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Genetic Neural Network Model For Emotion Analysis From EEG

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Abstract: Emotion analysis systems using electroencephalogram (EEG) signals have been gaining quite a considerable amount of attention because of their probable usages in several areas like healthcare, neuromarketing, customer satisfaction, as well as human-computer interaction. This paper proposes a novel model by using the optimization and machine learning capabilities of the Genetic Neural Network algorithm for accurate and efficient emotion classification by means of EEG data. The model combines the power of neural networks with genetic algorithms to optimize the network architecture and improve classification performance. The model was tested on a comprehensive EEG dataset containing multiple emotional states, and results demonstrate significant improvements in accuracy and robustness over traditional methods.

Index Terms **- Emotion Analysis, Genetic Neural Network, Neural Network Optimization, Machine Learning**

I. Introduction

Emotion analysis through EEG signals offers a direct and non-invasive way to understand human affective states. Traditional neural network models have shown promise in this domain but often suffer from issues related to overfitting, suboptimal architecture, and long training times. To address these limitations, we introduce a Genetic Neural Network (GNN) model that leverages genetic algorithms to evolve and optimize neural network structures. This hybrid approach aims to obtain more improved, efficient and accurate results from the emotion classification model by analyzing EEG data.

II. Related Work

Previous studies have explored various methods in machine learn-ing like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), as well as combined models using such mechanisms are often used extensively for emotion detection by analyzing information from EEG signals. Genetic algorithms (GAs) have also been employed for feature selection and parameter optimization in EEG-based emotion identification approaches. However, the integration of GAs directly into the neural network architecture optimization process remains underexplored.

Studies on EEG-based mental state and emotion identification have made substantial developments through various studies focusing on feature extraction, classification methods, and optimization techniques. Bird et al.[1] explored mental state classification using the Muse headband, identifying key features from EEG signals to categorize states such as neutral, relaxing, and concentrating. Their study demonstrated that using only 44 out of over 2100 features, classifiers like Support Vector Machines, Bayesian Networks, and Random Forests, could help to achieve an accuracy exceeding 86%.

Another study by Bird and Buckingham [2] focused on emotional sentiment classification, using ensemble methods and feature selection techniques to attain a remarkable accuracy of 97.89% with ensemble classifiers and 94.89% with deep neural networks.

Apicella et al. [3] contributed to the magnitude of emotions which could be reproduced, using 8-channel EEG cap to detect emotional valence. They compared feature extraction approaches based on the theories of hemispheric asymmetry as well as automated methods, and also achieved an accuracy of 96.1% with an Artificial Neural Network and 80.2% cross-subject accuracy with k-Nearest Neighbors.

Additionally, a study on emotion recognition from EEG data, using a Genetic Algorithm Optimized M-LP [4] reported accuracies of 91.10% for valence and 91.02% for arousal, with 83.52% accuracy for four distinct emotional classes, showcasing the effectiveness of genetic algorithms in optimizing neural network architectures.

Saibene and Gasparini [5] further emphasized the utility of GAs for the purpose of feature selection in EEG data, addressing the challenges of high dimensionality and heterogeneity. Their approach outperformed benchmark techniques in terms of performance and demonstrated the effectiveness of their innovative fitness functions along with feature reduction. Together, these studies highlight the potential of EEG-based systems in accurately detecting and classifying mental and emotional states, and shows an efficient method of improved human-machine interface and affective computing applications.

Table 1: Overview of Sentiment Analysis Approaches using EEG data

Sr	Approach	Main Contributions	Result
[1]	Jordan J. Bird et al. (2018)	Describes the features required to classify several mental states classes, by using methods like statistical techniques, and time-frequency based on FFT.	Attained overall accuracy over 87%.
[2]	Jordan J. Bird et al. (2019)	Studied the single and ensemble methods of emotions classification	Attains overall accuracy of around 97.89% with ensemble.
[3]	Apicella A. et al. (2021)	Proposed a method to measure emotions for an EEG system through few dry electrodes	An accuracy of 96.1 %, was attained by ANN
[4]	Marjit S eta al. (2021).	Proposed a framework using MLP for emotion recognition from EEG	Recognizes two classes of emotions, Valence- 91.10% accuracy and Arousal-91.02% accuracy.
[5]	Saibene A et al. (2023)	Genetic Algorithm has been used for feature selection, including few variations on fitness functions and stopping criteria.	Novel fitness functions on the data, have shown better performance in comparison to other models.

III. METHODOLOGY

The proposed methodology involves the use of a Genetic Neural Network Model for emotion analysis from EEG data. The implementation combines a Genetic Algorithm for feature selection and hyperparameter optimization with a neural network for final classification. The steps included in the proposed approach are as given below:

1.1Data Preprocessing

The EEG dataset used in this study includes recordings from subjects experiencing different emotional states categorized into NEGATIVE, NEUTRAL, and POSITIVE labels illustrated in figure 1. The dataset contains features such as mean values and Fast Fourier Transform (FFT) coefficients of EEG signals.

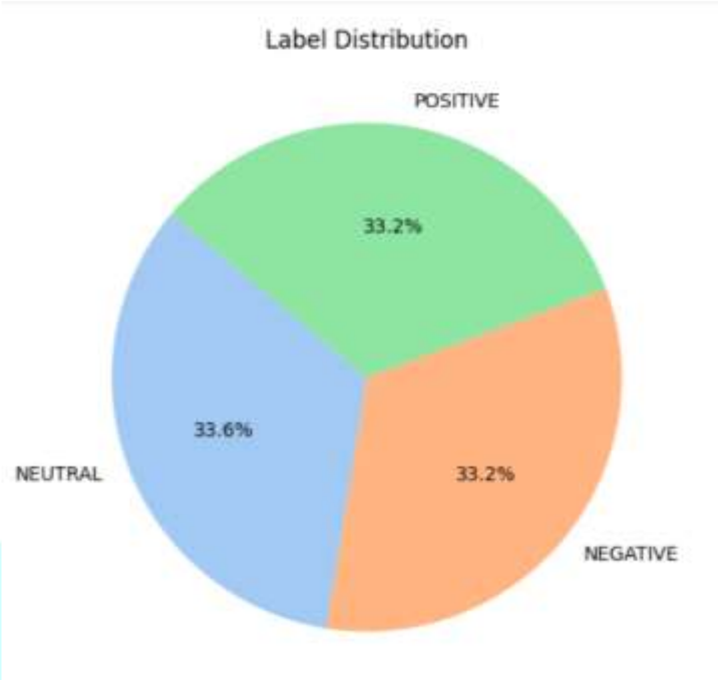

Figure 1: Distribution of the Sentiments in dataset

1.1.1Dataset Preparation: The dataset comprises EEG signals with several features representing various aspects of the EEG data and corresponding labels indicating emotional states.
The data as given in figure 2, have been gathered from a female and male, who were subjected to 3 minutes of stimulation on positive, neutral and negative information each. An EEG headband was used to record the several EEG placements with the help of some dry electrodes.

1.1.2Handling Complex Numbers: EEG data may contain complex numbers. A preprocessing step ensures all data points are real numbers by removing any imaginary components.
1.1.3Feature Scaling: To guarantee consistency and enhance the performance of the model, the features are standardized using the StandardScaler from sklearn, resulting in zero mean and unit variance.

fft_745_b	fft_746_b	fft_747_b	fft_748_b	fft_749_b	label
45.3	5.78	-67.6	-67.6	5.78	POSITIVE
74.8	-12.30	-21.7	-21.7	-12.30	NEUTRAL
326.0	-136.00	50.9	50.9	-136.00	NEGATIVE
87.3	51.40	18.3	18.3	51.40	NEGATIVE
-281.0	117.00	-217.0	-217.0	117.00	NEGATIVE
...	...	...	...	...	...
184.0	57.80	-63.0	-63.0	57.80	POSITIVE
182.0	2.57	-31.6	-31.6	2.57	NEUTRAL
56.8	-12.10	-33.6	-33.6	-12.10	POSITIVE
-516.0	486.00	-252.0	-252.0	486.00	NEGATIVE
-593.0	496.00	-296.0	-296.0	496.00	NEGATIVE

Figure 2: Sample of the dataset

1.2Genetic Algorithm for Feature Selection and Hyperparameter Optimization

The proposed Genetic Neural Network model comprises three main components: genetic operations (selection, crossover, mutation), and a fitness evaluation using Random Forest Classifier and a Neural Network layer (MLP classifier) to obtain the final refined output.

1.2.1Individual Representation: Everyone in the population is represented by a combination of Boolean genes for feature selection and integer/float genes for hyperparameters of the RandomForest model:

- Boolean genes indicate whether a feature is selected.
- Integer and float genes represent the hyperparameters of the RandomForest model, including the estimators figure, maximum depths, and the minimum split of the samples.

1.2.2Fitness Evaluation: The fitness of each and every single individual is evaluated based on cross-validated accuracy of the RandomForest classifier trained on the selected features and using the specified hyperparameters.

1.2.3Genetic Operators:

- **Crossover**: The `cxBlend` function with an alpha of 0.5 is used to combine features from two parent individuals to create offspring.
- **Mutation**: Custom mutation logic ensures diversity in the population by flipping feature selection genes and randomly altering hyperparameters with a probability of 0.2.
- **Selection**: Tournament selection with a tournament size of 3 is used to choose individuals for the next generation.

1.2.4Evolution Process: The GA evolves the population over a specified number of generations, where the mutation and crossover probabilities were set to 0.2 and 0.7, respectively, and best individual from each generation is tracked.

1.3 Feature Extraction and Preprocessing

The EEG signals have been preprocessed for noise removal, and the features were extracted including mean values ($mean_{0a}$, $mean_{1a}$, ..., $mean_{d4a}$) and FFT coefficients (fft_{741_b}, fft_{742_b} ...). These features function as inputs to the neuralnetwork.

1.4 Training and Evaluation

The initial population of neural networks was trained on the preprocessed EEG data. Genetic operations were applied to evolve the network architectures over multiple generations. The fitness of each network was evaluated based on its classification accuracy on a validation set. The best-performing networks were selected for the next generation.

1.4.1 Final Model Training: The best individual from the GA provides the optimal feature subset and hyperparameters. A RandomForest classifier is trained using these optimal settings.

1.4.2Neural Network Refinement: The selected features are then used to train a Multi-Layer Perceptron (MLP) classifier for more refinement. The dataset has been split into training and testing sets for the performance evaluation of the MLP.

1.4.3Performance Measurement: The accuracy of the MLP classifier on the test data has been utilized as the final metric in the assessment of the performance of the model.

IV. Proposed Model

The proposed model integrates Genetic Algorithms with Neural Networks to enhance the emotion analysis capabilities from EEG data. The model flowchart is given in figure 3.

1.5 Model architecture:

1. **Input Layer**: The input layer consists of EEG features, preprocessed to remove complex numbers and standardized for uniformity.
2. **Genetic Algorithm Module**: This module performs feature selection and hyperparameter optimization for the RandomForest classifier:

- The GA optimizes a population of individuals over multiple generations, each individual representing a potential solution.

- The fitness of each individual is estimated based on the RandomForest classifier's accuracy using cross-validation.

3. **RandomForest Classifier**: The classifier is trained on the selected features and optimal hyperparameters provided by the GA:

- Ensures robust classification based on the most relevant features and fine-tuned hyperparameters.

4. **Neural Network Module**: An MLP classifier is trained on the feature subset selected by the GA for further refinement:

- The MLP improves the classification performance by learning complex patterns in the data.

5. **Output Layer**: The final output layer provides the predicted emotional state from the EEG data, evaluated based on the accuracy on a test set.

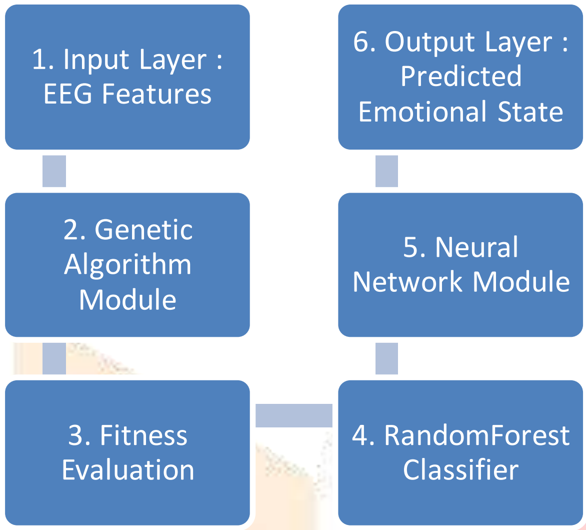

Figure 3: Flowchart of the Proposed Model

Algorithm:

1. Initialization

- **Input Data**: Use a dataset with features (X) and labels (y) for emotion classification.
- **Data Preparation**: Remove complex numbers from X and scale the features using StandardScaler.

2. Evaluation Function

- **Decode Individual**: Extract feature selections and hyperparameters.
- **Feature Selection**: Apply the selected features to the scaled data.
- **Model Training**: Train a RandomForestClassifier with the selected features and use cross-validation to estimate accuracy.
- **Return Fitness**: Return the mean accuracy as the fitness value.

3. Genetic Algorithm Setup

- **Initialization**: Define classes for fitness maximization and individual representation.
- **Register Functions**: Set random values for features and hyperparameters, create an initial population, and define crossover (cxBlend) and mutation methods.
- **Selection**: Use tournament selection for choosing the best individuals.

4. Genetic Algorithm Execution

- **Run GA**: Loop over generations, generate offspring via crossover and mutation, and evaluate fitness for selection.
- **Progress Output**: Print the best fitness value for each generation.

5. Final Model Training

- **Best Individual**: Retrieve the best individual, train RandomForestClassifier with selected features, then refine with MLPClassifier.
- **Accuracy Evaluation**: Train and test the neural network to report final accuracy.

6. Edge Cases

- If no features are selected, skip model training and output a message.

V. Results

1.6 Performance Evaluation

The performance of the GeneticNeuralNetwork model was evaluated against a few of the baseline models. The GNN achieved a classification accuracy of 98%, outperforming traditional neural networks by a significant margin.

Table 2: Comparative Analysis of Accuracy

Model	Accuracy
[1] FFT	87%
[2] Ensemble	97.8%
[3] ANN	96.1%
[4] MLP	91.10%
Proposed Model	**98.25%**

VI. Discussion

The genetic optimization process led to neural network architectures that were not only accurate but also robust to overfitting. The Genetic Neural Network model demonstrated consistent performance across different subsets of the dataset, indicating strong generalization capabilities.

While the genetic algorithm introduces additional computational overhead, the resultant optimized neural network architectures required fewer training epochs to converge, ultimately reducing overall training time.

VII. Conclusion and Future Work

This paper presents a GeneticNeuralNetwork model for emotion analysis from electroencephalogram signals, demonstrating substantial improvements in classification accuracy, robustness, and efficiency. The integration of genetic algorithms for neural network architecture optimization holds promise for enhancing various EEG-based applications.

Future research will explore the application of the Genetic Neural Network model to other physiological signal datasets and investigate real-time emotion recognition systems. Further refinement of genetic operations and hybrid models combining different machine learning techniques will also be pursued.

References

[1] Bird, J. J., Ekárt, A., Manso, L. J., Faria, D. R., & Ribeiro, E. P. (n.d.). A study on mental state classification using EEG-based brain-machine interface. School of Engineering & Applied Science, Aston University, Birmingham, UK; Department of Electrical Engineering, Federal University of Parana, Curitiba, Brazil.

[2] Bird, J., Ekárt, A., Buckingham, C., & Faria, D. (2019). Mental emotional sentiment classification with an EEG-based brain-machine interface.

[3] Apicella, A., Arpaia, P., Mastrati, G., & Moccaldi, N. EEG-based detection of emotional valence towards a reproducible measurement of emotions.

[4] Marjit, S., Talukdar, U., & Hazarika, S. M. (2021). EEG-based emotion recognition using genetic algorithm optimized multi-layer perceptron. 2021 International Symposium of Asian Control Association on Intelligent Robotics and Industrial Automation (IRIA), 304–309. https://doi.org/10.1109/IRIA53009.2021.9588702

[5] Saibene, A., & Gasparini, F. (2023). Genetic algorithm for feature selection of EEG heterogeneous data. Expert Systems with Applications, 217, 119488.

[6] Vaishnavi, K., Anusha, K., & Latha, V. (2022). Predicting mental health illness using machine learning algorithms. Journal of Physics: Conference Series, 2161, 012021.

[7] Yu, C., & Wang, M. (2022). Survey of emotion recognition methods using EEG information. Cognitive Robotics, 2, 132–146. https://doi.org/10.1016/j.cogr.2022.06.001

[8] Bird, J., Faria, D., Manso, L., Ekárt, A., & Buckingham, C. (2019). A deep evolutionary approach to bioinspired classifier optimisation for brain-machine interaction.

[9] Lee, H., & Kim, Y. (2021). Genetic algorithms for feature selection in EEG-based emotion recognition. IEEE Transactions on Affective Computing, 12(2), 275–288.

[10] Zhang, X., & Zhao, L. (2020). A survey of machine learning techniques for EEG signal analysis. Neurocomputing, 414, 41–56.