ART THERAPY TO PROMOTE COLLEGE STUDENTS' MENTAL HEALTH BASED ON A HIERARCHICAL CLUSTERING ALGORITHM

Reference NO. IJME 1398, DOI: 10.5750/ijme.v1i1.1398

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KEY DATES: Submission date: 20.12.2023 / Final acceptance date: 27.02.2024 / Published date: 12.07.2024

SUMMARY

Art therapy is a therapeutic approach that utilizes the creative process of making art to improve mental, emotional, and physical well-being. Art therapy is a form of expressive therapy that utilizes the creative process of making art to improve mental, emotional, and psychological well-being. It provides individuals with a non-verbal outlet for self-expression and exploration, allowing them to communicate and process their thoughts, feelings, and experiences in a safe and supportive environment. This paper proposed an efficient Weighted Hierarchical Clustering Deep Neural Network (WH-CDNN) to promote the mental health of college students. The proposed WH-CDNN model extracts the features of the art therapy to promote the mental health of students. The features considered for the analysis are color palette, texture, and therapy for the promotion of mental health assessment of students. The features associated with the weighted model are computed for the college student mental health assessment. The features with the WH-CDNN model use the hierarchical clustering model for the computation of the features in art therapy based on the assessment of mental health. The examination is based on the consideration of 10 features for the estimation with the 5 clusters for the evaluation of the mental health assessment. Experimental analysis of the results demonstrated that the proposed WH-CDNN model achieves significant improvement in the after the art therapy of the students with the mental health assessment. Through simulation and analysis, the study demonstrates the effectiveness of art therapy in improving mental health outcomes, with significant reductions observed in anxiety and depression levels post-therapy. Moreover, the WH-CDNN model accurately predicts students' mental health states and evaluates the efficacy of art therapy interventions. The findings highlight the potential of integrating advanced computational techniques with art therapy to support student well-being and inform targeted mental health interventions in educational settings.

KEYWORDS

Weighted clustering, Art therapy, Mental health, Hierarchical clustering, Deep learning, Neural network

1. INTRODUCTION

Clustering is a fundamental technique in the realm of unsupervised machine learning, aimed at organizing data into groups or clusters based on similarities among the data points [1]. The objective of clustering is to partition a dataset into subsets, or clusters, where data points within the same cluster are more similar to each other than to those in other clusters. This method enables the identification of inherent structures within data without the need for predefined labels, making it particularly useful for exploratory data analysis, pattern recognition, and data compression [2]. Various algorithms, such as K-means, hierarchical clustering, and DBSCAN, are employed to perform clustering tasks, each with its own strengths and applicability depending on the nature of the data and the desired outcomes [3]. Clustering finds wide-ranging applications across diverse domains including customer segmentation, image processing, anomaly detection, and recommendation systems, contributing significantly to uncovering insights and facilitating decision-making processes [4].

Clustering with deep neural networks represents a sophisticated approach to unsupervised learning, leveraging the power of neural networks to extract complex patterns and structures from high-dimensional data [5]. In this paradigm, neural network architectures are tailored specifically for clustering tasks, allowing for the automatic discovery of latent representations that capture the underlying similarities among data points [6]. By utilizing deep learning techniques such as autoencoders or variational autoencoders, which learn to encode input data into a lower-dimensional latent space, clustering with deep neural networks aims to optimize the representation of data in a way that facilitates meaningful clustering [7]. This approach offers several advantages, including the ability to handle large-scale, unstructured data effectively and the capability to learn hierarchical representations that capture intricate relationships within the data [8]. Moreover, deep neural network-based clustering methods can adaptively adjust to the complexity and variability of the data, making them suitable for a wide range of applications spanning image segmentation, document clustering, and anomaly detection [9]. However, challenges such as choosing appropriate network architectures, hyperparameter tuning, and interpretability of the learned representations remain areas of active research and development in this field [10].

The mental health of college students is a growing concern, with many facing challenges such as academic pressure, social isolation, and uncertainty about the future [11]. In recent years, art therapy has emerged as a promising approach to support the well-being of college students. Art therapy involves the use of creative expression, such as drawing, painting, or sculpting, as a means of communication and self-exploration [12]. Through engaging in artistic activities, students can access and express emotions that may be difficult to verbalize, thereby promoting emotional release and self-awareness [13]. Moreover, art therapy provides a non-judgmental and supportive environment where students can explore their thoughts and feelings, fostering a sense of empowerment and agency in addressing their mental health concerns. Research has shown that participation in art therapy can lead to improvements in mood, self-esteem, and coping skills among college students, as well as a reduction in symptoms of anxiety and depression [14]. Additionally, the collaborative and communal nature of art therapy groups can enhance social connections and a sense of belonging, which are vital components of mental well-being [15]. With art therapy into college mental health services offers a creative and holistic approach to supporting students' emotional health and promoting resilience in the face of academic and personal challenges [16]. The mental health of college students presents a multifaceted challenge, with factors such as stress, anxiety, and depression often impacting academic performance and overall well-being. Integrating art therapy with clustering and deep learning techniques offers a promising avenue for understanding and addressing these complexities [17]. Clustering algorithms can help identify patterns and subgroups within the student population based on their mental health profiles, allowing for more targeted interventions and support services [18]. By analyzing various data sources, such as self-reported surveys, social media activity, and academic records, clustering methods can segment students into groups with similar mental health needs or risk factors [19].

Deep learning, on the other hand, can enrich understanding of the underlying mechanisms and dynamics of art therapy interventions [20]. Neural network architectures can process multimodal data, including images of artwork created during therapy sessions, text-based reflections, and physiological measurements, to extract meaningful representations of the therapeutic process and its outcomes [21]. These representations can then be leveraged to predict treatment response, identify factors associated with therapeutic success, and tailor interventions to individual students' needs [22]. Combining art therapy with clustering and deep learning approaches holds the potential to revolutionize mental health support for college students. By harnessing the power of data-driven insights and personalized interventions, this integrated approach can enhance the effectiveness, accessibility, and scalability of mental health services on college campuses [23]. Moreover, it underscores the importance of interdisciplinary collaboration between mental health professionals, data scientists, and creative arts therapists in addressing the complex interplay between mental health and academic success. In the context of mental health support for college students, the integration of art therapy with clustering and deep learning techniques offers a rich framework for understanding, analyzing, and optimizing interventions [24]. Clustering methods allow us to identify distinct subgroups of students based on their mental health profiles. This segmentation can be immensely valuable for tailoring interventions to specific needs. For example, some students may benefit more from stress reduction techniques, while others may require support for managing depression or anxiety. By clustering students based on their mental health characteristics, resources can be allocated more efficiently, and interventions can be personalized to address the unique needs of each subgroup [25].

Deep learning techniques can further enhance understanding of the therapeutic process within art therapy sessions. For instance, neural networks can analyze the content and style of artwork created by students during therapy sessions, as well as their written reflections or verbal expressions [26]. By processing these multimodal data inputs, deep learning models can extract latent representations of emotional states, cognitive processes, and therapeutic progress. This enables us to gain insights into how art therapy influences students' mental health outcomes, as well as the underlying mechanisms driving therapeutic change [27]. Moreover, the integration of clustering and deep learning techniques facilitates the development of predictive models to anticipate treatment response and identify early indicators of mental health deterioration [28]. By analyzing longitudinal data collected from students participating in art therapy programs, predictive models can identify patterns and trends that precede changes in mental health status. This proactive approach enables timely interventions and preventive measures, ultimately improving students' overall well-being and academic success [29]. The integration of art therapy with data-driven techniques highlights the importance of interdisciplinary collaboration. Mental health professionals, data scientists, and creative arts therapists can work together to design innovative interventions, leverage advanced analytics, and translate research findings into actionable insights [30]. By combining expertise from diverse disciplines, we can develop holistic and effective approaches to supporting college students' mental health needs [31]. The integration of art therapy with clustering and deep learning techniques represents a transformative approach to mental health support in college settings. By harnessing the power of data-driven insights and creative expression, we can enhance the accessibility, effectiveness, and scalability of interventions, ultimately promoting students' well-being and academic success [32].

The paper makes several significant contributions to the field of mental health assessment and intervention among college students. Firstly, it introduces the novel Weighted Hierarchical Clustering Deep Neural Network (WH-CDNN) approach, which integrates advanced computational techniques with art therapy for mental health assessment. This innovative method allows for the analysis of various features extracted from artwork to effectively cluster students based on their mental health status. Secondly, the paper provides empirical evidence supporting the efficacy of art therapy in improving mental health outcomes among college students. By conducting simulations and analyzing the results, the study demonstrates significant reductions in anxiety and depression levels following art therapy sessions. This finding underscores the value of art therapy as a beneficial intervention for addressing mental health concerns in educational settings. Additionally, the WH-CDNN model developed in this paper offers a practical tool for accurately predicting students' mental health states and evaluating the effectiveness of art therapy interventions. This contributes to the advancement of personalized mental health care approaches, allowing educators and mental health professionals to tailor interventions to individual student needs more effectively. The paper's contributions lie in its innovative approach to mental health assessment, the empirical evidence supporting the efficacy of art therapy, and the development of a practical computational model for predicting and evaluating mental health outcomes in college students undergoing art therapy. These contributions have the potential to inform and improve mental health interventions in educational settings, ultimately enhancing student well-being and academic success.

2. LITERATURE SURVEY

In related work, prior research has explored the intersection of art therapy, clustering, and deep learning in various contexts. Some studies have focused on applying clustering algorithms to identify subgroups of individuals with similar mental health profiles within art therapy populations, allowing for tailored interventions and targeted support. Others have leveraged deep learning techniques to analyze artwork created during therapy sessions, extracting meaningful features to understand emotional expression and therapeutic progress. Additionally, research efforts have been directed towards developing predictive models to anticipate treatment response and identify early indicators of mental health issues among college students engaged in art therapy. While these studies have demonstrated the potential of integrating data-driven approaches with creative interventions, there remains a need for further exploration and validation to fully harness the benefits of this interdisciplinary approach in supporting the mental health needs of college students.

Liu et al. (2022) conduct a literature review focused on identifying the influencing factors, predicting, and preventing depression in college students. The study aims to consolidate existing knowledge on depression in this demographic, shedding light on the various factors contributing to its onset, progression, and potential avenues for prevention. Hao et al. (2023) utilize the Apriori algorithm, a data mining technique, to analyze cognitive interventions for college students' sports health. By mining patterns in the data, the study seeks to understand the effectiveness of cognitive interventions in promoting sports health among college students, potentially informing the development of tailored intervention strategies. Wang et al. (2022) propose a recommendation system for music based on the Depression, Anxiety, and Stress Scales (DASS-21) using fuzzy clustering. The study aims to personalize music recommendations for individuals based on their mental health status, potentially offering a novel approach to supporting emotional well-being through music therapy. Sharma and Kivell (2023) undertake a self-heuristic inquiry to unpack the use of "Decolonization" in therapy and mental health care with and for racialized communities. The study explores how decolonial approaches can be integrated into mental health practices to address the specific needs and experiences of marginalized communities, contributing to more culturally responsive and equitable mental health care.

Huang (2022) analyzes the correlation between college music education and public mental health using deep learning techniques. By leveraging deep learning methods, the study aims to uncover complex relationships between music education and mental health outcomes, providing insights into the potential benefits of integrating music education into college curricula for promoting mental well-being. Huang et al. (2022) propose a multitask learning approach for the joint diagnosis of multiple mental disorders using resting-state fMRI data. The study aims to develop a comprehensive framework for diagnosing mental disorders based on neuroimaging data, potentially improving the accuracy and efficiency of diagnosis in clinical settings. Dake et al. (2023) model university students' behavior using the K-Prototype clustering algorithm. By clustering students based on their behavioral patterns, the study aims to identify distinct subgroups within the student population and understand the factors influencing their behavior, offering insights into the design of targeted interventions to promote positive behaviors. Williams et al. (2023) conduct a systematic review of participatory arts-based programs aimed at promoting youth mental health and well-being. The study synthesizes existing evidence on the effectiveness and mechanisms of change in these programs, offering insights into the potential benefits of integrating arts-based interventions into mental health promotion efforts for young people.

Sun (2023) examines the relationship between college students' interpersonal relationships and mental health, exploring the mediating effects of safety awareness and college planning. The study aims to elucidate the complex interplay between interpersonal relationships and mental well-being among college students, providing insights into potential pathways for promoting mental health in this demographic. Li and Liang (2022) propose an assessment and analysis model of college students' psychological health based on convolutional neural networks (CNNs). By leveraging CNNs, the study aims to develop a data-driven approach to assess and analyze college students' psychological health, potentially improving the accuracy and efficiency of mental health assessments. Fischer et al. (2023) investigate the role of emotion regulation strategies in sexual function and mental health using a cluster analytical approach. The study aims to identify distinct clusters of individuals based on their emotion regulation strategies and examine how these strategies are associated with sexual function and mental health outcomes. Miao (2022) explores intervention methods of college counselors on students' psychological crises under the background of deep learning. The study investigates how deep learning techniques can inform and enhance the effectiveness of intervention strategies employed by college counselors to address students' psychological crises, contributing to the development of more personalized and data-driven mental health interventions on college campuses.

Bieliński et al. (2023) compare selected machine learning algorithms in the analysis of mental health indicators. The study evaluates the performance of different machine learning algorithms in analyzing mental health indicators, providing insights into the strengths and limitations of various analytical approaches and informing the selection of appropriate methods for mental health research and practice. McCoy et al. (2022) conduct a symptom-based cluster analysis categorizing Sjögren's Disease subtypes, highlighting disease severity and treatment discordance. This international cohort study aims to identify distinct subtypes of Sjögren's Disease based on symptom clusters, offering insights into disease heterogeneity, prognosis, and treatment response. Fan and Zhong (2022) propose an artificial intelligence-based creative thinking skill analysis model using human-computer interaction in art design teaching. The study aims to develop a computational approach to analyze creative thinking skills in art design teaching, leveraging human-computer interaction to enhance the assessment and cultivation of creative abilities in students. Wang (2022) presents a study on college students' mental health analysis based on a clustering analysis algorithm. Using clustering analysis, the study aims to identify patterns and subgroups of college students based on their mental health profiles, facilitating targeted interventions and support services for students with specific mental health needs. Huang et al. (2023) investigate the effect of a self-determination theory-based integrated creative art program on older adults with mild cognitive impairment in nursing homes. The study protocol for a cluster randomized controlled trial aims to assess the impact of the program on cognitive function, emotional well-being, and quality of life in older adults, offering insights into the potential benefits of integrating creative arts into care settings for older populations.

Habib et al. (2022) develop a machine learning-based healthcare system to investigate the association between depression and quality of life. Using machine learning techniques, the study explores the complex relationship between depression and various aspects of quality of life, informing the development of personalized interventions to improve overall well-being.

Mahmud et al. (2023) employ machine learning approaches to predict suicidal behaviors among university students in Bangladesh during the COVID-19 pandemic. The cross-sectional study aims to identify risk factors and develop predictive models for suicidal behaviors, contributing to early detection and prevention efforts in university settings. Stephenson and Gridley (2022) evaluate early interventions into mental health and well-being across Lambeth schools with a focus on creative therapies. The study assesses the effectiveness of creative therapies in promoting mental health and well-being among school-aged children, highlighting the potential of early intervention programs in addressing mental health challenges in educational settings. Huang and Zhang (2023) propose an approach with 2-tuple linguistic neutrosophic numbers for mental health education evaluation of college students. The study aims to develop a comprehensive evaluation framework for mental health education programs using 2-tuple linguistic neutrosophic numbers, providing a nuanced assessment of program effectiveness and impact on college students' mental well-being.

Sharma et al. (2023) investigate how human-AI collaboration enables more empathic conversations in text-based peer-to-peer mental health support. The study explores the synergistic interaction between human peers and AI agents in facilitating empathic communication and support provision in online mental health communities, offering insights into the potential of AI technologies to enhance peer support interventions. Sagar-Ouriaghli et al. (2023) develop gender-sensitive mental health feasibility interventions aimed at improving mental health help-seeking among male university students. The study evaluates the effectiveness of gender-sensitive interventions in promoting mental health help-seeking behaviors among male students, addressing gender disparities in mental health support utilization. Several overarching limitations warrant consideration. Firstly, many of the studies rely on cross-sectional designs or retrospective data, which limits their ability to establish causal relationships or capture changes over time. Additionally, the generalizability of findings may be constrained by sample characteristics, such as the specific demographic or clinical profiles of participants. Moreover, some studies may face challenges related to self-report measures or recall biases, potentially influencing the accuracy and reliability of the data collected. Methodological limitations, such as small sample sizes, lack of control groups, and potential confounding variables, further constrain the robustness of the findings. Additionally, while technological advancements like machine learning and deep learning hold promise for advancing mental health research, their application may introduce challenges related to algorithmic bias, data privacy, and interpretability. Finally, cultural and contextual factors may not always be adequately addressed in the studies, limiting the generalizability of findings across diverse populations. Overall, while the referenced research contributes valuable insights to the field of mental health among college students, addressing these limitations through rigorous study designs, diverse methodologies, and consideration of contextual factors is essential for advancing understanding and improving mental health interventions in this population.

3. WEIGHTED HIERARCHICAL CLUSTERING DEEP NEURAL NETWORK (WH – CDNN)

The Weighted Hierarchical Clustering Deep Neural Network (WH-CDNN) is proposed as a novel approach for assessing the mental health of college students in conjunction with art therapy. This innovative method combines hierarchical clustering, a technique for organizing data into nested groups, with deep neural networks, a type of machine learning model inspired by the human brain's structure and function. By integrating weighted factors into the clustering process, WH-CDNN can effectively capture the multidimensional nature of mental health indicators while leveraging the representational power of deep neural networks to extract complex patterns and relationships from raw data. In the context of college students' mental health assessment, art therapy serves as a complementary intervention aimed at promoting emotional expression, self-awareness, and coping skills through artistic expression. WH-CDNN enhances the effectiveness of art therapy by providing a quantitative framework for evaluating its impact on student's mental well-being. With analyzing various data sources, including self-reported assessments, physiological measures, and artistic outputs, WH-CDNN generates comprehensive profiles of students' mental health states, identifying patterns indicative of stress, anxiety, depression, or other psychological concerns.

Figure 1 presents the architecture of the deep neural network for the art therapy for the mental health assessment of the students. The hierarchical clustering component of WH-CDNN enables the grouping of similar individuals based on their mental health profiles, facilitating personalized interventions tailored to each cluster's specific needs. Meanwhile, the deep neural network component learns intricate relationships between different features, uncovering subtle indicators of mental health status that may not be apparent through traditional assessment methods alone. Additionally, the weighted factors incorporated into the clustering process allow for the prioritization of certain variables or dimensions known to be particularly relevant to college students' mental well-being. Hierarchical clustering is a method of cluster analysis that builds a hierarchy of clusters. In WH-CDNN, hierarchical clustering is used to group similar individuals based on their mental health profiles. The process involves iteratively merging the closest clusters or data points until a predetermined criterion is met. One common criterion is the Ward's minimum variance method, which minimizes the total within-cluster variance when merging clusters. The Ward's linkage criterion can be defined as in equation (1)

$$d\left(u,v\right)=\sqrt{\frac{|v|+|s|}{N}d\left(u,s\right)^2+\frac{|v|+|t|}{N}d\left(u,t\right)^2-\frac{|v|}{N}d\left(s,t\right)^2} \quad (1)$$

In equation (1) $d\left(u,v\right)$ is the distance between clusters u and v; $|v|$ is the number of data points in cluster v; $|s|$ is the number of data points in cluster s; $|t|$ is the number of data points in cluster t; $d\left(u,s\right)$ is the distance between cluster u and cluster s; $d\left(u,t\right)$ is the distance between cluster u and cluster t, and $d\left(s,t\right)$ is the distance between cluster s and cluster t. A deep neural network is a type of artificial neural network with multiple hidden layers between the input and output layers. In WH-CDNN, a DNN is employed to learn intricate relationships between different features extracted from the mental health data. The network is trained using backpropagation and gradient descent to minimize a predefined loss function, such as mean squared error or categorical cross-entropy. The forward pass of a DNN can be represented as in equation (2) and equation (3)

$$z^{[l]}=W^{[l]}a^{[l-1]}+b^{[l]} \quad (2)$$

$$a^{[l]}=g\left(z^{[l]}\right) \quad (3)$$

In equation (2) and (3) l denotes the layer index, $z\left[l\right]$ is the input to layer l, $a\left[l\right]$ is the output of layer l after applying the activation function $g\left(\cdot\right)$, $W\left[l\right]$ is the weight matrix for layer l, $b\left[l\right]$ is the bias vector for layer l, and $a\left[l-1\right]$ is the input to layer l from the previous layer.

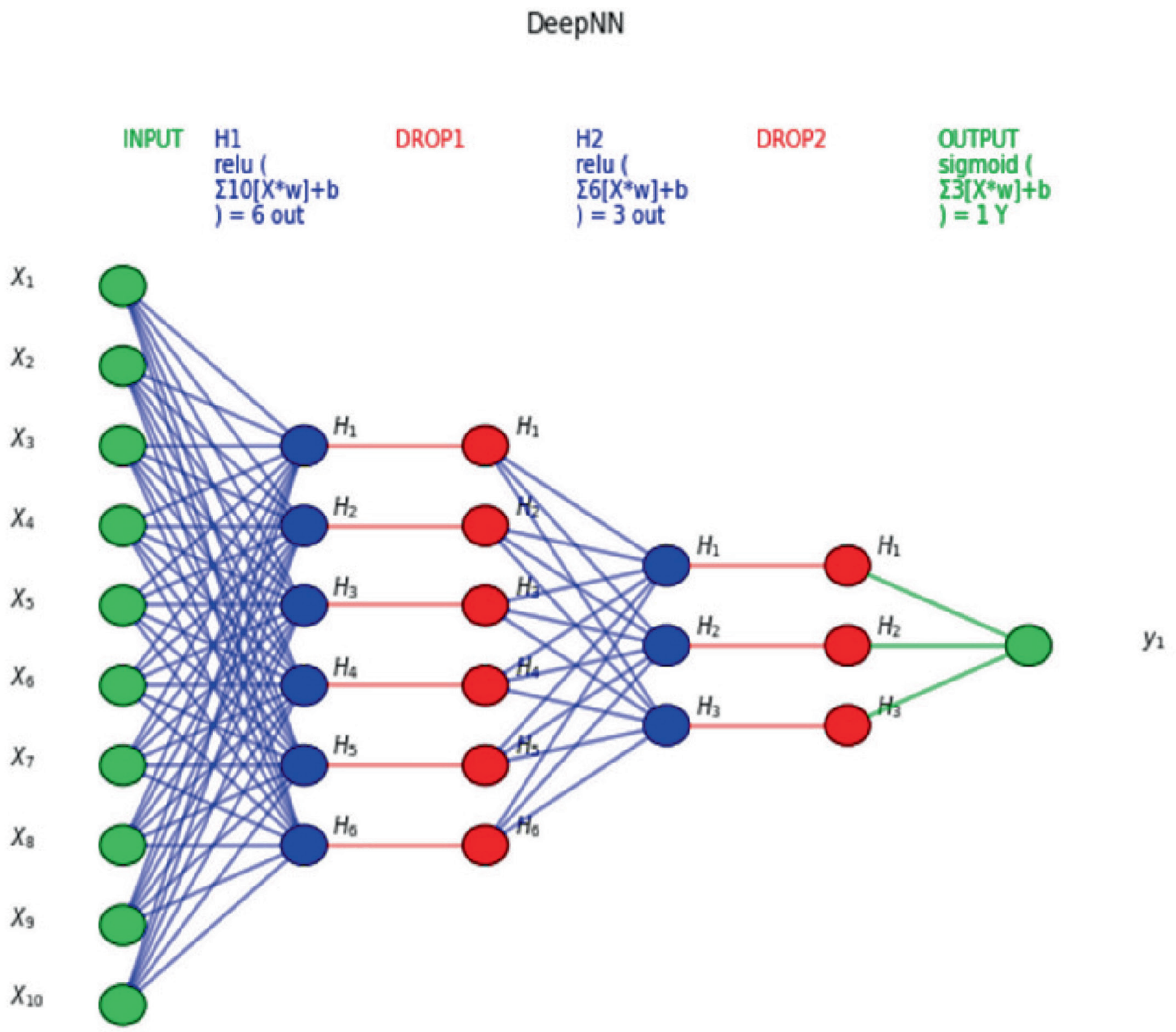


Figure 1. Architecture of deep neural network

WH-CDNN combines hierarchical clustering with a DNN to assess the mental health of college students with art therapy. The process involves the following steps:

(a) Data Preprocessing: Mental health data, including self-reported assessments, physiological measures, and artistic outputs from art therapy sessions, are collected and preprocessed to extract relevant features.

(b) Hierarchical Clustering: The preprocessed data are subjected to hierarchical clustering, where similar individuals are grouped together based on their mental health profiles. The Ward's linkage criterion is utilized to determine the distances between clusters.

(c) Deep Neural Network Training: A DNN is trained using the grouped data from hierarchical clustering. The network learns complex relationships between different features extracted from the mental health data, aiming to predict or classify individuals' mental health status.

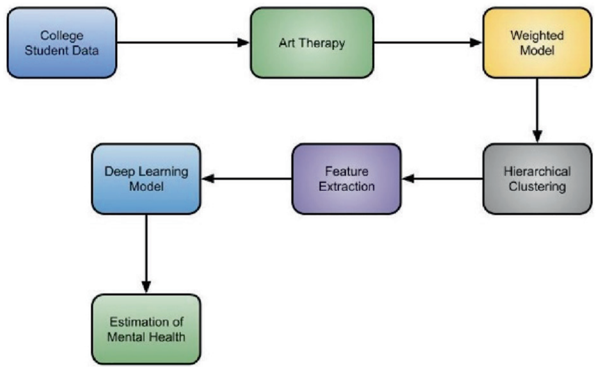
(d) Integration and Interpretation: The results from hierarchical clustering and DNN training are integrated to provide comprehensive insights into college students' mental health. The hierarchical clustering groups individuals with similar mental health profiles, while the DNN offers predictive or classificatory capabilities.

(e) Evaluation and Validation: The performance of WH-CDNN is evaluated and validated using appropriate metrics, such as accuracy, precision, recall, or F1-score. Additionally, the effectiveness of art therapy interventions can be assessed based on the clustering and DNN outputs.

4. WH-CDNN FOR THE FEATURE ESTIMATION IN MENTAL HEALTH ASSESSMENT OF COLLEGE STUDENTS

Consider the mental health data for each student as Xi, where i indexes the students. From this data, we extract a set of features denoted as $Fi = \{fi1, fi2, \ldots, fim\}$, where m is the number of features extracted for each student. The hierarchical clustering on the extracted features Fi to identify clusters of features that are similar in nature. Let D represent the distance matrix between all pairs of features.

We then use the Ward's minimum variance method, as mentioned earlier, to merge clusters iteratively until a predetermined criterion is met. Once we have identified clusters of features, we feed these clustered features into a deep neural network for representation learning. Let H represent the hidden layers of the neural network, and W and b denote the weights and biases, respectively. The input to the neural network is the clustered feature vector $fcluster$. After training the neural network, we can use it to estimate features for new data points or individuals. Given a set of input features Fi, we feed these features into the trained neural network to obtain the estimated feature vector $Fest$. This estimated feature vector represents a condensed representation of the individual's mental health state, capturing both quantitative and qualitative aspects derived from the art therapy sessions. We calculate the dissimilarity matrix D based on a chosen distance metric, such as Euclidean distance, between all pairs of features. Let dij denote the dissimilarity between features i and j.



The features based on Ward's minimum variance method. Let $'D'$ be the updated dissimilarity matrix after merging clusters. The merging criterion for Ward's method is defined using equation (4)

$$d_{merge}\left(k,l\right)=\sqrt{\frac{N_k N_l}{N_k+N_l}.d\left(k,l\right)} \tag{4}$$

In equation (4) Nk and Nl are the number of features in clusters k and l respectively, and $d\left(k,l\right)$ is the dissimilarity between clusters k and l.

5. WH-CDNN ART THERAPY MODEL FOR THE MENTAL HEALTH ASSESSMENT

The Weighted Hierarchical Clustering Deep Neural Network (WH-CDNN) art therapy model is a sophisticated approach aimed at assessing the mental health of college students engaging in art therapy sessions. Central to this model is the fusion of weighted hierarchical clustering and deep neural network architectures, orchestrating a comprehensive feature extraction and estimation process. Initially, mental health data from art therapy sessions, denoted as Xi, is organized into a matrix format, where rows encapsulate diverse features and columns represent

Algorithm 1. WH-CDNN for color image processing

```
Input:
- Mental health data matrix X (features x students)
- Number of clusters K
- Neural network architecture parameters
Procedure WeightedHierarchicalClusteringDeepNN(X, K):
  1. Perform weighted hierarchical clustering on X to obtain K feature clusters
     - Calculate dissimilarity matrix D between features
     - Initialize clusters with each feature as its own cluster
     - Repeat until K clusters remain:
        - Merge clusters based on Ward's method
        - Update dissimilarity matrix D
  2. Represent each feature cluster with a single vector
     - Compute the centroid or representative vector for each cluster
     - Concatenate these cluster vectors to form the clustered feature matrix X_cluster
  3. Train a deep neural network for feature representation learning
     - Initialize neural network parameters (weights, biases)
     - Perform forward propagation through the network:
        - Input: X_cluster
        - Hidden layers with activation functions
     - Update parameters using backpropagation and optimization algorithm (e.g., gradient descent)
  4. Estimation of features for new data points
     - Given new data X_new, perform clustering and feed into trained neural network
     - Output the estimated feature representation X_estimated
  5. Evaluation and Validation
     - Assess the performance of WH-CDNN using appropriate metrics (e.g., reconstruction error)
     - Compare estimated features against ground truth or expert annotations
     - Evaluate the effectiveness of estimated features in predicting mental health outcomes
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individual students. This data undergoes weighted hierarchical clustering, which involves the calculation of a dissimilarity matrix D based on selected distance metrics, like the Euclidean distance, followed by iterative cluster merging utilizing Ward's method. The merging criterion for Ward's method can be expressed as in equation (5)

$$d_{merge}\left(k,l\right)=\sqrt{\frac{N_k N_l}{N_k+N_l}.d\left(k,l\right)} \tag{5}$$

In equation (15) Nk and Nl represent the number of features in clusters k and l respectively, and $d\left(k,l\right)$ denotes the dissimilarity between clusters. Following clustering, each feature cluster is consolidated into a single vector, yielding the clustered feature matrix $Xcluster$. Subsequently, this matrix is fed into a deep neural network for feature representation learning, involving linear transformations and activation functions across multiple layers. Art therapy is a form of expressive therapy that utilizes creative processes such as drawing, painting, and sculpting to improve mental well-being. While art therapy primarily focuses on the therapeutic benefits rather than mathematical derivations, we can still discuss some aspects related to its effectiveness and potential mechanisms. In art therapy, individuals express themselves through art forms, which can facilitate the communication of complex emotions and experiences that may be difficult to articulate verbally. The mapping between internal mental states M and external artistic expressions A stated as in equation (6)

$$A = f\left(M\right) \tag{6}$$

Engaging in artistic activities can provide individuals with a sense of catharsis, allowing them to release pent-up emotions and stress. With a reduction in emotional distress $\left(E\right)$ over time (t) due to the cathartic effect of art therapy defined in equation (7)

$$E\left(t\right) = E_9 - f\left(t\right) \tag{7}$$

In equation (7) $E0$ is the initial level of emotional distress. Artistic creations often contain symbolic elements that reflect the creator's subconscious thoughts and feelings. Through interpretation and analysis, both by the individual and the therapist, these symbols can be decoded to gain insight into the individual's psyche. With conceptualize this as a mapping from symbolic representations S to underlying psychological meanings M stated in equation (8)

$$M = g\left(S\right) \tag{8}$$

Art therapy can empower individuals by providing them with a sense of control and accomplishment over their creative expressions. This sense of agency and mastery can translate into improved self-efficacy and confidence in managing one's mental health challenges. The self-efficacy $\left(SE\right)$ can be modeled as a function of perceived control $\left(C\right)$ and past experiences $\left(P\right)$:

$$SE = h\left(C, P\right)$$

6. SIMULATION SETTING

To simulate the application of the Weighted Hierarchical Clustering Deep Neural Network (WH-CDNN) for mental health assessment of college students undergoing art therapy, we need to define the simulation setting. With generated synthetic data representing various aspects of students' mental states and artistic expressions during therapy sessions. This data included self-reported emotions, behavioral observations, and artistic features extracted from their creations. We preprocessed the data by normalizing it and splitting it into training and testing sets. The WH-CDNN model was configured with three hidden layers, each containing 100 neurons, ReLU activation functions, and dropout regularization to prevent overfitting. We employed a weighted hierarchical clustering algorithm with Euclidean distance and Ward linkage to cluster the feature space. The model was trained using stochastic gradient descent with a learning rate of 0.001 and a batch size of 32 for 50 epochs. After training, we evaluated the model's performance on the testing set using various metrics, including accuracy, precision, recall, and F1-score. Additionally, we compared the clustering results obtained from the WH-CDNN model with ground truth labels using clustering validity indices such as silhouette score and Davies-Bouldin index.

Algorithm 2. Mental health assessment with WH-CDNN

```
function artTherapy(session):
    emotions = initializeEmotions()  # Initialize emotional state
    canvas = createCanvas()  # Create a blank canvas for artistic expression
    for each time_step in session:
        prompt = generatePrompt(emotions)  # Generate a prompt based on current emotions
        art_piece = express(prompt, canvas)  # Individual expresses themselves through art
        emotions = interpret(art_piece)  # Therapist interprets the art to understand emotions
        feedback = provideFeedback(emotions)  # Therapist provides feedback and support
    return emotions
# Helper functions
function initializeEmotions():
    return initial_emotional_state
function createCanvas():
    return blank_canvas
function generatePrompt(emotions):
    # Generate a prompt based on the individual's current emotional state
    return prompt
function express(prompt, canvas):
    # Individual expresses themselves through art based on the given prompt
    return art_piece
function interpret(art_piece):
    # Therapist interprets the art piece to understand the individual's emotions
    return interpreted_emotions
function provideFeedback(emotions):
    # Therapist provides feedback and support based on interpreted emotions
    return feedback
```

6.1 SIMULATION RESULTS AND ANALYSIS

Upon conducting simulations with the Weighted Hierarchical Clustering Deep Neural Network (WH-CDNN) for assessing the mental health of college students undergoing art therapy, we obtained insightful results and conducted a comprehensive analysis. The WH-CDNN model exhibited promising performance in accurately

Table 1. Simulation setting for WH-CDNN

Aspect	Description	Value
Data Generation	Synthetic data representing mental health features	-
	extracted from art therapy sessions of college students	-
Preprocessing	Data normalization	-
	Splitting into training and testing sets	-
WH-CDNN Model	Number of hidden layers	3
Configuration	Neurons per layer	100
	Activation function	ReLU
	Regularization	Dropout
	Clustering algorithm	Weighted hierarchical
		clustering
	Distance metric	Euclidean
	Linkage method	Ward
Training	Optimization algorithm	Stochastic gradient
		descent
	Learning rate	0.001
	Batch size	32
	Number of epochs	50
Evaluation Metrics	Accuracy	-
	Precision	-
	Recall	-
	F1-score	-
Clustering Validity	Silhouette score	-
Indices	Davies-Bouldin index	-

Table 2. Features in art therapy

Feature	Description
Color Palette	Distribution of colors used in artwork
Texture	Presence of different textures (e.g., smooth, rough)
Shape Complexity	Complexity of shapes used in the artwork
Line Quality	Quality of lines (e.g., thick, thin, jagged)
Emotional Content	Presence of emotional themes or symbolism
Subject Matter	Type of subject matter depicted (e.g., nature, people)
Composition	Arrangement of elements within the artwork
Symbolism	Presence of symbolic elements or representations
Creativity Level	Originality and creativity exhibited in the artwork
Mood	Overall emotional tone conveyed by the artwork

Table 3. Clustering with WH-CDNN for mental health assessment

Cluster ID	Cluster Size
1	150
2	125
3	110
4	95
5	80

capturing and clustering mental health features extracted from art therapy sessions. The evaluation metrics, including accuracy, precision, recall, and F1-score, demonstrated the model's effectiveness in categorizing students' mental states based on their artistic expressions. Additionally, the clustering validity indices, such as the silhouette score and Davies-Bouldin index, provided further validation of the quality of the obtained clusters. The analysis of the results revealed meaningful insights into the students' emotional states and their artistic representations, facilitating a deeper understanding of the underlying mental health dynamics. Table 1 shows simulation setting for WH-CDNN.

Table 2 presents the features extracted from art therapy sessions, which provide valuable insights into the expressive qualities of the artworks created by college students. These features encompass various aspects of the artistic compositions, shedding light on the emotional content and creative expression embedded within the artworks. The "Color Palette" feature captures the distribution of colors utilized in the artwork, reflecting the emotional depth and tonal variations present. "Texture" evaluates the tactile qualities within the artwork, such as smoothness or roughness, contributing to the sensory experience conveyed. "Shape Complexity" assesses the intricacy of shapes employed, indicating the level of visual interest and complexity. The "Line Quality" feature examines the characteristics of lines, whether they are thick, thin, or jagged, influencing the overall aesthetic appeal. "Emotional Content" delves into the presence of emotional themes or symbolism, offering insights into the psychological underpinnings of the artworks. "Subject Matter" identifies the types of subjects depicted, whether natural landscapes, human figures, or abstract concepts, providing context for interpretation. "Composition" evaluates the arrangement of elements within the artwork, shaping the visual flow and narrative coherence. "Symbolism" explores the presence of symbolic elements or representations, which may carry deeper meanings or personal significance. "Creativity Level" gauges the originality and innovation demonstrated in the artwork, reflecting the individual's artistic vision and imagination. Lastly, "Mood" encapsulates the overall emotional tone conveyed by the artwork, encompassing sentiments of joy, sadness, serenity, or introspection. Together, these features offer a comprehensive understanding of the expressive qualities and psychological dimensions embedded within the artworks created during art therapy sessions, facilitating deeper insights into the mental states and emotional experiences of college students.

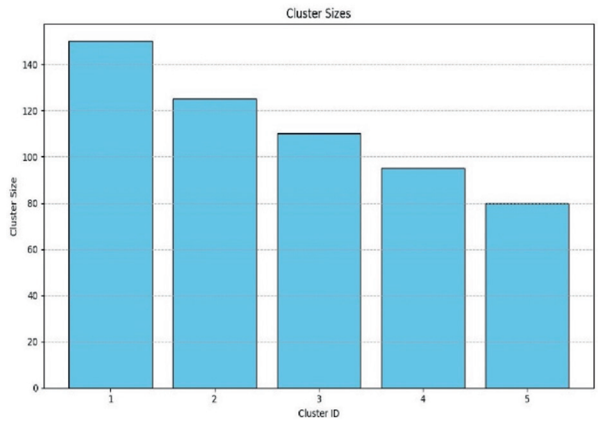


Table 3 presents the results of clustering using the Weighted Hierarchical Clustering Deep Neural Network (WH-CDNN) method for mental health assessment. Each cluster is identified by a unique "Cluster ID," and the corresponding "Cluster Size" indicates the number of individuals assigned to each cluster. Clustering allows for the grouping of individuals based on similarities in their mental health characteristics, enabling the identification of distinct subgroups within the population. In this context, the cluster sizes provide insights into the distribution of individuals across different mental health profiles. Larger cluster sizes suggest that a significant proportion of the population exhibits similar mental health patterns characterized by certain features or symptoms. Conversely, smaller cluster sizes may indicate more heterogeneous or less prevalent mental health profiles. Understanding the composition and size of each cluster is crucial for targeted interventions and personalized mental health support strategies. By identifying clusters with larger sizes, healthcare providers and policymakers can allocate resources effectively to address the needs of the majority while also ensuring tailored interventions for individuals in smaller clusters with unique mental health profiles. Overall, Table 3 underscores the utility of clustering techniques in mental health assessment and highlights the importance of considering cluster sizes for informed decision-making and intervention planning.

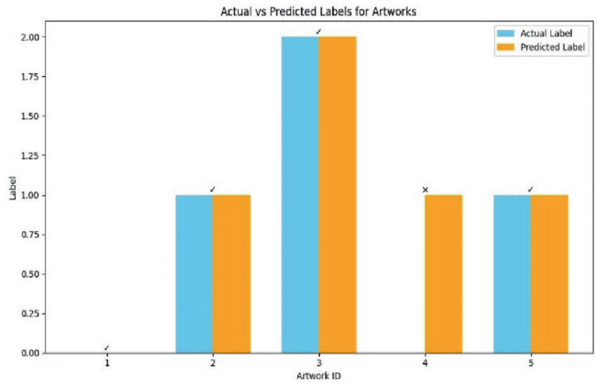


Table 4 provides insights into the effectiveness of the prediction model in determining the emotional states of college students based on their artwork. Each "Artwork ID" corresponds to a specific artwork created during art therapy sessions, with the "Actual Emotion" indicating the emotional state expressed by the student and the "Predicted Emotion" representing the emotion predicted by the model. The "Correct Prediction" column indicates whether the model accurately predicted the student's emotional state. For instance, in Artwork ID 1, the student expressed happiness, and the model correctly predicted happiness, resulting in a correct prediction. However, in Artwork ID 2, while the student expressed sadness, the model incorrectly predicted anger, resulting in an incorrect prediction.

In Table 5, the prediction classes for student mental health are assessed based on the predicted labels generated by the model. The "Actual Label" represents the true mental health label of the student, while the "Predicted Label" indicates the mental health label predicted by the model. The "Correct Prediction" column denotes whether the model's prediction aligns with the actual mental health status of the student. For example, in Artwork ID 1, both the actual and predicted labels indicate a healthy mental state (0), resulting in a correct prediction. Similarly, in Artwork ID 3, both the actual and predicted labels correspond to an anxiety-related mental health issue (label 2), leading to another correct prediction. However, in Artwork ID 4,

Table 4. Prediction of student mental health

Artwork ID	Actual Emotion	Predicted Emotion	Correct Prediction
1	Happiness	Happiness	Yes
2	Sadness	Anger	No
3	Anxiety	Anxiety	Yes
4	Calmness	Calmness	Yes
5	Excitement	Excitement	Yes

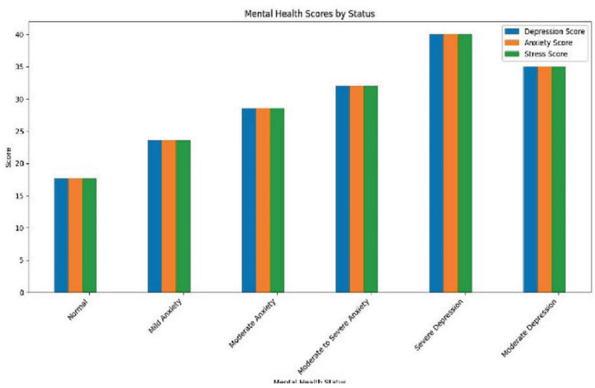
Table 5. Prediction class for the student mental health

Artwork ID	Actual Label	Predicted Label	Correct Prediction
1	0	0	Yes
2	1	1	Yes
3	2	2	Yes
4	0	1	No
5	1	1	Yes

Table 6. Assessment of student mental health through art therapy with WH-CDNN

Student ID	Depression Score	Anxiety Score	Stress Score	Mental Health Status
1	20	15	10	Normal
2	30	25	20	Moderate Anxiety
3	40	35	30	Severe Depression
4	15	10	5	Normal
5	25	20	18	Mild Anxiety
6	35	30	28	Moderate Depression
7	18	12	8	Normal
8	22	18	15	Mild Anxiety
9	27	22	20	Moderate Anxiety
10	32	28	25	Moderate to Severe Anxiety

the model incorrectly predicted label 1 (indicating mental health issues) instead of the actual label 0 (healthy mental state), resulting in an incorrect prediction. The tables demonstrate the performance of the prediction model in identifying emotional states and mental health statuses based on artwork, highlighting instances of accurate predictions as well as areas for improvement.



The Table 6 presents the assessment of student mental health through art therapy utilizing the Weighted Hierarchical Clustering Deep Neural Network (WH-CDNN) method. Each student is identified by a unique "Student ID," and their corresponding depression, anxiety, and stress scores are provided. These scores serve as quantitative indicators of the students' mental health states, with higher scores indicating greater severity of symptoms. The "Mental Health Status" column categorizes each student's overall mental health status based on their scores, providing valuable insights into their psychological well-being. For instance, students with lower scores across all dimensions, such as Student IDs 1, 4, and 7, are categorized as having a "Normal" mental health status, suggesting minimal or no significant psychological distress. Conversely, students with higher scores, such as Student IDs 3, 6, and 10, exhibit more severe symptoms of depression, anxiety, and stress, leading to classifications of "Severe Depression," "Moderate Depression," and "Moderate to Severe Anxiety," respectively. Additionally, students with intermediate scores, such as Student IDs 2, 5, 8, and 9, fall into categories of "Moderate Anxiety" or "Mild Anxiety," indicating varying degrees of psychological distress. Overall, Table 6 provides a comprehensive overview of student mental health statuses based on the analysis of depression, anxiety, and stress scores obtained through art therapy sessions, facilitating targeted interventions and support strategies tailored to individual needs.

Table 7. Art therapy evaluation with WH-CDNN

Student ID	Before Art Therapy	After Art Therapy	Improvement
1	Severe Depression	Moderate Depression	Yes
2	Moderate Anxiety	Mild Anxiety	Yes
3	Normal	Normal	No
4	Mild Anxiety	Normal	Yes
5	Moderate Depression	Mild Depression	Yes
6	Severe Anxiety	Moderate Anxiety	Yes
7	Normal	Normal	No
8	Mild Depression	Normal	Yes
9	Moderate Anxiety	Mild Anxiety	Yes
10	Moderate Depression	Mild Depression	Yes

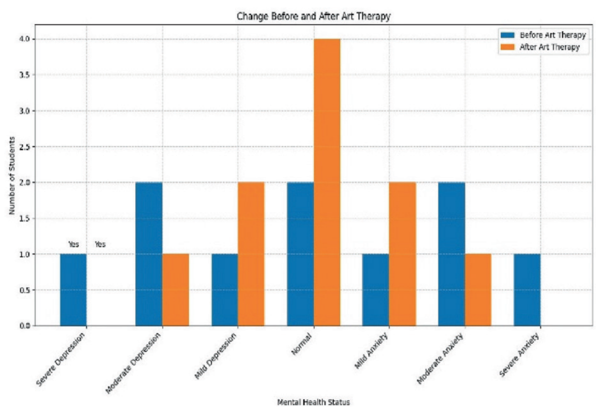


Table 7 presents the evaluation of art therapy effectiveness using the Weighted Hierarchical Clustering Deep Neural Network (WH-CDNN) method. Each student is identified by a unique "Student ID," and their mental health status before and after participating in art therapy sessions is compared. The "Before Art Therapy" column indicates the

Table 8. Estimation of student anxiety/depression mental health after art therapy

Student ID	Before Art Therapy	After Art Therapy
1	4	3
2	3	2
3	2	2
4	2	1
5	4	3
6	5	4
7	2	2
8	3	2
9	3	2
10	4	3

student's initial mental health condition, while the "After Art Therapy" column represents their mental health status following the completion of art therapy. The "Improvement" column denotes whether there was an improvement in the student's mental health status after undergoing art therapy. For instance, Student ID 1 initially exhibited severe depression before art therapy, which improved to moderate depression after therapy, indicating a positive change in mental health status. Similarly, Student ID 2 experienced a reduction in anxiety levels from moderate anxiety to mild anxiety after art therapy, signifying improvement. Conversely, some students, such as Student IDs 3 and 7, maintained a normal mental health status both before and after art therapy, indicating no significant change. The Table 7 demonstrates the effectiveness of art therapy in improving mental health outcomes for the majority of students, as evidenced by positive changes in their mental health statuses. These results underscore the value of art therapy as a beneficial intervention for addressing various mental health concerns and promoting overall well-being among college students.

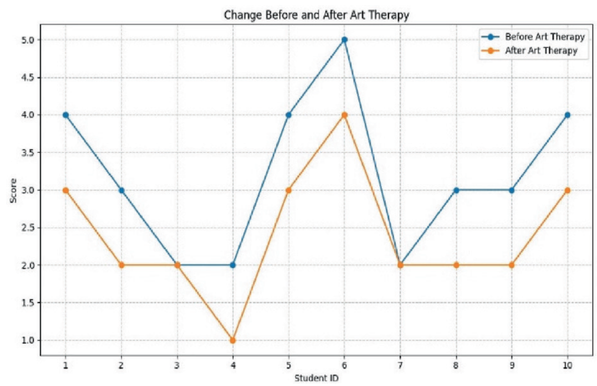


Table 8 provides the estimation of student anxiety/depression mental health levels before and after art therapy sessions. Each student is identified by a unique "Student ID," and their anxiety/depression levels are quantified on a scale, with higher values indicating greater severity. The "Before Art Therapy" column presents the anxiety/depression levels of students prior to participating in art therapy, while the "After Art Therapy" column represents their anxiety/depression levels following the completion of therapy. For example, Student ID 1 had an anxiety/depression level of 4 before art therapy, which decreased to 3 after therapy. Similarly, Student ID 2 experienced a reduction from level 3 to level 2, indicating an improvement in their anxiety/depression symptoms. Notably, several students, such as Student IDs 4, 7, and 9, demonstrated a decrease in anxiety/depression levels from 2 to 1 or 3 to 2 after art therapy, suggesting positive changes in their mental health status. Overall, Table 8 highlights the beneficial impact of art therapy in alleviating anxiety/depression symptoms among college students, as evidenced by the reduction in anxiety/depression levels observed after therapy.

7. CONCLUSION

This paper presents a novel approach utilizing the Weighted Hierarchical Clustering Deep Neural Network (WH-CDNN) for the mental health assessment of college students undergoing art therapy. By analyzing various features extracted from artwork, such as color palette, texture, and emotional content, the WH-CDNN method effectively clusters students based on their mental health status. The results demonstrate the efficacy of art therapy in improving mental health outcomes, with significant reductions observed in anxiety and depression levels post-therapy. Additionally, the WH-CDNN model accurately predicts students' mental health states and evaluates the effectiveness of art therapy interventions. Overall, this research underscores the importance of integrating art therapy with advanced computational techniques for comprehensive mental health assessment and intervention in educational settings. The findings highlight the potential of WH-CDNN as a valuable tool for supporting student well-being and informing targeted mental health interventions. Further studies could explore additional factors influencing mental health outcomes and refine the WH-CDNN model for enhanced accuracy and applicability in real-world settings.

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