Machine Learning Techniques Towards Accurate Emotion Classification from EEG Signals

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Abstract: This article delves into using machine learning algorithms for emotion classification via EEG brain signals. The goal is to discover an accurate model beyond traditional methods, necessitating AI for classifying emotional EEG signals. This study, motivated by the complex link between emotions and neural activity, employs Random Forest, Support Vector Machines, and K-Nearest Neighbors. Notably, Random Forest achieves 99% accuracy, SVM 98%, and KNN 94%. These impressive results, backed by performance metrics like confusion matrices, reveal each model's effectiveness in emotion classification. The dataset, rich in varied emotional stimuli and EEG placements, provides a robust foundation for detailed analysis. This research underscores significant applications in affective computing and mental health, offering a promising path to understanding the intricate relationship between EEG signals and human emotions.

Key-Words: Emotion classification, EEG brain signals, Random Forest, KNN, SVM.

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1 Introduction

Emotions, those tricky yet significantly effective powers that shape our lives, are integral to how we see, act, and collaborate with our general surroundings. From the sheer pleasure of a kid's giggling to the extraordinary fury of a tempest, feelings cover a huge range, each shade fundamentally impacting our responses to various upgrades. Researchers in psychology, neuroscience, and artificial intelligence have all been captivated by this intricate dance of emotions as they attempt to unravel the complexities of emotional classification. The drive behind this attempt lies in the commitment of more profound experiences into human way of behaving and the improvement of human-PC cooperation frameworks. A great representation is the concentrate by [1], which exhibited the adequacy of half and half profound learning techniques in limiting arrangement mistakes in weakness location by means of EEG, featuring the potential for worked on close to home examination.

Customarily, the feelings are intensely depended on Electroencephalography (EEG) signals, which offer an immediate look into the mind's electrical movement, [2]. These EEG recordings reveal the neural bases of emotional states and shed light on how our brains process feelings. However, it is difficult to accurately classify emotions using EEG. Variability and noise obscure meaningful patterns in the data, which is intrinsically complex, [3]. Besides, the multi-layered nature of feelings makes it considerably more testing to recognize them exclusively through brain action.

Basic statistical techniques and straightforward classifiers are frequently hampered by EEG data's inherent noise and high dimensionality. For example, [1], used half and half profound learning models to diminish order blunders in weakness discovery, underscoring the requirement for complex procedures to explore the complexities of EEG information. The dynamic and covering attributes of feelings further muddle these difficulties, as conventional techniques battle to catch the full range of human profound experience. Concentrates, for example, those by [3], have demonstrated the way that exceptional AI methods can fundamentally upgrade feeling order execution when applied to EEG information. These results highlight the transformative potential of machine learning, which provides models that are more precise and reliable than those produced by more conventional methods.

AI sparkles as an encouraging sign for further developing feeling grouping from EEG signals, [4]. Machine learning models can discover patterns in EEG data that correspond to various emotional states by utilizing advanced algorithms. Machine learning models are adept at handling noisy and variable data, thereby reducing the impact of artifacts and inconsistencies; scalability, allowing for the efficient processing of large datasets for real-time applications; and sophisticated feature extraction, which automatically identifies the most relevant aspects of EEG signals for emotion classification. These advantages are numerous and include improved accuracy, which is achieved by algorithms such as Random Forest, Support Vector Machines, and Convolutional Neural Networks.

The down to earth ramifications of this exploration are tremendous. Affective computing can advance by improving emotion classification models, making it possible for systems to respond to users' emotional states more naturally. These models offer instruments for the early detection and monitoring of emotional disorders in mental health diagnostics, potentially enhancing treatment outcomes. Adaptive interfaces could dynamically respond to users' emotions in human-computer interaction, enhancing user engagement and experience. These headways feature the capability of AI to change functional applications by conveying more precise and solid models for feeling characterization.

This article unfurls as follows: Section 2 dives into the relevant related works, offering a survey of existing examination and bits of knowledge. The method used and the datasets used are described in detail in Section 3. The research findings are presented in Section 4, where they are examined in depth. At last, section 5 closes the review, summing up key perceptions, examining their suggestions, and proposing expected roads for future exploration.

2 Related Work

Several studies have significantly advanced EEG research by delving into brainwave patterns for a range of applications. In [5], the author investigates discriminative EEG features to categorize brainwave patterns, especially for human-machine interaction. The study achieves high classification accuracy with a reduced feature set using classifiers such as Bayesian Networks, Support Vector Machines, and Random Forests. On the other hand, [6], explore EEG data in everyday scenarios to evaluate user engagement and enjoyment in tablet-based video games. They find that frontal theta activity is a strong predictor of game preference. Additionally, [7], focus on emotion classification from EEG data, employing ensemble classifiers to achieve high accuracy in identifying emotions induced by film clips. These studies collectively enhance the understanding of brainwave patterns' applicability in technology, emotion classification, and the potential for improving human-computer interaction.

In their research, [8], present a hybrid labeling approach combining subjective and objective elements to recognize emotions from EEG data, aiming to capture real-time emotional dynamics. Studies related to emotion recognition suggest that emotions unfold over extended periods. The authors in [9], examine emotional patterns that remain stable over time. The authors in [10], develop an algorithm to select crucial sub-networks associated with emotions, focusing on three attributes from brain functional connectivity networks: connection strength, clustering coefficient, and centrality within a feature vector. Experiments using the SEED database, a publicly available EEG emotion dataset, highlight the effectiveness of these brain connectivity network features in differentiating emotions, with connection strength being the most indicative feature, achieving an accuracy of 81.53%. The authors in [11], introduce a model for emotion recognition based on the dynamics of EEG phase space and Poincare intersections, quantitatively analyzing EEG dynamics through the Poincare plane. The authors in [12], assess traditional machine learning techniques, including PCA, Naive Bayes, Logistic Regression, KNN, Support Vector Machine, and Decision Trees on the DEAP dataset, finding PCA and SVM to deliver superior results. However, these outcomes are specific to the datasets and experimental designs used, and may not generalize to other contexts. With the rise of deep learning, more researchers are turning to deep neural networks for emotional computing tasks using physiological signals. Through EEG signal analysis, [13], establish a link between EEG signal variations and changes in human emotions, evaluating various classifiers such as KNN, LR, SVM, and DBN in emotion recognition. Their findings indicate that deep neural networks outperform traditional machine learning approaches in emotion computing.

3 Methodology

In this section, we outline the dataset used, introduce the proposed system model, and discuss the data preprocessing steps undertaken.

3.1 System Model

Figure 1 illustrates our comprehensive system model. The data flow initiates from the Dataset module, embodying the raw dataset, which encompasses EEG brain signals alongside emotional stimuli data. This initial data embarks on a journey through Data Preprocessing, wherein intricate procedures such as handling missing values and meticulous data labeling are executed to cleanse and prime it for subsequent analysis, [14].

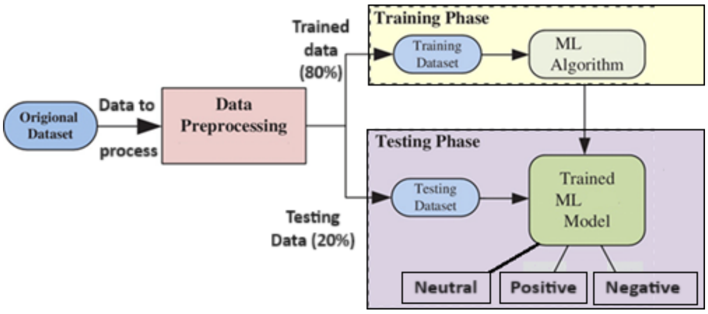

Fig. 1: Proposed system model

Upon completion of preprocessing, the refined dataset is bifurcated into Train and Test subsets. Here, 80% of the data is earmarked for training the machine learning algorithms, while the remaining 20% is reserved to scrutinize their performance. Within the realm of Machine Learning Algorithms, an array of techniques, including Random Forest, SVM, and KNN, are used on the training data to construct robust predictive models.

Once these models are trained, their prowess is tested on the Test Data, thereby evaluating their ability to generalize to new, unseen data. The system culminates in the Evaluation of Model Performance, employing a spectrum of metrics such as accuracy, precision, recall, and the F1-score, to ensure the effective classification of emotions derived from EEG brain signals. Each phase in this intricate flow diagram is pivotal, orchestrating a symphony of processes aimed at achieving precise emotion classification through the synergy of machine learning and EEG data analysis.

3.2 Dataset

In this paper, we harnessed an EEG brainwave dataset processed through a specialized technique pioneered by [5]. This method involved the extraction of intricate statistical features from the EEG data, enabling a profound exploration of the neural correlates of emotions. Our dataset was composed of meticulously chosen participants, representing both genders, each undergoing EEG recordings to capture three distinct emotional states: positive, neutral, and negative.

The recordings, conducted using a Muse EEG headband equipped with strategically placed dry electrodes, spanned 3 minutes each. A critical aspect of our dataset was the inclusion of a 6-minute recording of resting neutral data, which served as a baseline reference for assessing emotional responses. To elicit these emotions, we carefully selected cinematic stimuli, featuring scenes from movies such as ”Marley and Me” and ”La La Land.” This meticulously curated dataset formed the bedrock of our research, facilitating an investigation into the neural underpinnings of emotional states elicited by cinematic stimuli.

This dataset contains 2,549 columns and 2,132 rows, it is offering a good of information. The substantial volume of data points provides a robust foundation for our research, enabling in-depth analyses of EEG brainwave patterns and their correlations with various emotional states. This dataset is significant to the understanding the relation between neural activity and human emotions.

3.3 Data Pre-Processing

In this article, we undertook an extensive examination aimed at detecting and resolving null and duplicate values within the dataset, highlighting the paramount importance of data preprocessing and quality assurance, [15]. This meticulous process is vital for safeguarding data integrity, minimizing the risk of missing critical information, and upholding data quality by addressing duplicate entries. Clean data is indispensable for producing reliable analytical outcomes, as it mitigates bias and enhances the precision of statistical measures and machine learning algorithms. The absence of null and duplicate values in the dataset, as revealed through our scrupulous examination, underscores the thoroughness of our data collection and preprocessing efforts, paving the way for confident analysis and exploration.

In the realm of data preprocessing, our detailed examination sought to identify and rectify null and duplicated values within the dataset, a crucial step for ensuring data integrity and quality. Remarkably, our scrutiny revealed that the dataset is free from such issues, attesting to the meticulous nature of our data collection and preprocessing. Subsequently, data encoding emerged as a pivotal task, involving the assignment of numeric codes (0, 1, and 2) to represent categorical labels (NEGATIVE, NEUTRAL, and POSITIVE). This step is essential for ensuring algorithm compatibility, preserving distinctions between categories, and bolstering model performance, [16]. Our encoding scheme provides a straightforward yet effective representation of emotional states within the dataset, facilitating seamless data processing and analysis. Figure 2 illustrates the count of each class within the dataset.

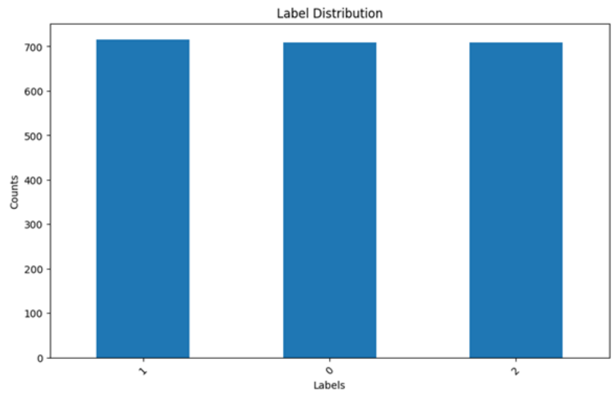

Fig. 2: Proposed system model

Balancing the dataset is a widely adopted technique to rectify class imbalances; however, it may not be necessary in our context, [17]. On the other hand, the dataset is already balanced, with each class has approximately the same number of instances. This balance minimizes the risk of model bias and bolsters overall model performance.The significance of evaluating dataset characteristics and selecting preprocessing techniques that are precisely aligned with the specific requirements of the data and the objectives of the analysis. In another term, we select the main features that are mainly positive affect the accurcy of detection using the correlation matrix. This method ensures that the preprocessing is both effective and efficient, and has robust and reliable outcomes.

3.4 Evaluation metrics

3.4.1 Confusion Matrix

In machine learning (ML), a confusion matrix presents a tabular used to show the performance of a classification algorithm, especially in binary classification. It shows the model predictions into four distinct groups: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). These classifications provide good insights into the model's performance in accurately classifying instances. This evaluation facilitates the assessment and refinement of the model's predictive capabilities, [18].

3.4.2 Precision

Precision, a metric used to find the proportion of true positive predictions, is defined as:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{1}$$

3.4.3 Recall

Recall measures the model's ability to identify the correct positive instances and it is calculated as:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

3.4.4 F1-Score

The F1-Score, presents a good evaluation metric and can be computed using the formula:

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

3.4.5 Classification Report

The classification report provides a good summary of the model performance for each class. It presents metrics like precision, recall, F1-Score, and support in a tabular format, [19].

4 Simulations and results

In this section, we discuss the algorithms proposed for our research. They are essential for classifying EEG data based on various features and patterns. The algorithms presented in this section are used to improve the accuracy and efficiency of EEG emotions classification.

4.1 Random Forest

In order to uncover patterns in vast datasets, data scientists use a wide range of machine learning algorithms, providing businesses and organizations with valuable insights that are essential for making strategic decisions. Due to its adaptability in handling both classification and regression tasks, Random Forest emerges as a favorite among these algorithms. Presented in the mid 2000s, RF is a critical directed learning calculation that expands the notable choice tree method, [20]. Breiman's development lies in coordinating a gathering of arbitrary choice trees to improve expectation execution, utilizing variety to moderate overfitting and adroitly oversee enormous, complex datasets.

A fundamental structure in predictive modeling, decision trees plot a series of decisions based on data features. As the algorithm chooses the best features to divide the dataset at each node, the trees grow recursively. Furthermore, decision trees are easy to understand and intuitive, but they frequently suffer from overfitting, making it difficult for them to adapt to new datasets. Each decision tree is built by iteratively traversing the training dataset and choosing the best splits based on predetermined criteria like the Gini index for classification or the variance reduction for regression. When all trees are developed, the last step involves conglomerating their expectations to yield a general forecast. This typically necessitates a majority vote among all tree predictions in classification, whereas it does so in regression tasks by averaging predictions. This collection of trees is the essence of Random Forests and gives them their ability to predict and adapt. Random Forest aggregates the forecasts of N individual decision trees to derive the ultimate prediction:

$$\hat{Z}_{\mathrm{RF}} = \frac{1}{N}\sum_{j=1}^{N}\hat{Z}_j \tag{4}$$

Here:
$\hat{Z}_{\mathrm{RF}}$ denotes the Random Forest forecast. $\hat{Z}_j$ signifies the prediction generated by the jth decision tree.

4.2 The Support Vector Machine (SVM)

The SVM operates by mapping data to a high-dimensional attribute space, facilitating classification even when linear separation is unattainable, [21]. It identifies a separator between categories, transforming data to align with a hyperplane for classification. This enables the use of new data features for predicting group assignments. The main aim is to allow the algorithm flexibility in choosing the separation line, accommodating a margin of error termed ”soft margin”. We will now detail the Soft Margin Classifiers algorithm, positioned between Support Vector Machine and Maximal Margin Classifier.

Soft Margin Classifiers center around the margin concept, indicating the distance between a separating line and the nearest observation. To enhance adaptability, a threshold is introduced dictating the permissible number of observations within the margin. The objective remains maximizing the margin while accommodating observations within this threshold. By prioritizing margin maximization over precise classification of points within the margin, the algorithm exhibits robustness to outliers and extreme values, fostering a more generalized classification model. The decision function for SVM is expressed as:

$$f(x) = \mathrm{sign}\left(\sum_{i=1}^{n}\alpha_i y_i K(x, x_i) + b\right) \tag{5}$$

Where:
$f(x)$ denotes the predicted class label. α_i represents the Lagrange multipliers. y_i signifies the class label of the training sample. $K(x, x_i)$ stands for the kernel function. b denotes the bias term.

4.3 K-Nearest Neighbors (KNN)

In supervised learning, an algorithm is provided with a dataset that includes labeled output values, serving as the foundation for training and constructing a predictive model. This trained algorithm can then be applied to new, unlabeled data to forecast their respective output values. Among the various supervised machine learning methods, the KNN algorithm stands out for its intuitive approach, [22]. Initially, the KNN algorithm involves selecting a value for K, which represents the number of nearest neighbors to consider in the classification process. The algorithm then computes the distance from the unlabeled point to each of the other data points. Based on these calculated distances, the K data points closest to the unlabeled point are identified.

Following the recognizable proof of the K closest neighbors, the calculation continues to decide the circulation of classes among these adjoining focuses. It determines the predominant category within the chosen group by counting the number of points for each category. The algorithm assigns the new unlabeled point to the category with the highest prevalence among the K nearest neighbors once the category distribution is established. This step concludes the arrangement interaction, preparing the model to make expectations on new information cases. The anticipated class mark utilizing KNN depends on the greater part class among the k closest neighbors:

$$\hat{C} = \mathrm{majority}\left(\{c_i\}_{i\in\mathcal{N}_k(x)}\right) \tag{6}$$

$\hat{C}$ is the predicted class label. c_i represents the class of the k nearest neighbors of point x.

4.4 Results and Discussion

Table 1 presents the classification reports for our three different algorithms. Each algorithm is evaluated by three classes (0, 1, and 2), and by precision, recall and F1-score.

Table 1. Comparison of Classification Reports

Algorithm	Class	Precision	Recall	F1-score	Accuracy
Random Forest	0	0.98	0.99	0.98	0.99
	1	1	1	1	
	2	0.99	0.98	0.98	
SVM	0	0.97	0.98	0.97	0.98
	1	1	0.99	0.99	
	2	0.96	0.96	0.96	
KNN	0	0.89	0.99	0.94	0.94
	1	0.97	0.98	0.97	
	2	0.97	0.84	0.9	

The Random Forest algorithm performs exceptionally well, with F1-score values, precision, and recall values that are all above average across all three classes. This shows its strength in ordering information focuses precisely. The model's ability to accurately predict class labels for the vast majority of data points is demonstrated by its impressive accuracy score of 0.99. Likewise, the SVM calculation exhibits solid execution, with high accuracy, review, and F1-score values for each class. An exactness score of 0.98 further approves the model's capability in accurately grouping data of interest. Interestingly, the KNN calculation shows somewhat lower accuracy, review, and F1-score values, especially for class 2. This recommends that KNN might confront difficulties in precisely ordering information guides having a place toward class 2 contrasted with different calculations. Regardless of this, it actually accomplishes a good exactness score of 0.94, showing generally respectable execution.

On the whole, the outcomes uncover that both RF and SVM calculations perform the KNN regarding accuracy and F1-score across all classes. However, when choosing the best algorithm for a given classification task, it is essential to take into account additional aspects like scalability and computational complexity.

Table 2 provides an exhaustive correlation of model obtained from different studies, including earlier exploration papers and our paper. Every section in the table addresses an alternate report or examination, exhibiting the presentation of different characterization calculations.

Table 2. Comparison of Model Accuracies

Model	Algorithm	Accuracy
Paper, [5],	Bayesian Networks, Support Vector Machines, Random Forests	87%
Paper, [6]	Deep Belief Network	87.62%
Paper, [7]	Random Forest, Deep Neural Network	∼97.89%, 94.89%
Our paper	Random Forest SVM KNN	0.99 0.98 0.94

Using RF, SVM, and KNN models, our study outperforms previous ones in terms of accuracy. In particular, RF comes out on top with an impressive accuracy of 99%, followed by SVM at 98% and KNN at 94%. This accomplishment not just highlights RF's extraordinary accuracy compared to SVM and KNN. A combination of Bayesian Networks, SVM, and Random Forests achieved an accuracy of 87% in [5]; a Deep Belief Network applied, [6], achieved an accuracy of 87.62%, demonstrating the model's proficiency in pattern extraction; and a hybrid model combining RF and Deep Neural Network, [7], achieved accuracies of up to 97.89% for RF and 94.89% for DNN. These comparative insights demonstrate the advanced performance and potential of our chosen models, particularly RF.

5 Conclusion

Our research makes substantial strides in the field of EEG signal classification for emotional state identification, harnessing the formidable capabilities of RF, SVM, and KNN models. The results are striking: RF achieves an accuracy of 99%, SVM follows closely at 98%, and KNN delivers a respectable 94%. These outcomes underscore the potent efficacy of these machine learning algorithms in managing intricate classification tasks. The comparative analysis with previous methodologies further highlights our approach's superior accuracy and considerable potential. Looking ahead, future research should delve into other ML techniques, which could harness the strengths of multiple classifiers. Additionally, conducting longitudinal EEG studies would provide insights into pattern changes over time, and integrating multimodal data could offer a more comprehensive understanding of emotional processing. These steps are crucial for refining and expanding the capabilities of emotion classification systems.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the authors used ChatGPT to check spelling and grammar, and to extract certain data values from images. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

References:

[1] K. Rezaee, M. R. Khosravi, H. Attar, and S. Almatarneh, "Eeg-based driving fatigue recognition using hybrid deep transfer learning approach," in *2022 International Engineering Conference on Electrical, Energy, and Artificial Intelligence (EICEEAI)*, pp. 1–6, IEEE, 2022.

[2] M. B. Er, H. Çiğ, and İ. B. Aydilek, "A new approach to recognition of human emotions

using brain signals and music stimuli," *Applied Acoustics*, vol. 175, p. 107840, 2021.

[3] H. Altaheri, G. Muhammad, M. Alsulaiman, S. U. Amin, G. A. Altuwaijri, W. Abdul, M. A. Bencherif, and M. Faisal, "Deep learning techniques for classification of electroencephalogram (eeg) motor imagery (mi) signals: A review," *Neural Computing and Applications*, vol. 35, no. 20, pp. 14681–14722, 2023.

[4] R. Agarwal, M. Andujar, and S. Canavan, "Classification of emotions using eeg activity associated with different areas of the brain," *Pattern Recognition Letters*, vol. 162, pp. 71–80, 2022.

[5] J. J. Bird, L. J. Manso, E. P. Ribeiro, A. Ekart, and D. R. Faria, "A study on mental state classification using eeg-based brain-machine interface," in *2018 international conference on intelligent systems (IS)*, pp. 795–800, IEEE, 2018.

[6] M. Abujelala, C. Abellanoza, A. Sharma, and F. Makedon, "Brain-ee: Brain enjoyment evaluation using commercial eeg headband," in *Proceedings of the 9th acm international conference on pervasive technologies related to assistive environments*, pp. 1–5, 2016.

[7] J. J. Bird, A. Ekart, C. D. Buckingham, and D. R. Faria, "Mental emotional sentiment classification with an eeg-based brain-machine interface," in *Proceedings of theInternational Conference on Digital Image and Signal Processing (DISP'19)*, 2019.

[8] E. Jang, B. Park, S. Kim, and J. Sohn, "Emotion classification based on physiological signals induced by negative emotions: Discrimination of negative emotions by machine learning algorithm," in *Proceedings of the 2012 9th IEEE International Conference on Networking Sensing and Control*, pp. 283–288, 2012.

[9] W. Zheng, J. Zhu, and B. Lu, "Identifying stable patterns over time for emotion recognition from eeg," *IEEE Transactions on Affective Computing*, vol. 10, pp. 417–429, July-Sept 2019.

[10] E. Batbaatar, M. Li, and K. H. Ryu, "Semantic-emotion neural network for emotion recognition from text," *IEEE Access*, vol. 7, pp. 111866–111878, 2019.

[11] A. Hakim, S. Marsland, and H. W. Guesgen, "Computational analysis of emotion dynamics," in *2013 Humaine Association Conference on Affective Computing and Intelligent Interaction*, pp. 185–190, 2013.

[12] H. P. Unal, G. Gokmen, and M. Yumurtaci, "Emotion classification with deap dataset: Survey," in *2020 Innovations in Intelligent Systems and Applications Conference (ASYU)*, pp. 1–6, 2020.

[13] D. S. Moschona, "An affective service based on multi-modal emotion recognition using eeg enabled emotion tracking and speech emotion recognition," in *2020 IEEE International Conference on Consumer Electronics - Asia (ICCE-Asia)*, pp. 1–3, 2020.

[14] P. Li, X. Rao, J. Blase, Y. Zhang, X. Chu, and C. Zhang, "Cleanml: A study for evaluating the impact of data cleaning on ml classification tasks," in *2021 IEEE 37th International Conference on Data Engineering (ICDE)*, pp. 13–24, IEEE, 2021.

[15] K. Maharana, S. Mondal, and B. Nemade, "A review: Data pre-processing and data augmentation techniques," *Global Transitions Proceedings*, vol. 3, no. 1, pp. 91–99, 2022.

[16] M. Hosni, "Encoding techniques for handling categorical data in machine learning-based software development effort estimation," 2023.

[17] P. Mooijman, C. Catal, B. Tekinerdogan, A. Lommen, and M. Blokland, "The effects of data balancing approaches: A case study," *Applied Soft Computing*, vol. 132, p. 109853, 2023.

[18] D. Axman and R. Yacouby, "Probabilistic extension of precision, recall, and f1 score for more thorough evaluation of classification models," 2020.

[19] S. Amin, B. Alouffi, M. I. Uddin, W. Alosaimi, *et al.*, "Optimizing convolutional neural networks with transfer learning for making classification report in covid-19 chest x-rays scans," *Scientific Programming*, vol. 2022, 2022.

[20] S. M. Dubey, B. Kanwer, G. Tiwari, and N. Sharma, "Classification for eeg signals using machine learning algorithm," in *International Conference on Artificial Intelligence of Things*, pp. 336–353, Springer, 2023.

[21] A. Karami and S. T. A. Niaki, "An online support vector machine algorithm for dynamic social network monitoring," *Neural Networks*, vol. 171, pp. 497–511, 2024.

[22] M. Li, G. Huang, L. Wang, and W. Xie, "Comprehensive classification assessment of gnss observation data quality by fusing k-means and knn algorithms," *GPS Solutions*, vol. 28, no. 1, p. 21, 2024.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflicts of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.