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AN ENHANCED MACHINE LEARNING FRAMEWORK FOR EMOTION RECOGNITION USING PAD MODEL AND DEEP LEARNING

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ABSTRACT: Emotion recognition plays an important role in affective computing and human–computer interaction. Previous research has used machine learning techniques to cluster emotions using the Pleasure–Arousal–Dominance (PAD) emotional model. In the existing approach, clustering methods such as K-means and machine learning algorithms like Decision Trees and Support Vector Machines were used to classify emotions based on PAD scores. However, the approach suffers from limitations such as overfitting, limited datasets, and inability to detect mixed emotions. This paper proposes an enhanced emotion recognition framework that integrates deep learning models with hybrid clustering techniques to improve classification accuracy and generalization. The proposed system uses dimensionality reduction, advanced clustering, and neural network–based classifiers to better map PAD scores to emotional categories. Experimental analysis shows that the proposed system improves emotion classification performance and provides a more scalable framework for real-world affective computing applications.

Index terms*: emotions, PAD, affective computing, machine learning*

1. INTRODUCTION

Recent advances in affective computing have significantly increased interest in understanding and analyzing human emotions. Emotions play an important role in shaping human behavior, communication, decision-making, and social interactions. Therefore, identifying the mechanisms that govern emotional experiences is essential for developing intelligent systems capable of recognizing, interpreting, and responding to human emotions in a natural and empathetic manner. Emotion recognition has become a key component in many modern applications such as human–computer interaction, mental health monitoring, virtual assistants, and smart learning environments.

In everyday life, people use a wide range of words to describe emotions such as excitement, shame, anger, or astonishment. However, psychological research suggests that many of these emotional expressions can be grouped into a smaller number of basic emotions. Previous studies have identified several fundamental emotional categories including happiness, sadness, fear, anger, disgust, and surprise. Although these discrete emotion categories help simplify emotional understanding, they do not fully capture the complexity of human emotional experiences, particularly when individuals experience mixed emotions simultaneously.

To better represent the complexity of emotions, researchers have developed

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several self-reporting frameworks. One widely used method is the Positive and Negative Affect Schedule (PANAS), which measures an individual's positive and negative emotional states. Another widely adopted model is the Pleasure–Arousal–Dominance (PAD) model, which represents emotions in a continuous three-dimensional space. The PAD model describes emotions based on three psychological dimensions: pleasure, which reflects the positivity or negativity of an emotional state; arousal, which represents the level of emotional intensity; and dominance, which indicates the level of control or influence felt by an individual.

To measure emotional responses based on the PAD model, researchers commonly use the Self-Assessment Manikin (SAM) scale. The SAM scale provides a visual representation of emotional dimensions using pictorial Likert scales ranging from 1 to 9. This approach allows participants to express their emotional responses through visual representations rather than verbal descriptions, making it suitable for diverse populations and experimental studies. Despite the advantages of the PAD model, mapping PAD scores directly to commonly used emotion labels such as happiness or sadness remains a challenging task.

In many affective computing studies, the dominance dimension is often ignored when analyzing PAD scores. However, recent research suggests that dominance plays an important role in accurately representing emotional states. Studies have shown that including the dominance dimension improves emotion modelling and clustering accuracy. Furthermore, researchers have proposed that emotion clustering within the three-dimensional PAD space can provide a more accurate representation of human emotional states.

Although several studies have attempted to classify emotions using machine learning techniques, there is limited research that effectively maps PAD scores to widely used emotion identifiers. Traditional approaches mainly rely on simple clustering algorithms and conventional machine learning models, which often suffer from limitations such as overfitting, reduced generalization capability, and difficulty in identifying mixed emotional states.

To address these challenges, this research proposes an enhanced emotion recognition framework that integrates hybrid clustering techniques and deep learning models to analyze PAD emotional data more effectively. The proposed approach aims to improve the mapping between PAD scores and emotional categories while addressing the limitations of traditional machine learning methods. By combining advanced clustering methods, dimensionality reduction, and neural network-based classification, the proposed system seeks to develop a more accurate and scalable emotion recognition model capable of identifying complex emotional patterns.

2. LITERATURE SURVEY

Emotion recognition has been widely studied in affective computing research. Various approaches have been proposed to analyze human emotional responses using physiological signals, facial expressions, and behavioral data. Ekman identified six basic emotions including happiness, sadness, fear, anger, disgust, and surprise. These emotions are considered universal across cultures and have been widely used

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in emotion recognition research.

Another widely used approach is the dimensional emotion model. The PAD model proposed by Mehrabian and Russell represents emotions using pleasure, arousal, and dominance dimensions. This model provides a more detailed representation of emotional states compared to categorical emotion models.

Several datasets have been developed for emotion recognition research. The DEAP dataset is a widely used dataset containing emotional responses recorded from participants while watching music videos. Participants rated their emotional responses using PAD scores.

Similarly, the International Affective Picture System (IAPS) contains standardized emotional images designed to evoke emotional responses in participants. Researchers have applied various machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, Random Forests, and Naïve Bayes for emotion classification. Although these algorithms provide reasonable performance, they often struggle with complex emotional patterns.

Deep learning techniques have recently gained attention for emotion recognition due to their ability to learn complex patterns from large datasets. Neural networks can automatically learn feature representations from emotional data.

Hybrid approaches combining clustering algorithms and deep learning models have shown promising results in emotion recognition tasks. Clustering helps identify groups of similar emotional responses, while deep learning models improve classification accuracy. Motivated by these findings, the proposed system integrates clustering techniques with deep learning models to improve emotion classification using PAD scores.

3. METHODS

The DEAP Dataset provides the PAD (Pleasure–Arousal–Dominance) scores obtained in response to emotional video stimuli. These scores represent emotional responses in a three–dimensional psychological model consisting of pleasure, arousal, and dominance dimensions. Although the DEAP dataset has been widely used for emotion recognition studies, most existing research focuses on analyzing physiological signals and PAD values without directly linking these numerical scores to emotion-identifying terms commonly used in everyday language. Therefore, there is a noticeable gap in the literature that connects PAD-based emotional measurements with descriptive emotional labels such as happiness, sadness, fear, and anger.

To address this limitation, a computational framework was developed using the DEAP dataset to map PAD scores into clusters representing basic emotions. The main objective of this research is to evaluate different machine learning models to identify patterns among PAD score combinations and group similar emotional responses into clusters. These clusters can then be associated with specific emotion-identifying terms, thereby enabling a more interpretable representation of emotional states.

For validating the proposed framework, additional data were collected from participants who viewed images from the International Affective Picture System (IAPS) and reported their emotional responses using the Self-Assessment Manikin (SAM) scale. The IAPS is a

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standardized database containing a large collection of emotionally evocative images spanning multiple semantic categories such as pleasant, neutral, and unpleasant scenes. Each image in the dataset is designed to evoke specific emotional reactions and has corresponding PAD ratings collected from participants.

Using both the DEAP dataset and the experimental data collected through IAPS and SAM, several computational models were developed to analyze and cluster PAD scores. These models help establish a relationship between PAD-based emotional measurements and clusters of identifiable emotions. By linking physiological signal-based emotional metrics with descriptive emotional categories, the proposed approach contributes to improved emotion recognition systems and supports applications in affective computing, human–computer interaction, and psychological analysis.

A. DEAP Dataset

The DEAP Dataset was used in this study, specifically the online subjective annotation component of the dataset (Table I). The dataset was originally created by asking participants to watch 40 one-minute music video clips online. After viewing each clip, participants were required to record their emotional responses using three different types of annotations.

First, participants rated their emotional state using the PAD (Pleasure–Arousal–Dominance) model through the Self-Assessment Manikin interface. This method allows participants to visually represent their emotional feelings across the three dimensions of pleasure, arousal, and dominance.

Second, participants were asked to self-identify their experienced emotion from a predefined list of 16 emotional categories. These emotions included Pride, Elation, Joy, Satisfaction, Relief, Hope, Interest, Surprise, Sadness, Fear, Shame, Guilt, Envy, Disgust, Contempt, and Anger. This provided categorical emotional labels that could later be compared with the PAD scores.

Third, participants rated the intensity of the selected emotion using a four-level scale, where Level 1 represents a weak emotional response and Level 4 represents a strong emotional response. This helped quantify the strength of the experienced emotion in addition to identifying its type.

Overall, the dataset contained 120 samples, where each one-minute music video clip was viewed by a minimum of 14 and a maximum of 16 participants. The participants involved in each trial were different, ensuring variability in emotional responses across the dataset. A detailed explanation regarding the selection of the music video stimuli and the experimental design was provided by Sander Koelstra et al. in their original study.

Online Subjective Annotation	
Stimuli	1 minute affective videos (60
selected via affective tags and 60	manually)
Number of Ratings 14-16 /video	*Outputs* Pleasure, Arousal, Dominance,
Emotion, Emotion Strength	*Pleasure, Arousal and Dominance*
Scores	Discrete scale 1-9
Emotions 16 Emotion Description Words	*Strength of Emotion* Scale 1-4

Table1: DEAP summary adapted from [8].

B. Data Collection

Participants (BDAT Dataset)

The BDAT Dataset consisted of 31 participants aged between 9 and 25 years, with a mean age of 21.8 years and a standard deviation of 3.8 years. All

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participants were typically developing individuals without disabilities. The study was conducted following ethical research standards and was approved by the Queen's University Health Sciences and Affiliated Teaching Hospitals Research Ethics Board. Informed consent or assent was obtained from each participant depending on their age, ensuring that all ethical guidelines for human subject research were properly followed.

Stimuli

To elicit emotional responses, the International Affective Picture System was used. The IAPS is a standardized database of emotionally evocative images widely used in psychological and affective computing research. Since this study is part of a broader research project focused on identifying emotions in children, the IAPS image set designed for children aged 7–9 years was selected. Prior to conducting the experiment, researchers carefully reviewed the image set and removed sensitive or inappropriate images. As a result, 52 images were selected and approved by the HSREB for use in the study.

Protocol

The experimental protocol required participants to view a sequence of 30 images from the selected IAPS set. Before each image was displayed, a grey slide with the message "Get ready to rate the next image…" appeared on the screen for five seconds. This step helped normalize participants' emotional states and establish a baseline before presenting the next stimulus. After the preparation slide, an image from the IAPS dataset was displayed for six seconds. Participants were then asked to report how they felt according to the three emotional dimensions of the Self-Assessment Manikin: pleasure, arousal, and dominance (PAD). Instead of verbal responses, participants pointed to the appropriate SAM image displayed on the screen that best represented their emotional state. A researcher observed the participant's response and recorded the corresponding PAD scores based on the selected SAM representation. Further methodological and experimental details regarding this study are provided in the work by Collins et al..

C. Computational Model

The objective of the computational model (Fig. 1) is to establish a relationship between the PAD scale and clusters representing different emotional states. Although PAD scores are widely used in affective computing research, they do not directly correspond to specific emotional labels used in everyday human communication. As a result, the PAD dataset is considered an unlabeled emotional representation space .

To assign meaningful emotion labels to the PAD scores, it was first necessary to determine the number of potential basic emotions present in the data. This was achieved using K-means clustering in combination with the elbow method on the DEAP dataset. The elbow method is a commonly used technique for identifying the optimal number of clusters in clustering algorithms. It works by plotting the within-cluster variance against the number of clusters (K) and observing the point where the rate of decrease in variance sharply changes, forming an "elbow" shape in the graph.

This elbow point indicates the optimal number of clusters that balances model complexity and clustering performance. Beyond this point, increasing the number of clusters provides only minimal

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improvement in explaining the variance of the data. By applying the elbow method to the DEAP dataset, the optimal number of clusters representing distinct emotional categories was determined.

Once the optimal value of K was identified, the K-means clustering algorithm was applied to group the PAD scores into clusters. Each cluster corresponds to a specific emotional category, and the PAD samples were labeled according to their respective cluster assignments. In this way, the originally unlabeled PAD data was transformed into labeled emotional groups, where each cluster represents a basic emotion.

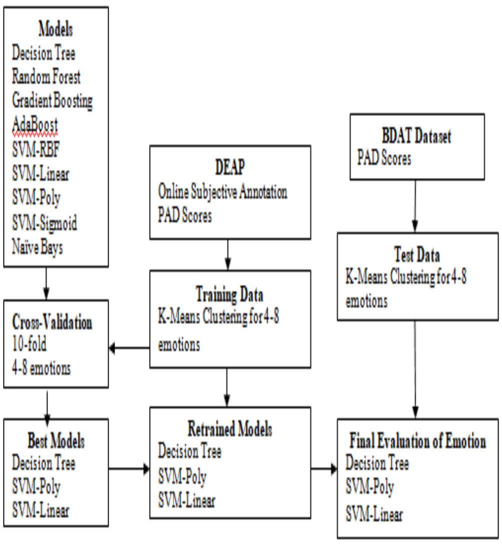

Fig1. Flowchart of Methodology

The next step in the proposed framework was to identify an appropriate machine learning model capable of classifying new PAD scores into the previously generated emotion clusters. To accomplish this, nine different machine learning algorithms were evaluated using cluster configurations ranging from 4 to 8 clusters. The models considered included several tree-based algorithms, support vector machine variants, and a Naïve Bayes classifier.

The tree-based algorithms consisted of Decision Trees, Random Forest, Gradient Boosting Machines , and AdaBoost. A Decision Tree is a supervised learning model that classifies data points through a sequence of decision rules. In this model, each node represents a decision based on specific features of the data, while the branches represent possible outcomes that lead to the final classification.

A Random Forest model is an ensemble learning method that combines multiple decision trees to improve prediction accuracy and reduce overfitting. In this approach, each tree is trained using a random subset of the training data and features, and the final prediction is obtained by aggregating the predictions from all trees. Each tree contributes equally to the final decision.

In contrast, Gradient Boosting Machines and AdaBoost also use an ensemble of decision trees but apply a boosting strategy. In these models, each tree contributes a weighted prediction, meaning that some trees may have a stronger influence on the final output than others. Boosting methods sequentially train trees such that each new tree attempts to correct the errors made by the previous ones, thereby improving overall performance.

The Support Vector Machine (SVM) models were also explored using different kernel functions, including Radial Basis Function (RBF), Linear, Polynomial, and Sigmoid kernels. SVM is a powerful classification technique that determines the optimal hyperplane separating data into distinct classes. By mapping the original data into a higher-dimensional feature space using kernel functions, the algorithm identifies a hyper plane that maximizes the margin between different

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classes, leading to better classification performance.

Additionally, a Naïve Bayes classifier was implemented as a probabilistic model. This approach applies Bayes' theorem under the assumption that all features are conditionally independent. Based on the observed features, the model calculates the probability of each class and assigns the data point to the class with the highest probability.

All models were trained and evaluated using a ten-fold cross-validation technique on the DEAP dataset to ensure robust performance evaluation. This method divides the dataset into ten subsets, where nine subsets are used for training and the remaining subset is used for testing. This process is repeated ten times so that each subset serves as the test set once.

Finally, the performance of all machine learning models was compared in terms of classification accuracy and computational efficiency. The three best-performing models—Decision Trees, Polynomial SVM, and Linear SVM—were further validated using BDAT Lab experimental data along with the corresponding International Affective Picture System (IAPS) PAD scores for each cluster. Since both datasets used the same emotional stimuli, the predicted emotion clusters derived from the participant data could be directly compared with the emotion clusters predicted from the original IAPS PAD scores.

4. RESULTS

Determination of Optimal Emotion Clusters

This study employed machine learning techniques to determine the optimal number of basic emotion categories that can be distinguished within the Pleasure–Arousal–Dominance (PAD) model of emotion. Multiple machine learning algorithms were implemented and evaluated based on their classification accuracy in order to identify the most effective model for mapping PAD scores to emotion clusters.

To determine the appropriate number of clusters, the elbow method was applied. This technique evaluates the relationship between the number of clusters (K) and the sum of squared distances (also referred to as inertia) within clusters. The analysis was performed by plotting inertia values for cluster sizes ranging from 1 to 20 clusters. As the number of clusters increases, the inertia decreases because data points become more closely grouped within clusters.

The optimal number of clusters is identified at the point where the rate of decrease in inertia begins to slow significantly, forming an "elbow" in the curve. In this study, the elbow point was observed at approximately five clusters, suggesting that this number provides a good balance between cluster compactness and model simplicity.

However, to avoid the potential loss of meaningful emotional distinctions in the data, a broader range of cluster values was considered. Therefore, cluster configurations ranging from four to eight clusters were evaluated in subsequent machine learning experiments. This approach allowed the study to explore multiple possible representations of emotional categories within the PAD space.

An illustration of the PAD data distributed into six clusters within the three-dimensional PAD space is presented in Fig. 2, demonstrating how different

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emotional states can be grouped based on their Pleasure, Arousal, and Dominance values.

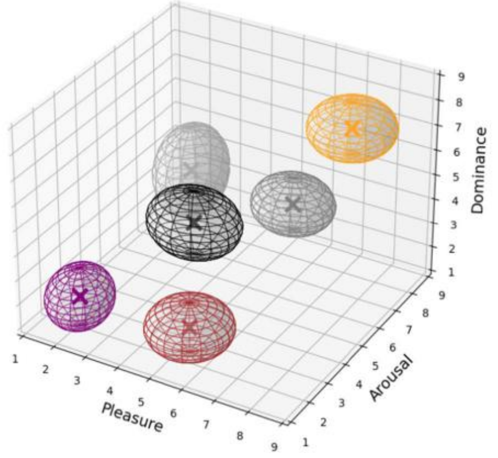

Fig. 2. Six Clusters of Emotion

Cross-Validation and Model Evaluation

To evaluate the performance of the proposed emotion classification models, ten-fold cross-validation was employed. In this method, the dataset is divided into ten equal subsets (folds). During each iteration, nine subsets are used for training the model, while the remaining subset is used for testing. This process is repeated ten times so that every subset serves as the testing set once. The final performance of the model is obtained by averaging the results across all folds, ensuring a reliable and unbiased evaluation.

Using this cross-validation strategy, nine different machine learning algorithms were tested for each cluster configuration ranging from four to eight basic emotion clusters using the DEAP dataset. This approach allowed the study to systematically analyze the classification performance of different models across multiple emotional cluster configurations.

Among the evaluated models, the Decision Tree classifier demonstrated promising results in several configurations. As an illustrative example, the results obtained for the six-cluster Decision Tree model across each of the ten cross-validation folds are presented in Table II. This table provides a detailed view of the model's performance during each fold, highlighting the consistency and reliability of the classification process.

The cross-validation results help assess the robustness of the model and ensure that the obtained performance metrics are not dependent on a specific data split. By analyzing the results across all folds, the study identifies the most effective machine learning model for mapping PAD scores to emotion clusters.

Fold	Score(%)	Score time($x10^{-4}s$)
0	99.3902	3.33
1	100	1.92
2	99.3902	1.56
3	98.1595	1.61
4	99.3865	1.67
5	98.773	1.51
6	98.1595	1.48
7	100	1.45
8	100	1.43
9	100	1.45

Table II: Decision Tree 10 Fold Results for Six Clusters

Performance Evaluation

Table II illustrates the performance of the Decision Tree model for the six-cluster configuration using ten-fold cross-validation. The model achieved 100% accuracy in 4 out of 10 folds, with a minimum accuracy of 98.1%, indicating strong consistency across different data splits. Additionally, the maximum scoring time recorded was 3.33×10−43.33 \times 10^{-4}3.33×10−4 seconds, demonstrating the model’s high computational efficiency.

This ten-fold cross-validation procedure was conducted for all cluster configurations ranging from four to eight

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clusters using the DEAP dataset, ensuring a comprehensive evaluation of model performance under varying emotional categorizations.

Table III presents an example of the comparative results for the six-cluster configuration across all evaluated algorithms. The results are color-coded to facilitate intuitive interpretation of performance. Specifically, green denotes the best-performing models with the highest accuracy and fastest execution times, while orange and yellow represent moderate performance levels. In contrast, red highlights the lowest-performing models, characterized by reduced accuracy and slower processing speeds.

Algorithm	Score (%)	Timing		
		Fit time ($x10^{-4}$)	Score time ($x10^{-4}$)	Total time ($x10^{-4}$)
Decision Tree	99.33	10.07	1.74	11.81
Random Forest	99.45	1293.45	125.32	1418.76
Gradient Boosting	99.51	5112.97	16.19	5129.16
AdaBoost	63.14	459.24	38.83	498.06
SVM-RBF	98.28	213.40	64.83	278.23
SVM-Linear	98.59	59.85	10.09	69.94
SVM-Poly	99.02	91.20	7.16	98.36
SVM-Sigmoid	21.44	2027.86	164.31	2192.18
Bayes	96.39	7.06	2.74	9.80

Table III: Analysis of Models for Six Clusters

Selection of Optimal Model and Cluster Configuration

The highest-performing machine learning model for each cluster configuration was selected by jointly evaluating classification accuracy and computational efficiency (training and scoring time). For instance, in the six-cluster configuration presented in Table III, the Gradient Boosting model achieved the highest accuracy. However, this model exhibited relatively slower performance in terms of computation time. In contrast, the Naïve Bayes classifier demonstrated the fastest training and scoring times but ranked among the lowest in terms of accuracy.

Considering both performance metrics, the Decision Tree model was selected as the optimal algorithm for the six-cluster configuration. Although its accuracy was slightly lower than the best-performing model (within 0.5% difference), it offered significantly faster scoring time, making it more suitable for practical applications. Additionally, the Polynomial and Linear Support Vector Machine (SVM) models were also identified as strong candidates, as they achieved accuracy levels exceeding 98% while maintaining relatively fast execution times.

To further validate the selected models, an external comparison was performed using datasets with identical emotional stimuli, specifically International Affective Picture System (IAPS) images. The predicted emotional clusters obtained from 890 PAD samples collected in the BDAT laboratory were compared against the predicted clusters derived from the original IAPS PAD scores for each stimulus.

The comparison results, summarized in Table IV, indicate that the six-cluster Decision Tree model achieved the highest level of consistency between the two datasets, with a similarity score of 47%. Other cluster configurations (ranging from four to eight clusters) showed significantly lower agreement, with similarity scores below 13%, indicating poor alignment between datasets.

Notably, the best-performing configuration—yielding a similarity score of 47%—was observed for both the six-cluster Decision Tree model and the six-cluster Linear SVM model. These findings suggest that a six-cluster representation

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provides the most effective mapping of basic emotions within the PAD framework for the datasets considered.

Although both Decision Tree and Linear SVM models demonstrated high accuracy during the testing phase, the Decision Tree model exhibited superior computational efficiency during the validation phase, making it the preferred choice for the proposed system.

Clusters	Decision Tree		Poly SVM		Linear SVM	
	Same	Different	Same	Different	Same	Different
4	111 (12%)	779 (88%)	113 (13%)	777 (87%)	122 (12%)	768 (86%)
5	86 (10%)	804 (90%)	87 (10%)	803 (90%)	92 (10%)	798 (90%)
6	416 (47%)	474 (53%)	384 (43%)	506 (57%)	416 (47%)	474 (57%)
7	80 (10%)	802 (90%)	95 (11%)	795 (89%)	86 (10%)	804 (90%)
8	67 (8%)	823 (92%)	74 (8%)	816 (92%)	71 (8%)	819 (92%)

Table IV: Similarity of Model Predictions for IAPS Vs Our Collected Data

5. DISCUSSION

The results of this study indicate that the six-cluster Decision Tree model is the most suitable approach for emotion classification using PAD scores. However, although the model achieved an average testing accuracy greater than 98%, the validation phase produced only 47% similarity, suggesting that overfitting may have occurred.

A key limitation of this study lies in the characteristics of the datasets used. The International Affective Picture System (IAPS) dataset provides PAD scores associated with each image but does not include explicit emotion labels. Similarly, the data collected in the BDAT Lab followed the same protocol and did not capture participant-reported emotion words. Consequently, while numerical comparisons between datasets were possible, there was no direct mapping between PAD-based clusters and the actual emotional expressions experienced by individuals.

In contrast, the DEAP dataset includes both PAD scores and corresponding emotion labels, enabling a partial linkage between numerical representations and emotional terms. Previous research exploring this relationship identified six clusters within PAD space; however, only four clusters could be explicitly labeled as happiness, anger, disgust, and sadness [6]. Evidence from this study and other related works [7], [11] suggests that six distinct emotion clusters may exist within the PAD framework.

The theory proposed by Paul Ekman identifies six fundamental emotions: fear, anger, happiness, sadness, disgust, and surprise [1]. This aligns with the six-cluster structure observed in this study and related research. However, due to the absence of explicit emotion labels in the datasets, it cannot be conclusively determined whether the two unlabeled clusters correspond to fear and surprise.

Another limitation arises from the selection of stimuli used in the BDAT Lab. The IAPS images were restricted due to ethical approval requirements, allowing only images suitable for children aged 7–9 years. As a result, stimuli capable of eliciting strong emotions such as fear and surprise were underrepresented, potentially limiting the diversity of emotional responses captured.

Furthermore, research by [2] demonstrated that emotional responses to IAPS images are often non-discrete, with participants experiencing mixed emotions. Their study identified multiple emotional labels, including awe, amusement, excitement, contentment, fear, sadness, disgust, and anger. In contrast, the current study focused exclusively on discrete emotion

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clusters, simplifying the classification process but failing to capture the complexity of mixed emotional experiences. This represents a significant limitation of the proposed approach.

Future work should consider filtering out images associated with mixed emotional responses, as identified in [2], to determine whether clearer and more distinct clusters can be achieved. Additionally, methods for modeling mixed emotions should be explored, as real-world emotional experiences are rarely purely discrete. The identification of independent emotional clusters should precede the classification of mixed emotional states.

A systematic review conducted in [12] highlighted that PAD-based emotional responses can vary significantly based on age, gender, and cultural background. This finding suggests the need for participant-specific emotion recognition models. However, due to the use of the DEAP dataset, it was not possible in this study to incorporate such personalization. Increasing the number and diversity of participants would likely improve the robustness and accuracy of the identified emotion clusters.

6. CONCLUSION

In conclusion, the present study investigated the optimal number of clusters for analyzing emotion representations using the Pleasure–Arousal–Dominance (PAD) model and identified the most effective machine learning algorithms for classifying basic emotions. The elbow method was employed to determine the appropriate number of clusters, revealing that the optimal range lies between four and eight clusters.

During the testing phase, the Decision Tree, Polynomial Support Vector Machine (SVM), and Linear SVM models emerged as the top-performing algorithms based on classification accuracy. However, further validation using both the International Affective Picture System (IAPS) dataset and the BDAT Lab dataset indicated that a six-cluster representation provides the most consistent and meaningful structure for modeling emotions within the PAD space. Among these, the Polynomial SVM model demonstrated strong performance in identifying these clusters during validation.

Despite these promising results, several limitations were identified. One key limitation is the presence of mixed emotions in response to certain stimuli, which may reduce classification accuracy by blurring the boundaries between discrete emotion clusters. Additionally, the inability to construct participant-specific models due to insufficient subject-level data in the DEAP dataset limited the model's ability to account for individual variability in emotional responses.

Overall, the findings of this study provide valuable insights for researchers aiming to establish a connection between numerical PAD representations and commonly used emotional vocabulary. By identifying an optimal cluster structure and effective classification models, this work contributes to advancing emotion recognition systems and improving the interpretability of affective computing models.

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