Enhancing EEG-Based Emotion Recognition in Computer Games Using KNN Optimized by the iHOW Optimization Algorithm

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Abstract

Emotion recognition using electroencephalogram (EEG) signals has become a pivotal area in affective computing, particularly within the context of human–computer interaction and game-based environments. This study aims to enhance the accuracy and robustness of EEG-based emotion classification by introducing a hybrid framework that combines the k-Nearest Neighbors (KNN) classifier with advanced metaheuristic feature selection techniques. Using the publicly available GAMEEMO dataset, which includes EEG recordings from 28 subjects engaged in four emotionally distinct computer games (boring, calm, horror, and funny), EEG data were acquired through a 14-channel Emotiv Epoc+ device and labeled using the Self-Assessment Manikin (SAM) scale. Baseline machine learning models including Support Vector Machine (SVM), Decision Tree (DT), Multi-Layer Perceptron (MLP), and KNN were evaluated, with KNN achieving the highest baseline performance. The KNN classifier was further optimized using several metaheuristic algorithms—namely WAO, BBO, GWO, GA, FA, PSO—and the proposed Improved Human Optimization Algorithm (iHOW). Experimental results show that the iHOW+KNN model achieved the best overall performance with an accuracy of 96.85%, sensitivity of 95.50%, specificity of 95.82%, and F1-score of 95.54%. Visual assessments using heatmaps, radar plots, and confidence intervals further validated the model's reliability. These findings demonstrate the effectiveness of the iHOW+KNN framework in addressing the challenges of high-dimensional EEG data and highlight the potential of wearable EEG devices for real-time emotion recognition in affective computing applications. into user experiences within the gaming environment.

Keywords: EEG signal processing; Affective computing; Metaheuristic optimization; iHOW algorithm; Computer games

1 Introduction

Emotions have always been recognized as one of the fundamental elements that drive behavior and decision-making. Studies on ancient philosophers reveal that they were deeply concerned about the origins, purpose, and expressions of emotions and the way they affect the economy of human life. Emotional expressions have distinct behavioral manifestations, such as pride leads to protectiveness, loss to withdrawal, anger to retribution, and so on. Those emotional experiences may relate not only to the subject experiencing the emotions but also to surrounding observers who often experience emerged affective reactions and altered behaviors across various domains such as social relationships, and wide scope decision-making . Furthermore, emotions affect how we acquire, process, and store information about the surrounding environment, influence our behaviors, and can even prevail over clashes against cognition.[1] From the perspective of consumer behavior, emotions

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influence not only purchasing decisions, but also engagement and overall experience.[2] The latter has become of critical importance in the context of computer systems and games due to the advancement of the technological community's understanding of the user experience concept and its implications in system success and adoption. The study of theories of emotions and their applications within the domain of user experience in digital systems has resulted in a distinct area of research named Affective Computing. Its central idea is the fact that if we wish computer systems to interact naturally and effectively with users, they must exhibit the capacity to understand user emotions so that they can adapt and respond with the appropriate qualities, such as empathy, offering support, and so on.

In the context of the arts, dramatists and writers of fiction have recognized that emotions are central to human experience and adaptation. Arts embed the duality of expressing and eliciting emotions. Aesthetic experiences allow artists and philosophers to convey feelings and ideas; at the same time, they deploy powerful techniques to allow a free experience of inherent feelings that hibernate because of lifestyle decisions or social norms. Such techniques can prove rather useful not only during causal experiences but also as parts of standard therapeutic intervention protocols.[3] Digital arts have modernized and widened the exposure to such experiences. On another note, play is another important process that provides opportunities for exploration not only for physical and technical skills, but also for building emotional intelligence, resilience, and adaptability. Research demonstrates that appropriate play can help children build self-regulation skills and executive functions . Moreover, playfulness has been correlated to increased emotional intelligence in a study among adult participants,[4] broadening the benefits of play beyond childhood. While art and play are two distinct phenomena, they can be utilized to enhance each other. Artistic creations can be physical components of a game, while playing games can be a form of artistic expression. Computer games can form a testbed platform for combining art and play to provide rich experiences that can elicit emotions through gameplay. Additionally, modern artificial intelligence algorithms embedded in the games can be used to recognize and measure emotional states. The latter results can provide direct feedback to the game designers about the player's experience, leading to refinements on the game design pipeline, which can improve the anticipated product's efficacy. Additionally, adaptive features can be implemented in the game, resulting in dynamic gameplay that changes to cater to the needs of individual players experiencing diverse emotions.[5]

Areas of interest for computer games comprise entertainment, training, therapy, and rehabilitation. Commercial games serve entertainment purposes, aiming to provide immersive and engaging experiences to players for monetary means. Elements of successful gameplay include mathematical balancing of challenges and features but also aesthetic elements that can elicit either positive feeling (such as sympathy or attachment) to fictional game characters, but also negative emotions (such as guilty, fear) that can likewise induce a pleasing experience of the story's narrative.[6] The worldwide entertainment games industry revenue for 2024 was estimated to be 455 billion US dollars,[7] and the active user base to 2.6 billion users[8] and while those numbers vary in other reports, it is evident that gaming is a leading entertainment industry. Game development companies compete to access this wide market, and they aim to deliver software products that not only offer functional capacities but also aesthetical and arousing emotional experiences; therefore, data and information on the emotional experiences are important during alpha and beta testing, but also post-release. Aside from commercial games, applied games (often called serious games) aim to transfer the persuasive value of computer games to learning gains that have non-entertaining purposes, such as education , training,[9,10] and therapy.[11,12]

Recognizing elicited or unelicited emotions in games requires defining emotions of interest, determining modalities that can express those emotions, and setting metrics that can quantify them. To define a model for emotions, affective states can be represented using distinct emotions like happiness, sadness, fear, anger, surprise, disgust, or by measuring and contextualizing emotions according to the two dimensions of valence and arousal.[13] Emotional arousal can be detected by the visceral motor; however, this is not easily accessible via non-intrusive modalities. A popular accessible modality that can provide emotional expressiveness is through facial expressions that can be captured using cameras and calculating facial cues.[14] Speech signals have been used to extract lexical cues and acoustic or linguistic features to achieve vocal affect recognition.[15] Darwin first described the association between body language and posture, and emotions in humans and animals. Researchers have used body expression notation systems to associate movements to emotions.[16] Affective data from facial, audio, and bodily modalities all interact, with body motion and posture intensifying the manifested emotion from the face and voice modalities. This has led to approaches of multimodal emotion recognition, which may improve recognition rates. Furthermore, Brain-Computer-Interfaces (BCI) have been developed in the past decades which are gradually adding value to the emotion analysis and recognition domain.[17] They have been used to show the success of computer games in contrast to video clips to aural-visual stimuli methods.[18]

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Artificial Intelligence Algorithms form the core of the mathematical model used to process data and develop emotion recognition capabilities. With the recent advancements of Machine Learning, researchers can analyze data and extract information, design classifiers that can perform the recognition task, and explore performance among different models. Further to this, they have the capacity to fine-tune the classifiers with optimization techniques. The current study extends the success of a previous study that deployed EEG signals and emotion annotations collected from 28 subjects during gameplay and self-reported levels of arousal and valence, which were used to provide multi-labels. The published data set from this study was used as input to the iHow Optimization Algorithm (iHowOA)[19] for feature selection in the EEG signals related to emotional responses in computer games. The purpose is to improve the classification accuracy of emotional labels based on the selected features using iHowOA, the iHow Optimization Algorithm, to optimize the k-nearest neighbors (KNN) model parameters. The study results can offer insights into the potential applications of optimized emotion recognition in enhancing user experiences in gaming environments.

2 Related Work

Recognizing emotions has been of interest since the early days of philosophy, and with the advancement of sciences became an area of cross-disciplinary research, intersecting psychology, sociology, cognitive and neuroscience, computer science, artificial intelligence, with applications in entertainment, business operations, arts, and humanities. This chapter provides background work in the philosophical and theoretical aspects of emotions, the different approaches to achieving emotion recognition, and the state of the art in the use of EEG in emotion recognition applicable to gaming applications.

2.1 Models of Emotion

Humans experience emotions because of stimuli from their environment and, in some cases, a set of personal values and beliefs. Emotions can have deep evolutionary roots,[20] making them a complex mechanism that may be difficult to place in the context of a model.[21] To define a model of emotions, one needs to consider a progressive set of inquiries, such as a definition for emotions, the causalities and effects (physiological and/or expressive), emotion spectrum, and dimensions, among others. Within the context of computer-based emotion recognition, the dimensionality and classification of emotions are the core modeling aspects, and theories of emotion manifestations can provide ideas on the type of modalities that can serve in designing solutions for the recognition task.

While early philosophers have questioned the impact of feelings and passions to human life, Darwin was among the first to provide the early foundation for the development of definitions and classification of emotions, and the biological aspects of them, including a set of discrete core emotions and universal manifestations and expressions.[22] A few years later, Wundt proposed a three-dimensional model of emotions, positioned among pleasure, arousal, and strain . Those two approaches have been further developed to represent emotions. An early example is by Tomkins the context of behaviorism has resulted in a set of 12 discrete emotions, and then classified them in another binary dimension of positive and negative types. Plutchik uses a set representation of emotions where basic ones are represented in inner circles encapsulated in outer circles that form more complex emotions, capturing intensities.[20] A narrowed-down version focuses on six core high-level emotions that can be expressed by facial expressions, and which form categories of sub-emotions.[23] Inspired by the multidimensional approach by Wundt, Russell developed the circumplex model of emotions that positions core emotions across a two-dimensional space (see figure 1) that uses the axes of arousal and valence. Defined emotions are then positioned at different areas of their space, indicating their levels of arousal and valence . This approach provides a way to represent emotions using modalities that can measure arousal levels, such as heart rate and velocity of movement, or valence, such as self-reporting, aural, and facial cues.

Emotions have also been modeled through psychological measures of non-verbal communication. The Pleasure-Arousal-Dominant (PAD) model provides the basis of the circumplex model of emotions but adds a dimension that represents the dominant nature of each embodied emotion.[24] Finally, the OCC model[25] provides 22 categories and uses a set of appraisal processes that create causalities from events to behaviors that are associated

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Figure 1: Regression weights for 28 affect words as a function of pleasure-displeasure and degree of arousal[23]

with emotions. Within the context of 3D games and virtual worlds, this has been useful in synthesizing emotional responses for virtual characters. Given the complexity of the origins of emotion development, manifestation and expressiveness[20–22] generalization of emotion expressiveness may not be possible, therefore studies that attempt to define or classify emotion in theoretical or computational manners must take into consideration cultural and personality traits of the population of the study and use ground truth methods[26] to establish valid definitions and methods.

2.2 Emotion recognition modalities

Scientists have experimented with different modalities as well as the fusion of multiple of them into one recognition system. Using facial expression features has been the most widely explored and the one that provided the most promising results due to the capacity of computer vision models to classify with high accuracy in facial emotion recognition (FER). Developed systems have utilized different notations of facial features. Examples comprise the Facial Action Coding System (FACS) that tracks movements of facial muscles that are defined as Facial Action Units (AUs)[27] and the Facial Landmarks System (FLS) that tracks vectors defined by pair-wise positions of landmarks [39], among others. Traditional classifiers were developed during the initial years targeting FER, and researchers engineered features out of landmarks as input to classifiers such as Random Forest and Support-Vector-Machines. Modern Deep Learning techniques utilized larger datasets and more complex models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to achieve accuracies as close as 99.52% or well-above chance levels in studies with novel emotion categories such as enthusiasm, awe and liking that may overlap.[28] In the context of video games, FER has been used to apply dynamic balancing to enhance user experience.[29]

Researchers have utilized audio expressions from speech signals as an emotion recognition modality. Early approaches engineered lexical cues and linguistic features for emotion recognition.[15] Sound fragments can be represented visually through waveforms and spectrograms, shifting the challenge to the computer vision domain. Latest trends in speech emotion recognition include combining verbal and non-verbal sounds to outperform traditional methods[30] and through other Deep CNNs. Audio signals have been fused with video to perform multimodal emotion recognition as well as emotion stability and diversity in computer games for children to offer insights into cognitive matters.

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3 Methodology

3.1 Dataset Description

The experimental study employed the publicly available *GAMEEMO* dataset, which comprises electroencephalography (EEG) signals collected during computer gameplay sessions designed to elicit various emotional states. The dataset includes recordings from 28 individual participants, each of whom engaged with four emotion-specific computer games—categorized as *boring*, *calm*, *horror*, and *funny*. Each game session lasted approximately 5 minutes, yielding a total of 20 minutes of EEG data per participant. Data acquisition was performed using the Emotiv Epoc+ headset, a 14-channel portable and wearable EEG device known for its accessibility and relatively high signal fidelity.

After completing each game, participants provided self-reported emotional assessments using the Self-Assessment Manikin (SAM) form, which captures subjective ratings along the dimensions of *arousal* and *valence*. These ratings were used to label the EEG data for emotion recognition tasks. The dataset includes both raw and preprocessed EEG signals, available in both `.csv` and `.mat` formats, providing flexibility for analysis in MATLAB and Python environments. Each subject's data is stored in a dedicated folder (e.g., `S01`, `S02`, ..., `S28`), containing three subdirectories: `Raw EEG Data`, `Preprocessed EEG Data`, and `SAM Ratings`.

Moreover, there is a subdirectory named `Gameplay` that contains short video clips of the game, which contains emotional elicitation context. Each of the subject folders contains the EEG recordings, divided by game, with corresponding identifiers: `G1`, `G2`, and `G3`. The structure supports both cross-subject and intra-subject analyses in models of emotion recognition. In general, the GAMEEMO dataset can be efficiently explored by researchers in emotion recognition studies, and GAMEEMO can also be used to determine the effectiveness of wearable EEG devices in carrying out affective computing.

To examine the statistical correlations and distribution patterns between the obtained features of EEG, Figure 2 presents an extensive pairwise scatter plot matrix. This visualization presents the interactions of features in a multivariate manner, featuring two-dimensional nail scatter histograms for each pair of variables, as well as histograms along a diagonal that represent each variable. The structure is dense and overlapped in the plots, representing the complexity and nonlinear nature of EEG signal features. Whereas some pairs of variables are strongly correlated with each other, either linearly or in a nonlinear manner, others appear to be less dependent, which provides evidence to support dimensionality reduction or feature selection. The histograms are presented along the diagonal axes and show different levels of skew and concentration, meaning that any transformation or normalization technology may be helpful before classification. This visual diagnosis, presented in Figure 2, becomes an essential step in further justifying the feature engineering strategy and helps confirm the wisdom of using metaheuristic optimization to optimize the input space.

To easily access a visual initial analysis of the unfiltered EEG signals recorded on the various electrodes, Figure 3 provides four visualizations of a chosen channel of the initial data. Two additional subplots, reading top-left: time-domain **line plot of channel F3**, which is a representation of signal amplitude variations over a set of 1000 sampled points. This is equivalent to the representation of temporal dynamics and noise artifacts of raw EEG data. The upper-right subplot shows a **scatter plot of channel F4** with a dispersion-centered point of view displaying clustering in amplitude and possible outliers as time progresses. On the bottom-left, **a histogram of channel F7** is shown, which shows the distribution of the amplitudes and central tendency of the signal, which are skewed to a Gaussian shape. Finally, there is the **3D trajectory plot of channel F8** at the bottom-right panel, whereby the temporal order of samples is plotted as a spatial trajectory, not only providing an idea of the amplitude development but also an impression of the volatility over samples. Taken together, Figure 3 gives a complex image of the EEG signal structure that will be useful in terms of finding noise patterns, baseline shift, and variability of signal across channels before preprocessing and extraction of features.

3.2 Data Preprocessing

A preprocessing pipeline was applied to all subjects before proceeding to classification, aiming to enhance the quality of the raw EEG signals and ensure uniformity among subjects. It started with the application

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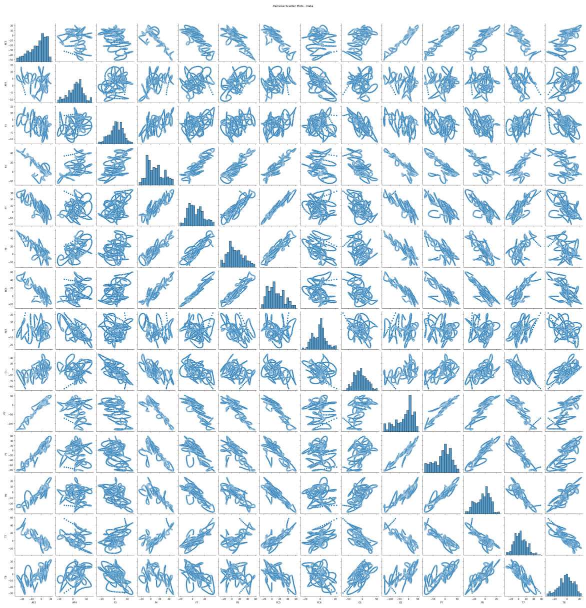

Figure 2: Pairwise scatter plot matrix of EEG features. Each subplot shows the bivariate relationship between two features, with histograms along the diagonal representing individual feature distributions.

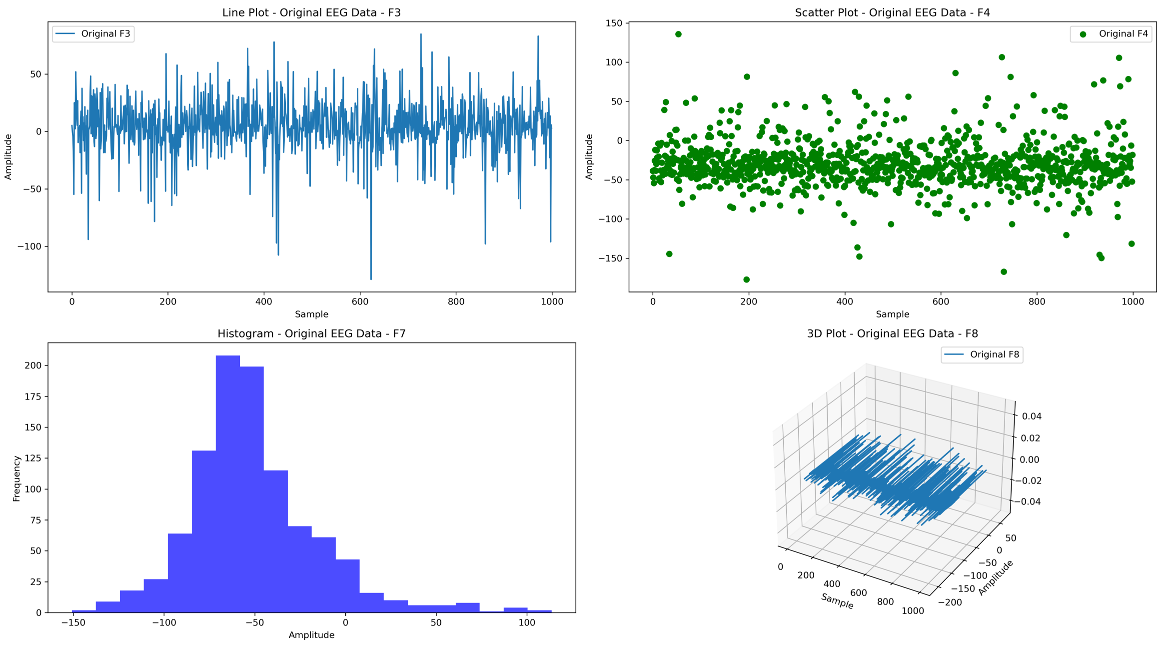

Figure 3: Multiple visualizations of original EEG signals: (top-left) Line plot of F3; (top-right) Scatter plot of F4; (bottom-left) Histogram of F7; (bottom-right) 3D plot of F8. Each view illustrates a different structural aspect of the raw EEG data.

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of a bandpass filter with a frequency range of 0.5–50 Hz, designed as a finite impulse response (FIR) filter. This filtering procedure helped eliminate low-frequency drift and high-frequency noise while conserving core components of brain activity in the delta, theta, alpha, beta, and gamma frequency bands.

After filtering, the continuous EEG recordings were divided into fixed-length epochs representative of the gameplay sessions, each approximately five minutes in length. This was carried out to align data in terms of time across emotional conditions and subjects, allowing for uniform comparison of the data.

Basic artifact reduction was achieved by filtering the signal to control the effects of eye movement, muscle movements, and three-phase powerline noise, among other factors. Other, more sophisticated artifact filtering methods, such as Independent Component Analysis (ICA), were not used to maintain the ease of computation and the ability to reproduce.

The preprocessing step included all 14 channels offered by the Emotiv Epoc+ headset and did not compromise the spatial nature of the EEG information. All channels were included and not discarded, allowing for the extraction and classification of features from the top of the head.

Lastly, total z-score normalization was performed on all EEG channels separately to standardize the amplitudes of the signals. The task of normalizing removed the amplitude variability between subjects, making all recordings comparable on the same scale. The normalization of the signal- z was calculated by the following formula: $z = (x - \mu)/\sigma$, where- x is the amplitude of the signal as it is, m is the channel means, and σ is the standard deviation.

Such forms of preprocessing of EEG data ensured that the data were clean, temporally synchronized, and had normalized amplitudes, thereby providing a consistent base of input to the succeeding stages of the research, which include classification and optimization.

3.3 Proposed iHow Optimization Algorithm (iHowOA)

3.4 iHowOA Inspiration

The iHow Optimization Algorithm (iHowOA) is inspired by human-like processes such as learning, knowledge acquisition, exploration, and experience-based decision-making. It follows the idea that, much like how humans start with basic information and gradually develop expertise through learning and the accumulation of knowledge, the algorithm mimics this process to optimize complex problems. The foundation of the algorithm begins with data gathering, where raw data is collected, serving as the elementary building blocks for solving a problem, similar to how humans begin with basic facts.

After this, it moves to the learning phase of the algorithm where it processes and analyses the data in a way that is similar to how human becomes wise after going through the world. After learning, the algorithm shifts to the information processing phase, where the data it has learned from is processed in a manner that humans process knowledge for practical use. This is followed by the knowledge acquisition, where the algorithm gathers and preserves new information to improve its performance in the long run. This accumulated know-how is all important in determining how the process is to be carried forward.

Just as man learns through possible ways and alternatives, iHowOA tries out all possible strategies of the solution space. This exploration is made more efficient and objective-oriented through the use of the store's knowledge and experiences. Moreover, the algorithm adapts knowledge gathered during its iterations by refining it and learning the parameters of newly dared approximate solutions. This erection of learning from previous versions is similar to how human beings get better in the subsequent decision making processes.

Like in real life, feedback is critical to growth, and that's why iHowOA avails feedback loops to boost its optimization processes. Algorithm further devises its tactics and answers, improving future recommendations and solutions, with reference to previous feedback until a better performing strategy is reached. Finally, as people master each of the given areas of specialization then the iHowOA gets to an optimum solution. By

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facilitating data collection, learning, knowledge aquisition, search, and feedback, iHowOA process models the human manner, from entry level knowledge up to an expert level to tackle optimization problems.

As presented in Figure 4, the iHow Optimization Algorithm (iHow OA) is organized as a hierarchy of the following stages: The Data is at the base of this pyramid and that it is the raw inputs that are collected. The next layer is the "Learning & Asking" layer where the algorithm starts parsing raw data and start differentiating between them. Above this, there is the "Information" layer, where data is processed and made useful in the construction of "Knowledge." The first layer is the "Knowledge" layer, which represents the compilation of the structured information that leads to improved decisions making. On the very apex of the pyramid, there is the "Expert" layer describing the algorithm's capacity to apply developed knowledge and experience for efficient solutions' improvement. Every layer represents a higher level of information processing, with feedback-that feeds back into the algorithm and resulting in the progress through its steps.

3.5 Experimental Setup

The choice of iHowOA is based on the various stages implemented in its experimental design which is essential for testing its performance against various benchmark functions. These stages include parameter initialization, the exploratory phase, the learning phase, the knowledge-acquisition phase and the exploitation phases. There is also feedback handling to make new adjustments to the solution proposed in the subsequent cycles. This section will describe each of them, as well as the mathematical equations deployed when guiding the behavior of the iHowOA throughout the experiments.

3.5.1 Constants and Parameters

In terms of search performances the iHowOA is regulated by a list of predefined constants and parameters. These parameters are necessary for the regulation of the algorithm exploration-exploitation in complex problems spaces which are fundamentally essential. The key parameters used in the experiments are defined as follows:

- $r_1 = 0.1$: Controls the weight of the first component in the exploration and learning phases.
- $r_2 = 0.1$: Modifies the contribution of the second component in the position update equations.
- $r_3 = 0.1$: Adjusts the influence of the third component during learning and knowledge acquisition.
- $r_4 = 0.2$: Scales the contribution of the fourth component during exploitation.
- $r_5 = 0.2$: Further adjusts the weight of the fifth component during solution refinement.

These parameters are used in various update equations, which allow the iHowOA to adjust its exploration and exploitation dynamically throughout the search process.

3.5.2 Exploration Phase

The exploration phase of the iHowOA is designed to ensure that the algorithm searches broadly across the solution space. This phase prevents premature convergence to local optima by allowing search agents to explore diverse regions. The position update equation for the exploration phase is as follows:

$$DS_{t+1} = r_1 \cdot DS_1 + r_1 \cdot r_2 \cdot DS_2 + r_1 \cdot r_2 \cdot r_3 \cdot DS_3$$

In this equation, DS_{t+1} represents the updated position of a search agent at iteration $t + 1$, and DS_1, DS_2, and DS_3 represent the current states of the search agent's exploration. The constants r_1, r_2, and r_3 control the magnitude of exploration by scaling the contributions of different components, ensuring diversity in the search.

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3.5.3 Learning Phase

After the exploration phase, the iHowOA enters the learning phase. In this phase, the algorithm processes the gathered data to extract meaningful insights and update its learning parameters. The position of the learning state at iteration $t+1$ is updated using the following equation:

$$LS_{t+1} = r_1 \cdot LS_1 + r_1 \cdot r_2 \cdot LS_2 + r_1 \cdot r_2 \cdot r_3 \cdot LS_3$$

Here, LS_{t+1} represents the updated learning state, and LS_1, LS_2, and LS_3 are the learning states from previous iterations. This equation allows the algorithm to adjust its learning process dynamically, depending on the experience accumulated during the search.

3.5.4 Knowledge Update

Once the learning phase is complete, the iHowOA integrates the newly learned information with the previously collected data to build a more comprehensive knowledge base. The knowledge update equation is formulated as:

$$KS_{t+1} = DS_{t+1} + LS_{t+1} + 2K + 1$$

In this equation, KS_{t+1} represents the updated knowledge state, which combines the current exploration state DS_{t+1}, the updated learning state LS_{t+1}, and the knowledge factor K. The knowledge factor K decreases exponentially over the course of iterations, allowing the algorithm to focus more on recent knowledge and less on earlier experiences.

The knowledge factor K is computed using the following equation:

$$K = 2 - 2 \times \left(\frac{\text{iteration count}}{\text{Train count}} \right)$$

As the number of iterations increases, the value of K decreases, allowing the algorithm to gradually shift from exploration to exploitation.

3.5.5 Exploitation Phase

In the exploitation phase, the iHowOA refines solutions by focusing its search on areas identified as promising during the exploration phase. The position update equation for the exploitation phase is defined as:

$$X_{1S_{t+1}} = X_{S_t} + [KS_{t+1} + DS_{t+1}] \cdot r$$

Where $X_{1S_{t+1}}$ represents the updated position of the agent at iteration $t+1$, and X_{S_t} is the current position. The exploitation process intensifies the search by refining solutions around promising regions.

Additional update equations for other variables during the exploitation phase include:

$$X_{2S_{t+2}} = X_{2S_t} + r_3 \cdot r_4 \cdot [KS_t + LS_{t+1}]$$

$$X_{3S_{t+3}} = X_{3S_t} + [r_3 \cdot r_4 \cdot r_5 \cdot KS_t + DS_{t+1} + LS_{\text{new}}]$$

These equations ensure that the algorithm exploits the most promising solutions, refining them through learned knowledge and feedback loops.

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3.5.6 Calculation of the Best Solution

At each iteration, the iHowOA computes the best solution by combining the contributions from the exploration, learning, and knowledge phases. The equation for calculating the best solution is:

$$X_{\text{best}} = DS_{t+1}+LS_{t+1}+KS_{t+1}\cdot DS_{t+1}\cdot X_{1S_{t+1}}+DS_{t+1}+LS_{t+1}+KS_{t+1}\cdot LS_{t+1}\cdot X_{2S_{t+1}}+KS_{t+1}\cdot X_{3S_{t+1}}$$

By enabling the iHowOA to determine the best solution available at every step, while accommodating for exploration and exploitation alike, this equation is a crucial factor behind the efficiency of the approach.

3.6 Pseudo-code of iHow Optimization Algorithm

The subsequent specific Algorithm 1 of iHow Optimization Algorithm illustrates the general framework of the algorithm with steps of initialization, iterative updating till convergence point. Every stage allows the algorithm to effectively scan through the solution space and either update the candidates or stop when a required or almost required solutions are found according to set criteria.

[H] [1] Initialize the population size, learning rates $(r_1, r_2, r_3, ...)$, knowledge factor K, and maximum iterations. Initialize the population with random solutions. Set the maximum number of iterations. Set learning rates $(r_1, r_2, r_3, ...)$ and knowledge factor K.

Step 1: Data Collection Phase: each individual in the population Collect raw data D. Store the collected data for future processing.

Step 2: Learning Phase: each individual in the population Perform learning using the collected data. Update learning parameters LS using r_1, r_2, r_3. Store the learning outcomes for the next iteration.

Step 3: Information Processing: each individual in the population Process the learned data to extract useful information. Generate insights from the processed information. Update the knowledge pool based on processed data.

Step 4: Knowledge Acquisition: each individual in the population Combine information and experience to build knowledge. Update knowledge parameter KS. Store the updated knowledge state.

Step 5: Exploration and Optimization Phase: each iteration until maximum iterations each individual in the population Explore the solution space using knowledge and data. Update exploration parameters DS and learning parameters LS. Calculate the knowledge factor K based on exponential decay. If a new solution is better, update the individual's position X. Update X_{best} if the current solution is the best found.

Step 6: Convergence: optimal solution is reached or maximum iterations are completed Output X_{best} as the final optimized solution. Continue learning and exploration.

End of Algorithm.

Another advantage of the pseudo-code of iHowOA is it reveals the flow chart of algorithm and details the flow of actions from the initialization to convergence. The flow chart starts with population initialization and key parameters, then enters cycles of retrievals, update, information extraction and acquisition of knowledge. Optimisation phase ensures that in the course of the search for the best solutions, iHowOA brings out the best solution once it assesses the final solutions. Next, the convergence criterion guarantees the algorithm provides the best solution after running through it.

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3.7 Evaluation Metrics

To assess the classification performance of the proposed models, six standard evaluation metrics were utilized. These metrics provide complementary insights into predictive accuracy, sensitivity to emotional states, and robustness against false classifications. The metrics are defined as follows:

- **Accuracy (ACC)** measures the proportion of correctly classified instances among all samples:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

- **Sensitivity (True Positive Rate, TPR)** quantifies the model's ability to correctly identify positive instances (e.g., emotional states):

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

- **Specificity (True Negative Rate, TNR)** measures the model's ability to correctly identify negative instances (e.g., absence of emotion):

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{3}$$

- **Positive Predictive Value (PPV or Precision)** reflects the proportion of true positives among all predicted positives:

$$\text{PPV} = \frac{TP}{TP + FP} \tag{4}$$

- **Negative Predictive Value (NPV)** captures the proportion of true negatives among all predicted negatives:

$$\text{NPV} = \frac{TN}{TN + FN} \tag{5}$$

- **F1-Score** is the harmonic mean of precision and sensitivity, and provides a balanced assessment between false positives and false negatives:

$$\text{F1-Score} = 2 \cdot \frac{\text{PPV} \cdot \text{Sensitivity}}{\text{PPV} + \text{Sensitivity}} \tag{6}$$

In the above equations, TP denotes true positives, TN true negatives, FP false positives, and FN false negatives. These metrics were computed for each model configuration, facilitating a robust and multi-faceted evaluation of classification performance in the context of EEG-based emotion recognition.

4 Results

This section presents the experimental evaluation and performance analysis of the proposed iHow Optimization Algorithm (iHowOA) for emotion recognition using EEG signals collected during gameplay. A comprehensive assessment was conducted to compare conventional machine learning classifiers and hybrid models incorporating feature optimization. The evaluation metrics used include **accuracy**, **sensitivity** (true positive rate), **specificity** (true negative rate), **positive predictive value (PPV)**, **negative predictive value (NPV)**, and **F1-score**.

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4.1 Baseline Classifier Performance

The initial phase of experimentation assessed the performance of four standard machine learning models: Support Vector Machine (SVM), Decision Tree (DT), Multi-Layer Perceptron (MLP), and k-Nearest Neighbors (KNN). These classifiers were applied to raw EEG features without any feature selection or optimization. The results are summarized in Table 1.

To complement the tabulated results, a visual comparative analysis was conducted to highlight the differences in performance metrics across the four baseline classifiers: SVM, DT, MLP, and KNN. Figure 5 presents a set of time-series plots for each performance metric, facilitating an intuitive comparison across models.

The first subplot in Figure 5 displays the **accuracy** values for all models. This plot clearly shows the progressive improvement in classification accuracy from SVM to KNN, with KNN achieving the highest performance.

The second subplot illustrates the **sensitivity (true positive rate)**. It highlights the increasing ability of the classifiers to correctly identify positive emotional states, with KNN again outperforming the others.

The third subplot presents the **specificity (true negative rate)** values, showing that KNN also excels at correctly identifying negative instances, thus maintaining balance in classification.

The fourth subplot visualizes the **positive predictive value (PPV)**, reflecting the precision of each model. KNN shows a significant advantage in this regard, making it a reliable choice for emotion detection.

The fifth subplot shows the **negative predictive value (NPV)**, which measures how accurately each model identifies non-target instances. Here too, KNN leads, with a steep improvement compared to SVM.

Finally, the sixth subplot in Figure 5 presents the **F1-score**, which harmonizes precision and recall. The trend confirms KNN's superiority in achieving the most balanced classification outcome across all metrics.

To complement the tabular results and support comparative interpretation, Figure 6 presents a bar chart visualization of six key evaluation metrics—accuracy, sensitivity (TPR), specificity (TNR), positive predictive value (PPV), negative predictive value (NPV), and F1-score—across four baseline classifiers: SVM, Decision Tree (DT), Multi-Layer Perceptron (MLP), and k-Nearest Neighbors (KNN). Each subplot highlights a specific metric's distribution across the models. The accuracy and F1-score plots clearly indicate that KNN outperforms the others, while the sensitivity and specificity plots show incremental improvements from SVM to KNN. Similarly, KNN yields superior precision (PPV) and reliability in negative predictions (NPV), reinforcing its consistent classification advantage across all measured dimensions.

To assess the distributional properties of the classification metrics and validate their assumptions for parametric statistical testing, Figure 7 presents Q-Q (quantile-quantile) plots for the six primary evaluation metrics: accuracy, sensitivity (TPR), specificity (TNR), positive predictive value (PPV), negative predictive value (NPV), and F1-score. These plots compare the empirical quantiles of the observed model outputs with the theoretical quantiles of a normal distribution. The Q-Q plot for accuracy shows mild deviation at lower quantiles but overall reasonable linearity, suggesting approximate normality. Similarly, the sensitivity and specificity plots reflect a consistent upward trend with only minor deviations. The PPV and NPV plots exhibit slightly more spread among lower quantiles but retain alignment at upper values. Lastly, the F1-score plot demonstrates the closest adherence to the diagonal line, indicating a relatively symmetric and normal distribution. Collectively, the Q-Q plots in Figure 7 support the conclusion that these evaluation metrics approximate normality sufficiently for subsequent statistical inference.

Among the tested classifiers, the KNN model achieved the best performance with an accuracy of **84.99%**, a sensitivity of **84.82%**, and a specificity of **85.44%**. The KNN model also attained the highest F1-score of **94.88%**, indicating a strong balance between precision and recall. Based on this superior baseline performance, KNN was selected as the core classifier for the subsequent hybrid modeling with metaheuristic optimization.

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Figure 4: Hierarchical Knowledge Pyramid in iHow Optimization Algorithm

Table 1: Performance of baseline classifiers on EEG emotion data

Model	Accuracy	Sensitivity	Specificity	PPV	NPV	F1-score
SVM	0.8176	0.8214	0.8074	0.9014	0.8661	0.9253
DT	0.8249	0.8245	0.8260	0.9078	0.8792	0.9298
MLP	0.8295	0.8273	0.8352	0.9115	0.8861	0.9331
KNN	**0.8499**	**0.8482**	**0.8544**	**0.9205**	**0.9191**	**0.9488**

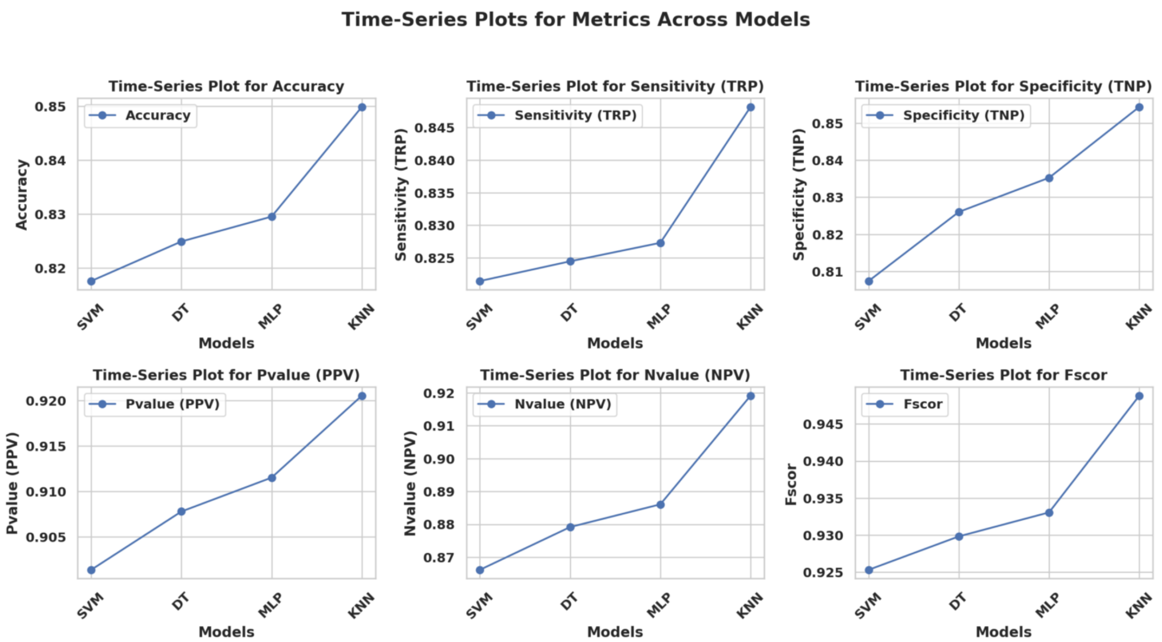

Figure 5: Time-series plots for six classification metrics across baseline models: Accuracy, Sensitivity (TPR), Specificity (TNR), PPV, NPV, and F1-score.

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4.2 Performance of Hybrid Models with Metaheuristic Optimization

To enhance classification performance, the KNN classifier was combined with several well-known metaheuristic optimization algorithms to select the most informative features from the EEG dataset. The algorithms used include Whale Optimization Algorithm (WAO), Biogeography-Based Optimization (BBO), Grey Wolf Optimizer (GWO), Genetic Algorithm (GA), Firefly Algorithm (FA), Particle Swarm Optimization (PSO), and the proposed iHow Optimization Algorithm (iHowOA). The performance of these hybrid models is presented in Table 2.

To enable a holistic visual comparison of classification performance across hybrid models, Figure 8 presents a detailed heatmap of evaluation metrics for each combination of optimization algorithm with the KNN classifier. The models include WAO+KNN, BBO+KNN, GWO+KNN, GA+KNN, FA+KNN, PSO+KNN, and the proposed iHOW+KNN. The heatmap encodes the numerical values of six metrics—Accuracy, Sensitivity (TPR), Specificity (TNR), Positive Predictive Value (PPV), Negative Predictive Value (NPV), and F1-score—using a gradient color scale for quick interpretability. As shown, the iHOW+KNN model consistently dominates across all metrics, most notably achieving the highest Accuracy (0.9685), Specificity (0.9582), PPV (0.9661), and F1-score (0.9554). Other models such as PSO+KNN and FA+KNN also demonstrate strong and balanced performance, but iHOW+KNN clearly maintains a superior metric profile. The heatmap in Figure 8 thus effectively highlights the robustness and generalization capacity of iHOW+KNN as an advanced hybrid classification approach for EEG-based emotion recognition.

To visually assess the overall performance distribution and comparative dominance of hybrid models across multiple evaluation metrics, Figure 9 presents a radar plot covering six key classification measures: Accuracy, Sensitivity (TPR), Specificity (TNR), Positive Predictive Value (PPV), Negative Predictive Value (NPV), and F1-score. Each polygonal layer represents one hybrid model combining an optimization algorithm with the KNN classifier. The radar plot reveals that all models demonstrate strong and balanced performance across most metrics, forming near-regular hexagons. Notably, the iHOW+KNN model (highlighted in pink) consistently exhibits the outermost perimeter across all axes, indicating top-tier values for every evaluated criterion. PSO+KNN and FA+KNN also show competitive coverage, particularly in specificity and F1-score, while WAO+KNN trails slightly in precision and NPV. As a multidimensional comparative visualization, Figure 9 effectively reinforces the superiority and consistency of iHOW+KNN over its counterparts.

To provide a more detailed statistical visualization of model performance across multiple evaluation metrics, Figure 10 illustrates a line plot of metric values for hybrid models, overlaid with corresponding confidence intervals. The x-axis represents seven hybrid configurations combining KNN with various optimization algorithms, while the y-axis displays metric values ranging from 0.90 to 0.97. Each line traces the progression of one specific metric—Accuracy, Sensitivity (TPR), Specificity (TNR), Positive Predictive Value (PPV), Negative Predictive Value (NPV), and F1-score—across the models. The shaded bands surrounding each line represent the estimated confidence interval, capturing the variability and reliability of metric measurements. Notably, iHOW+KNN consistently attains the highest values with narrow intervals, especially for Accuracy and PPV. Other models such as PSO+KNN and FA+KNN follow closely, whereas WAO+KNN and BBO+KNN display comparatively lower central values and broader uncertainty in NPV. As shown in Figure 10, this visualization confirms both the superior performance and statistical stability of the proposed iHOW-enhanced model across all six evaluation criteria.

To facilitate the visualization of high-dimensional model performance metrics in a two-dimensional space, Figure 11 displays Andrews curves for each hybrid model configuration. Andrews curves transform multidimensional data points into continuous functions using a Fourier-based projection, where similar data instances produce similar curves. In this context, each curve corresponds to a hybrid model (e.g., WAO+KNN, PSO+KNN, iHOW+KNN), and the input vector comprises its normalized performance metrics—accuracy, sensitivity, specificity, PPV, NPV, and F1-score. As shown in Figure 11, the iHOW+KNN model closely aligns with the top-performing configurations, with only subtle deviations in curve shape. This representation is especially valuable for detecting outliers and assessing the structural similarity of models across multiple evaluation dimensions simultaneously.

The results demonstrate that all hybrid models significantly outperformed the standalone KNN model. Among them, the proposed **iHow+KNN** model achieved the highest performance across all metrics. Specifically, it reached an accuracy of **96.85%**, sensitivity of **95.50%**, specificity of **95.82%**, PPV of **96.61%**, NPV of

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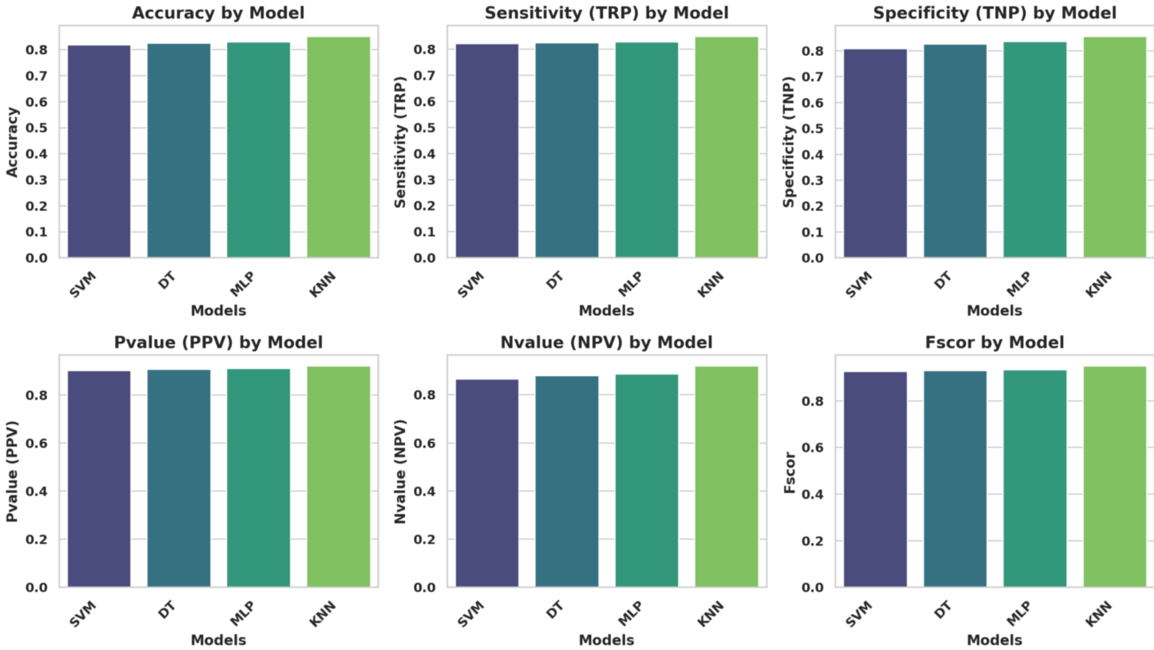

Figure 6: Bar chart visualization of classification performance metrics for baseline models: SVM, DT, MLP, and KNN. Metrics include Accuracy, Sensitivity, Specificity, PPV, NPV, and F1-score.

Table 2: Performance of hybrid metaheuristic models with KNN classifier

Model	Accuracy	Sensitivity	Specificity	PPV	NPV	F1-score
WAO+KNN	0.9325	0.9237	0.9461	0.9593	0.8948	0.9412
BBO+KNN	0.9357	0.9265	0.9495	0.9608	0.9015	0.9434
GWO+KNN	0.9387	0.9305	0.9507	0.9614	0.9078	0.9457
GA+KNN	0.9399	0.9325	0.9511	0.9623	0.9085	0.9472
FA+KNN	0.9418	0.9345	0.9525	0.9627	0.9133	0.9484
PSO+KNN	0.9463	0.9398	0.9556	0.9647	0.9212	0.9521
iHow+KNN	**0.9685**	**0.9550**	**0.9582**	**0.9661**	**0.9595**	**0.9554**

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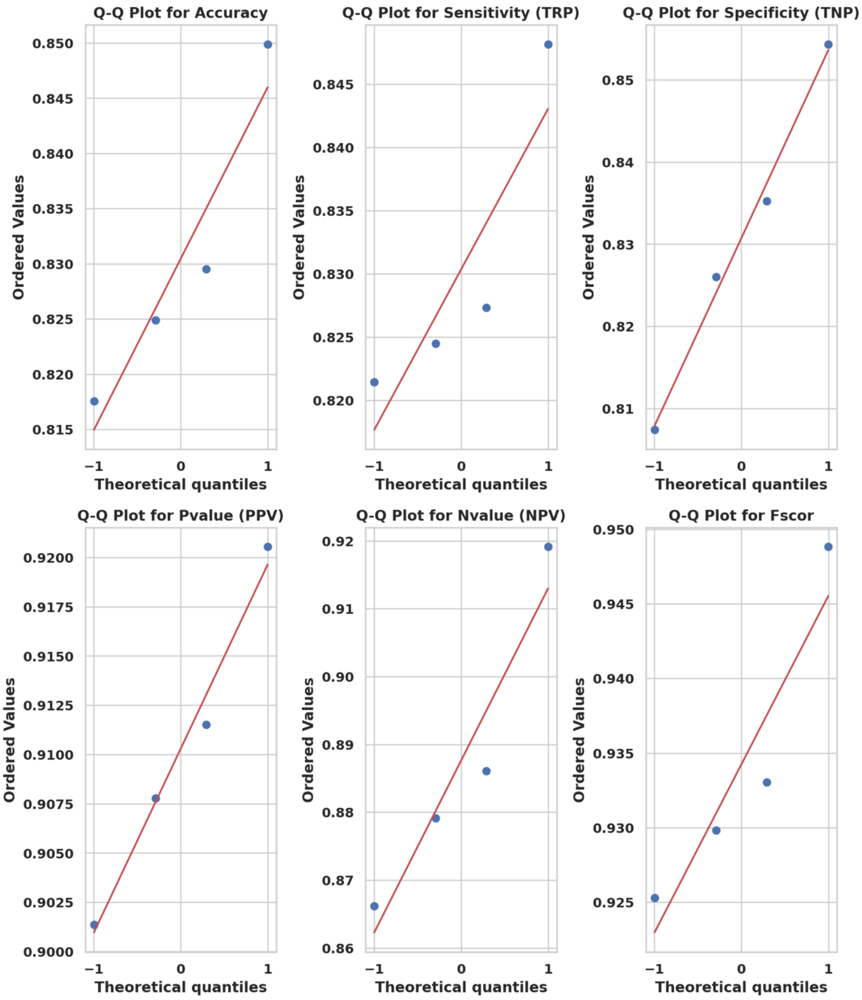

Figure 7: Q-Q plots comparing empirical quantiles of classification metrics to theoretical quantiles of a normal distribution: Accuracy, Sensitivity (TPR), Specificity (TNR), PPV, NPV, and F1-score.

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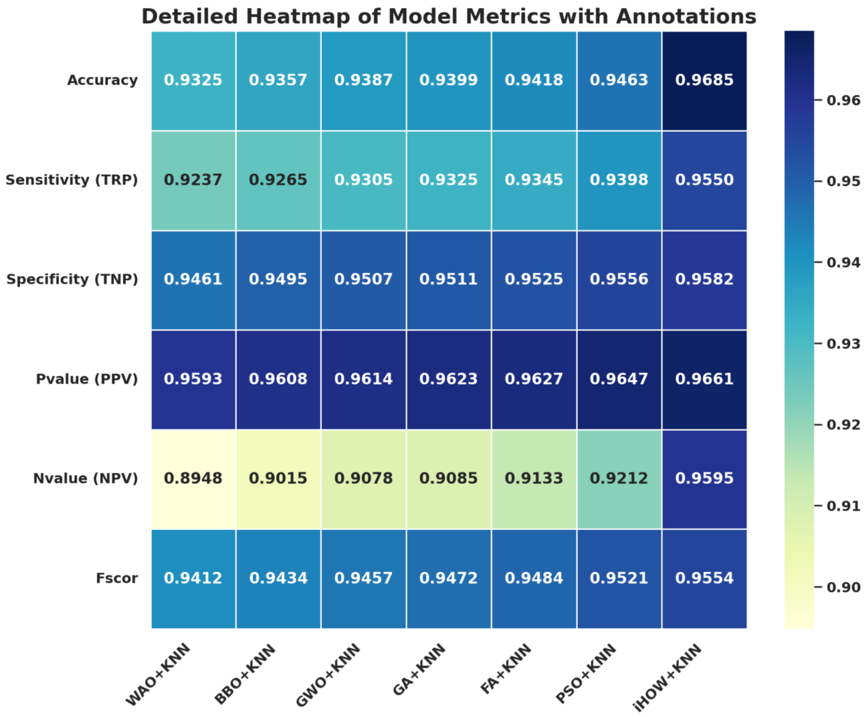

Figure 8: Heatmap of classification performance metrics across hybrid models combining optimization algorithms with KNN. Metrics include Accuracy, Sensitivity, Specificity, PPV, NPV, and F1-score.

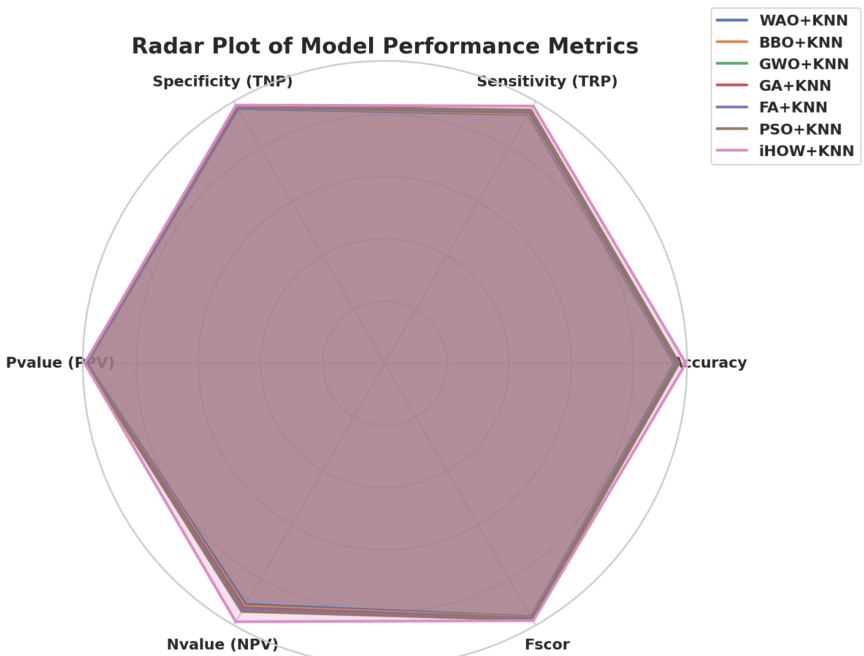

Figure 9: Radar plot comparing hybrid model performance (Optimization Algorithm + KNN) across six classification metrics: Accuracy, Sensitivity, Specificity, PPV, NPV, and F1-score.

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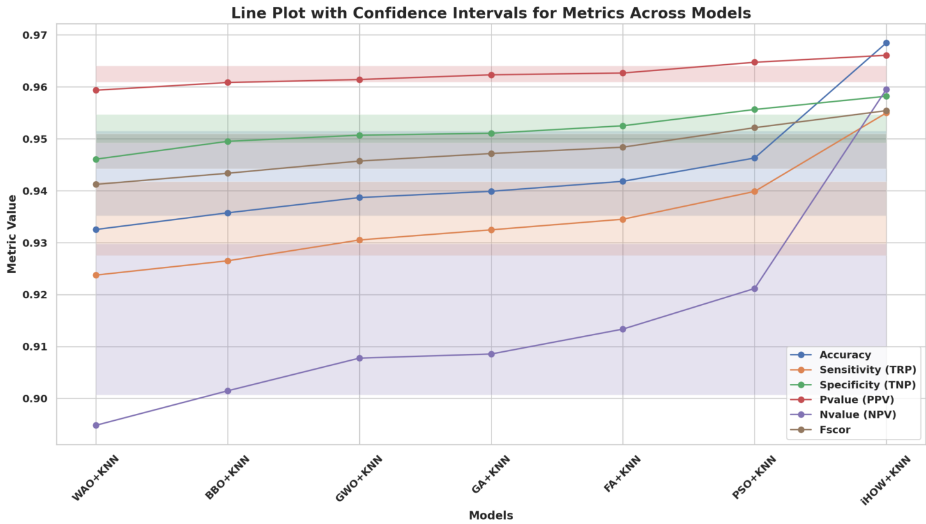

Figure 10: Line plot of hybrid model performance metrics with shaded confidence intervals for Accuracy, Sensitivity (TPR), Specificity (TNR), PPV, NPV, and F1-score.

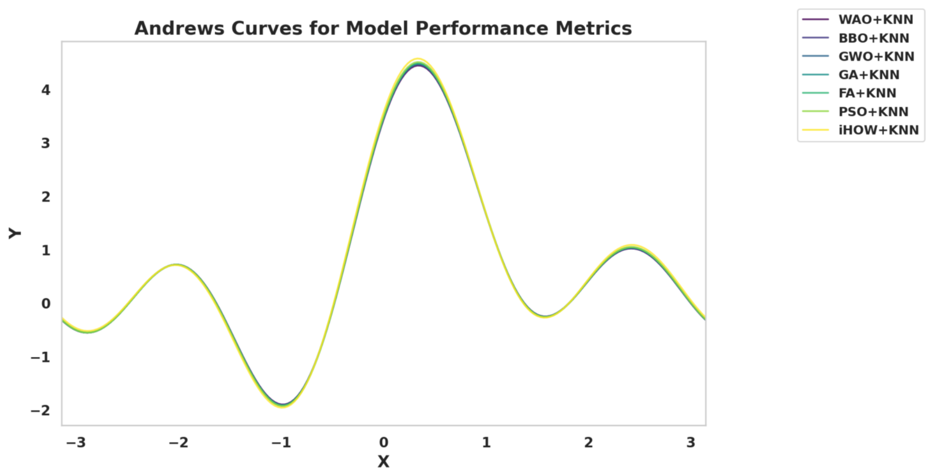

Figure 11: Andrews curves representing normalized performance metrics for hybrid models combining meta-heuristic optimization with KNN.

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95.95%, and an F1-score of **95.54%**. These outcomes highlight the effectiveness of the iHow Optimization Algorithm in identifying optimal feature subsets and tuning classifier performance, thereby contributing to more accurate and reliable emotion recognition.

5 Conclusion and Future Work

This study introduced a comprehensive emotion recognition framework based on EEG signals elicited during gameplay. By employing the GAMEEMO dataset—comprising 28 subjects and four emotionally charged games—the research leveraged both traditional machine learning models and hybrid approaches combining KNN with various metaheuristic optimization algorithms. Among all configurations, the proposed iHOW+KNN model exhibited outstanding performance across all classification metrics, achieving an accuracy of 96.85%, a sensitivity of 95.50%, a specificity of 95.82%, and an F1-score of 95.54%. These outcomes emphasize the strength of combining KNN with intelligent feature selection strategies to handle the high dimensionality and non-stationary nature of EEG signals. Furthermore, the visual analytics—through heatmaps, radar plots, confidence intervals, and pairwise distributions—validated the statistical consistency and discriminative capability of the selected features. The iHOW algorithm, inspired by human cognitive development, demonstrated robust exploration and exploitation behaviors, leading to superior generalization when compared with standard metaheuristics such as PSO, FA, GA, and GWO.

Future research directions will focus on several promising avenues. First, the proposed method can be extended to real-time EEG-based emotion tracking in adaptive gaming or neurofeedback environments, necessitating low-latency processing pipelines and online learning algorithms. Second, the integration of deep learning techniques—such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs)—could further capture spatial and temporal dynamics within raw EEG signals, potentially improving classification performance without heavy manual feature engineering. Additionally, exploring cross-subject transfer learning and domain adaptation techniques could help generalize the model to unseen individuals with minimal calibration. Another important direction involves embedding the framework into mobile or edge computing platforms for practical deployment in wearable BCI (Brain-Computer Interface) systems. Finally, future studies may incorporate multimodal affective signals, such as facial expressions, speech, and physiological responses, to enable multimodal fusion and further enhance emotion recognition accuracy.

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