Decoding Emotions: A Review Of Sentiment Analysis And Physiological Measures

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Abstract:

Human Emotion Recognition (HER) Holds an important role across various fields, including human-computer interaction (HCI), mental health monitoring, and affective computing. In this study, we propose a new method to enhance the efficiency and accuracy of human emotion recognition by combining electroencephalogram (EEG) signal analysis with fuzzy inference systems (FIS). EEG signals offer crucial information about the brain's electrical functioning, closely related to emotional states. Fuzzy inference systems, on the other hand, offer a powerful framework for modelling complex relationships and uncertainties in the data. By integrating these two techniques, our goal is to create a durable and effective system for recognising emotions. This entails initially pre-processing EEG signals to identify important features and then designing and implementing a fuzzy inference system to predict emotions. We explore various fuzzy logic rules and membership functions to capture the nonlinear relationships between EEG features and emotional states. We assess the efficacy of the suggested system through examination of real-world EEG datasets, against existing methodologies. Our findings indicate a notable enhancement in both efficiency and accuracy of human emotion recognition when employing the integrated approach, as opposed to conventional methods the results of this research carry significant consequences for the development of advanced emotion recognition systems with potential applications in healthcare, gaming, virtual reality, and beyond.

Keywords: Human Emotion Recognition, Fuzzy system, Non-Invasive, EEG, HCI.

I. Introduction:

Identifying and understanding human emotions presents a perennial challenge. Emotions significantly influence individuals' daily lives, impacting the process of making choices, actions, and overall well-being. Historically, the study of emotions has relied on self-reporting techniques like questionnaires and interviews, as well as non-physiological and physiological records. Nevertheless, self-reporting methods possess inherent limitations due to their reliance on subjective interpretations and susceptibility to various influencing factors.

On the contrary, Non-physiological manuscripts can consist of text-based data inputs, such as handwritten text,

social media-designed posts, or transcripts of conversations, which provide valuable insights into an individual's thoughts, expressions, and emotions. These manuscripts offer a piece of valuable contextual information that contains semantic meaning, linguistic nuances, and sentiment. Moreover, these manuscripts can be available by sourcing data from the internet, enabling a comprehensive analysis on a large scale. Despite the strengths of non-physiological manuscripts in emotion prediction, constraints arise for considering the subjective nature of language and the possibility of misunderstanding or ambiguity in written communication. Ongoing challenges include understanding context and accurately interpreting sarcasm, irony, or cultural variations.
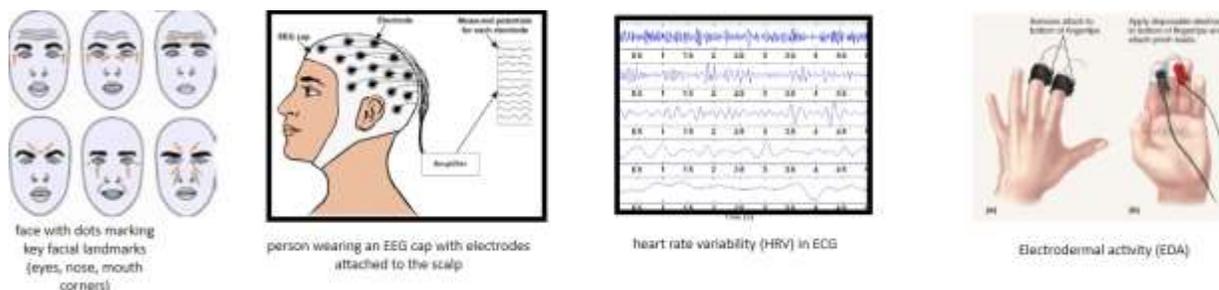
Figure 1. Techniques used to detect human emotions

On the contrary to non-physiological indicators, the EEG signals offer a direct measurement of the body's physiological responses associated with emotional experiences. Some examples of these signals comprise facial expressions, heart rate variability (HRV), Electroencephalography (EEG), and electrodermal activity (EDA). These signals capture alterations in heart rate, facial muscle movements, brain activity, and skin conductance, respectively (see Fig. 1). These waves provide a goal and immediate Indicator of the body's emotional reactions, providing an understanding of the automatic and Central Nervous System (CNS) changes associated with different emotions. In contrast to non-physiological indicators, physiological signals are inherently less prone to subjective interpretation, thus enhancing their reliability for the prediction of emotions.

EEG signals (Fig. 2) are particularly significant in emotion prediction due to their ability to directly measure the activity of the brain, their ability to capture data with precise timing and without invasive procedures, their ability to pinpoint correlations of neural, potential applications in emotion detection, and opportunities for tailored interventions.
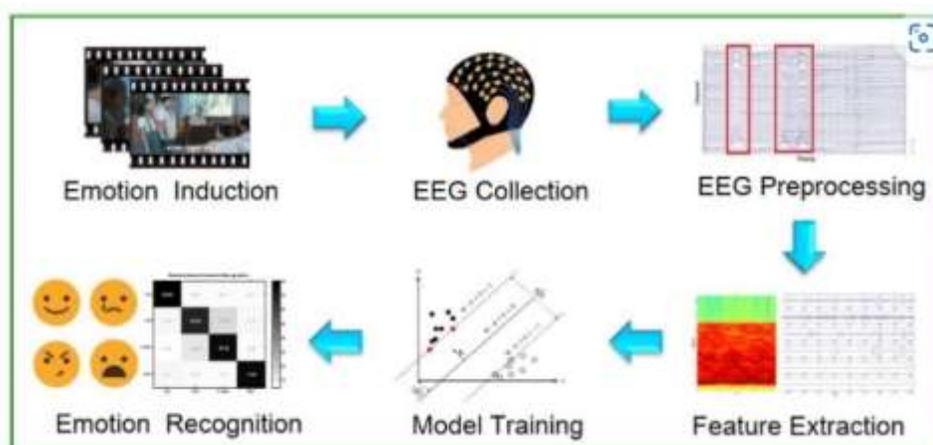
**Figure 2**. The Process of Emotion recognition using EEG signals

They facilitate an examination of neural mechanisms associated with emotions, bolster prediction abilities, and provide avenues for customized treatments. Nevertheless, individual emotions are not only intricate but also susceptible to unforeseen fluctuations based on circumstances. Consequently, numerous researchers delineate these intricate emotions utilizing two distinct methodologies.

Figure 3. Valance-Arousal & Dominance 3D Model

Among these approaches, discrete basic emotion recognition emotions into six main categories: joy, fear, anger, sadness, disgust, and surprise. Another approach referred to as dimensional emotion recognition, this method defines emotions based on two factors (fig.3) or three (fig.4) dimensions: valence, arousal or Valence and Arousal, and Dominance, (VAD) models. In psychology, VAD models frequently employ dimensions to characterize and assess emotions. The valence model indicates the emotional quality as negative or positive, where negative emotions exhibit negative valence (e.g., sadness, anger), and positive emotions exhibit positive valence (e.g., happiness, joy). Arousal denotes the degree of activation of physiological signals or stimulation that is connected with emotions, with heightened model emotions corresponding to fear, excitement, or anxiety, while diminished arousal emotions correspond to relaxation or tranquillity. Dominance indicates the level of influence or authority an individual perceives in response to emotion and emotions of high dominance are associated with a sense of mastery, while emotions of low dominance are linked to a sense of vulnerability. All the dimensions are frequently utilized in conjunction to offer a holistic comprehension of an individual's emotional condition. For instance, an emotion characterized by a high VAD model could be depicted as a potent, positive emotion linked with enthusiasm and authority. Conversely, an emotion characterized by low valence, arousal, and dominance might be portrayed as a subdued, negative emotion associated with despondency and helplessness

Thus, VAD dimensions are Invaluable instruments for researchers and psychologists to evaluate and comprehend emotional states. Assessing these three dimensions is vital for the recognition of emotions, a key component in Human-Computer interaction (HCI), as it allows electronic devices can accurately perceive changes in an individual's emotions and deliver appropriate responses.
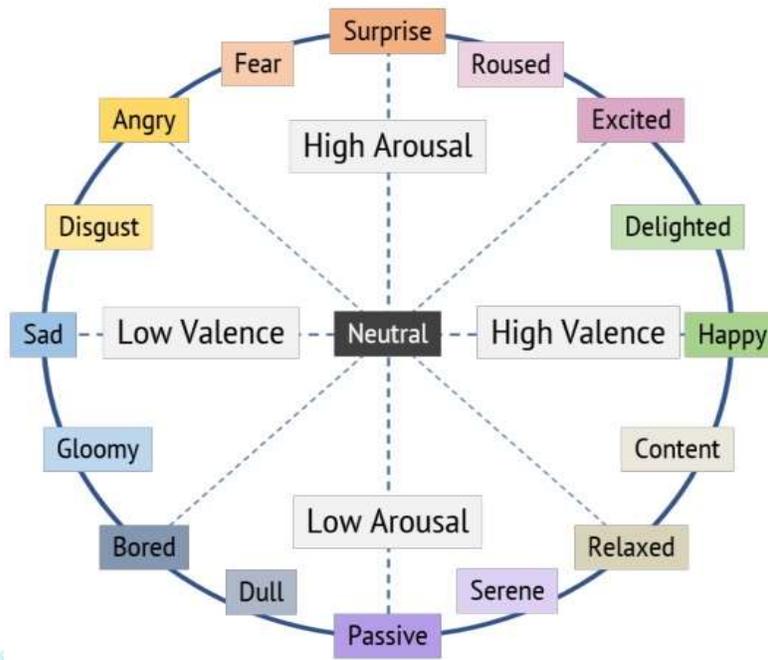
Figure 4. Valance-Arousal Model

Consequently, leveraging Fuzzy Inference Systems (FIS) or Artificial Neural Networks (ANNs) has become imperative for the pursuit of recognition of emotion, a focal point in numerous research endeavours. This endeavour sheds light on the intricate and multifaceted realm of emotions of humans, aiding in the formulation of strategies and interventions to facilitate individuals in regulating their emotional feedback.

Fuzzy Inference Systems (FIS) (fig.5) are computational frameworks based on fuzzy logic principles, enabling the processing of uncertain, imprecise, or vague information.
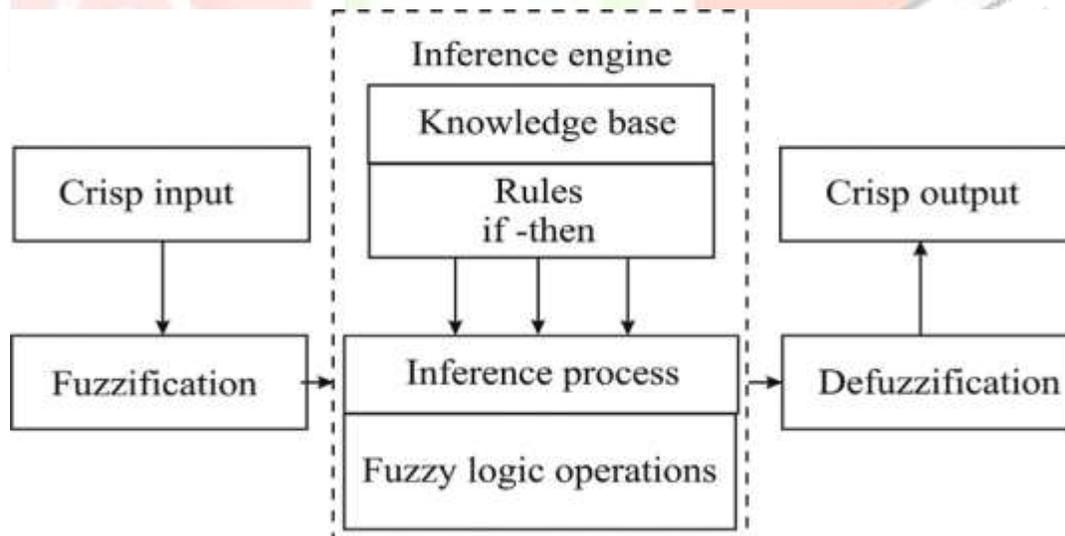
Figure 5. Architecture of Fuzzy Inference System.

Unlike traditional binary logic systems that operate with absolutes (true or false, 0 or 1), fuzzy logic accommodates the nuances of real-world phenomena by considering degrees of truth or membership.

This characteristic makes FIS particularly useful in fields requiring nuanced decision-making and interpretation, such as emotion recognition from EEG signals. Here's an overview of how FIS works and its utility in the recognition of emotions from Electroencephalogram:

Fuzzification: FIS starts with the process of fuzzification, where crisp numerical input data (such as the amplitude or frequency components of EEG signals) are transformed into fuzzy sets through the application of membership functions. These functions determine the extent to which each input is a member of one or more fuzzy sets reflecting the concept that physiological signals can exhibit characteristics of multiple emotional states to varying degrees.

Rule Evaluation: The core of FIS lies in its rule base, a collection of if-then rules that describe how to infer the fuzzy output based on fuzzy inputs. In the context of emotion recognition, these rules might encode relationships between specific patterns in EEG data and emotional states, such as "If the alpha wave amplitude is high, then the emotional state might be relaxed."

Aggregation: The outputs of individual rules are combined into a single fuzzy set for each output variable, using aggregation methods. This step consolidates the various pieces of evidence from the rule base about the emotional state being inferred.

Defuzzification: Finally, the aggregated fuzzy output is converted back into a crisp value or decision, using defuzzification methods. This could be, for example, identifying the most likely emotional state represented by the EEG data.

Fuzzy inference systems aid in EEG-based emotion recognition:

Handling Ambiguity and Uncertainty: Emotions are inherently complex and subjective, with significant variability from person to person. EEG signals capturing emotional states are also prone to noise and ambiguity. FIS can manage this uncertainty effectively, providing a flexible approach to interpreting EEG data in terms of emotional states.

Modelling Complex Nonlinear Relationships: The association between emotional states and physiological signals is highly nonlinear & varies across individuals. FIS can model these complex relationships without requiring precise mathematical formulations, making it easier to develop personalized emotion recognition systems.

Incorporating Expert Knowledge: FIS gives direction to the incorporation of specialized expertise Expressed as conditional statements of "if-then" nature. This is particularly useful in emotion recognition, where domain expertise can guide the interpretation of EEG patterns associated with different emotions.

Real-Time Processing Capability: FIS can process EEG signals in real-time, making it suitable for applications requiring immediate feedback, such as adaptive user interfaces or therapeutic interventions for emotional regulation.

Integration with Other Methods: FIS can be easily integrated along with computational models, known as neural networks or machine learning algorithms, enhancing the overall accuracy and robustness of emotion recognition systems.

II. Recent Related Work in the Relevant Field

Research recognition of emotion with EEG has captivated researchers for an extensive duration, yielding numerous articles outlining diverse methodologies for constructing systems adept at discerning human emotion detection. These investigations commonly categorize emotions into binary, ternary, or quaternary classifications. When focusing on binary classifications in existing literature,

F. Kebire Bardak, M. Nuri Seyman, Feyzullah Temurtas (2022): [1] the authors proposed an adaptive neuro-fuzzy-based hybrid classification model for emotion recognition from EEG signals, focusing on the neural computing and applications domain. This model integrates neuro-fuzzy systems developed for the classification Precision of emotion recognition using EEG signals systems, offering a promising approach for more robust and accurate emotion recognition.

Song T, Zheng W, Song P et al (2020): [2] the authors presented a novel approach for EEG emotion recognition utilizing dynamical graph convolutional neural networks. This technique leverages structural information of EEG data through graph convolutional networks, achieving notable advancements in emotion recognition accuracy compared to traditional methods.

Stajic´ T, Jovanovic´ J, Jovanovic´ N, Jankovic´ MM (2021) [3]: This work explored emotion recognition based on DEAP database physiological signals. Through this analysis of EEG from the DEAP database, the authors aimed to develop a deeper understanding association between wave responses and states of emotion, contributing valuable insights into to field of affective computing.

Luo Y, Fu Q, Xie J et al (2020) [4]: The authors proposed an EEG-based emotion classification approach using spiking neural networks. By harnessing the computational power of spiking neural networks, this method demonstrates promising results in emotion recognition tasks, offering potential advantages in terms of computational efficiency and biological plausibility.

Zhang J, Zhou Y, Liu Y (2020) [5]: This study introduced an EEG-based emotion recognition method using an improved radial basis function neural network. By enhancing the neural network architecture, the authors achieved notable improvements in the recognition of emotion accuracy, highlighting the effectiveness of advanced machine learning techniques of EEG data analysis.

Yin Y, Zheng X, Hu B et al (2021) [6]: The authors proposed an EEG emotion recognition approach using a fusion model of graph convolutional neural networks and LSTM. By combining different neural network architectures, this model aims to encompass both spatial and temporal interrelationships in physiological signals, leading to more accurate and robust emotion recognition performance.

Moussa MM, Tariq U, Al-Shargie F, Al-Nashash H (2022) [7]: This work focused on discriminating fake and real smiles using electroencephalogram signals with convolutional neural networks. By leveraging EEG signals, the authors developed a novel approach for detecting genuine emotional expressions, offering possible uses in affective computing and machine interaction with humans.

Bardak FK, Seyman MN, Temurtas F (2022) [8]: The authors explored EEG-based emotion prediction with neural network models, contributing to the development of more effective and efficient emotion recognition systems. By leveraging neural network architectures, this study Strives to improve the precision and resilience of emotional analysis prediction from EEG signals, offering promising prospects for real-world applications.

Bird JJ (2022) [9]: This work investigated EEG wavelet classification for fall detection with genetic programming, focusing on the application of EEG signals in healthcare monitoring systems. By combining wavelet analysis and genetic programming techniques, the authors developed an innovative approach for

detecting falls based on EEG data, addressing critical challenges in healthcare monitoring and assistive technologies.

Gu¨ler I, U¨ beyli E (2005) [10]: The authors proposed an adaptive-fuzzy inference system for the classification of EEG signals using wavelet coefficients. This method integrates fuzzy logic and wavelet analysis to enhance the precision in categorizing physiological data, providing a sturdy foundation for EEG-based applications, including recognition of emotion and cognitive state monitoring.

Zhang J, Chen M, Hu S, et al. (2017) [11]: Zhang et al. proposed a method for EEG-based emotion recognition using Probabilistic Neural Networks (PNN), submitted in the 2016 IEEE International Conference on Systems, Man, and Cybernetics. Their approach leverages the inherent probabilistic nature of PNNs to classify physiological data into different states of emotions. By utilizing PNNs, which are known for their ability to model complex relationships in data, the authors aimed to enhance the exact results and robustness recognition of emotion systems depending on Electroencephalogram signals.

Krisnandhika et al. [14] introduced a novel emotion recognition algorithm model termed the multi-feature deep forest (MFDF). Results indicate that the MFDF achieved accuracies of 69.75% and 75.7% for valence and arousal, respectively.

Zhong et al. [15] introduced a regularized graph neural network (RGNN) designed for EEG-based emotion recognition. The authors devised two regularization techniques to effectively address cross-subject noisy labels and EEG variations. They extensively evaluated the proposed RGNN model across three emotion categories: neutral, positive, and negative. Their findings demonstrate that the accuracy achieved by the proposed model reaches 94.24%.

Table 1: Emotion Recognition Different Approaches

Author(s) Name	Methodology/Approach	Accuracy (%)	Emotion Classes	Dataset	Key finding (Research Gap)	Future Scope
F. Kebire Bardak, M. Nuri Seyman, Feyzullah Temurtas 2022	Proposed hybrid model combining CNN, RNN and ANFIS (Adaptive Neuro-Fuzzy Inference System)	91.53 %	High/Low Arousal, High/Low Valence, Neutral	Database for Emotion Analysis using Physiological Dataset	Did not consider personalized models	Testing on larger multi-modal datasets with person-specific customization
Song T, Zheng W, Song P et al 2020	Proposed dynamical graph CNN to model EEG graph structure and temporal dependencies	86.89 %	Happy, sad, fear, neutral	SEED and SEED-IV EEG emotion datasets	Small sample size. Did not consider personalized models.	Test approach on larger multi-modal dataset and with personalized models
Stajic, T., Jovanovic, J., Jovanovic, N., Jankovic,	SVM, Random Forest	63-73%	Low/High Arousal, Low/High Valence	DEAP Dataset	Small sample size, limited contextual detail	Evaluating the recognition performance in real-time applications like adaptive interfaces,

M.M. 2021						health monitoring etc. is valuable
Luo, Y., Fu, Q., Xie, J. et al. 2020	Proposed spiking NN architecture for EEG feature learning	92.51 %	Positive, Negative, Neutral	SEED EEG Dataset	Did not explore other EEG datasets	Expanding to larger datasets like DEAP, MAHNOB-HCI can demonstrate scalability
Zhang, J., Zhou, Y., Liu, Y. 2020	Proposed optimized RBF neural network architecture	93.6%	Positive, Negative	SEED EEG dataset	Evaluation of only one dataset	Along with EEG, incorporating other signals like facial expressions, voice features, etc.
Yin, Y., Zheng, X., Hu, B. et al. 2021	Proposed GCN-LSTM fusion model	86.03 %	Positive, Negative	SEED	Evaluation of a single dataset	Other signals like facial expressions, voice features, etc., are incorporated along with EEG
Moussa, M.M., Tariq, U., Al-Shargie, F., Al-Nashash, H. 2022	CNN model for EEG feature learning and classification	97.5%	Fake Smile Detection Accuracy	Custom EEG dataset	Small sample size	Scalability can be demonstrated by expanding to larger datasets like DEAP, MAHNOB-HCI
Bardak, F.K., Seyman, M.N., Temurtas, F. 2022	CNN and LSTM models for EEG	83.53 %	High/Low Arousal, High/Low Valence	DEAP Dataset	Did not explore art for the state in deep networks	Approach to be tested on larger multi-modal datasets and with personalized models.
Bird, J.J. 2022	Genetic programming for EEG wavelet feature classification	85%	Detecting falls using EEG signals	Custom EEG dataset with falls/ADLs	Small sample size, limited context	Evaluating the recognition performance in real-time applications like adaptive interfaces, health monitoring etc.
Güler I, Übeyli E 2005	Implemented ANFIS for Categorizing EEG signals according to emotional states.	97.50 %,	electrocardiographic changes to partial in patients	EEG dataset	Evaluation of a single dataset	This model can be implemented in large data sets like DEAP
Zhang J, Chen M, Hu S, et al.	Probabilistic Neural Network	81.30 %	High/Low Arousal,	DEAP	Did not explore other EEG sets	The test approach on the larger multi-modal dataset and with

(2017)	(PNN)		High/Low Valence			personalised models is carried out.

III. Conclusion:

   In summary, the examination of all the above findings reveals an inadequate level of accuracy in emotion classification, indicating a need for improvement. Hence, to enhance system efficiency in the recognition of emotion from physiological data. The primary aim of this review is to offer a thorough examination of how fuzzy inference systems are applied in the recognition of human emotion. Fuzzy inference systems offer a flexible and effective approach to processing complex emotional data, leveraging the principles of fuzzy logic to handle uncertainty and ambiguity inherent in human emotions. Through our examination of existing literature and research findings, we have highlighted the versatility and potential of fuzzy inference systems in accurately identifying and categorizing emotions across various contexts and modalities. From analysing physiological signals to interpreting textual data, fuzzy inference systems have demonstrated their capability to enhance emotion recognition accuracy and efficiency. Additionally, the review has underscored the importance of integrating fuzzy logic with other methodologies, such as artificial neural networks or physiological signal analysis, to further improve emotion recognition performance. Overall, this review contributes to comprehending the significance of fuzzy inference systems in advancing recognition of human emotion technology, with implications for fields ranging from human-computer interaction to mental health assessment and beyond.

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