Initially, the SHAP explainer is trained on random background samples, after which it predicts the corresponding spectrogram for each emotion. The explainer elucidates the spectrogram by generating a resultant spectrogram. The signal is reconstructed using the resultant spectrogram. This is achieved by applying the inverse Short-Time Fourier Transform (STFT) to convert it back into the magnitude-time domain, i.e., the original signal. A thresholding filter is applied by visually inspecting the magnitude of the signal strength of the reconstructed signal. After thresholding, we obtain the discrete time frames corresponding to the output of a particular emotion.

In Figure 2, representing the emotion classification process, we have illustrated three emotions for clarity (as there are 24 emotions in total, illustrating them all wasn't feasible). For instance, for the "Amused" emotion, the model targets time ranges from 300 to 550 and 850 to 1050, as highlighted. These delineated time intervals showcase the specific segments considered by the model during the prediction of each emotion. It's important to note that the model integrates both negative and positive magnitudes in its computations, facilitating a thorough analysis for precise emotion prediction.
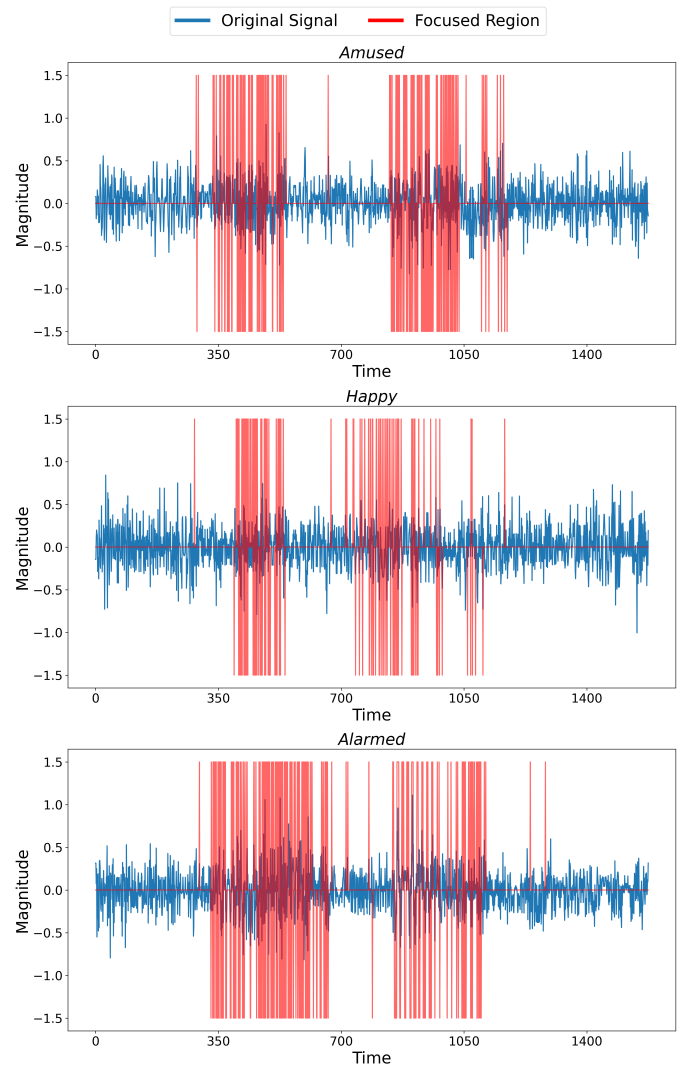

Fig. 3. XAI Emotion Frequencies

C. Ablation Study

We conducted an ablation research on the GA optimized CNN-LSTM architecture to acquire a better understanding of how each component contributes to the model's overall performance. We eliminated crucial elements from the model in a methodical manner and assessed their impact on classification accuracy.

TABLE II
COMPARISON OF MODEL PERFORMANCE

Model	Mean Accuracy (%)	Mean F1 Score (%)
CNN	85.04	85.00
CNN-LSTM	89.78	89.80
Optimized Model	93.28	93.20

As depicted in Table II, the CNN model achieved a mean accuracy of 85.04% and a mean F1 score of 85.00%. Introducing the LSTM layer into the architecture in the CNN-LSTM model led to notable improvements in performance, with the

mean accuracy increasing to 89.78% and the mean F1 score to 89.80%. Finally, the optimized model, which incorporates additional enhancements beyond the CNN-LSTM architecture, achieved the highest performance, with a mean accuracy of 93.28% and a mean F1 score of 93.20%.

These results demonstrate the effectiveness of each architectural modification in enhancing the model's predictive capabilities.

VI. CONCLUSION

Our investigation introduces a robust methodology for emotion recognition employing EEG data, integrating CNN and LSTM networks refined via a Genetic Algorithm. By fine-tuning hyperparameters, we attained a notable classification accuracy of 93.28% across 24 distinct emotional states. The incorporation of explainable AI techniques enriches the interpretability of our model. This research contributes not only to the advancement of emotion recognition frameworks but also provides valuable insights for the evolution of future affective computing technologies.

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