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Mechanism and Sustainable Development of the Practical Ability Enhancement Mechanism for Art Students in Colleges and Universities Based on Internet Plus

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Abstract: - Currently, art students in colleges and universities see computer technology as a tool for daily living and enjoyment, but often fail to incorporate it into their studies. This paper, introduces the mechanism of the practical ability enhancement mechanism for art students in colleges and universities based on internet plus. The work aims to enhance students' creative imagination, aesthetic skill, and quality, as well as to support their overall growth. Initially, the input images gathered from Art Images: Drawing/Painting/Sculptures/Engravings data set collected image is pre processed by using Privacy-Preserving Distributed Kalman filtering (PP-DKF) preprocessed the image to enhance image clarity. Then the preprocessed output is fed to the Mix Style Neural Networks (MSNN) predicting the grades of art students in colleges and universities based on the internet plus. The weight parameter of the MSNN optimized with secretary bird optimization algorithm (SBOA) for accurate prediction. The proposed MDEACUI-MSNN-SBOA proposed is implemented on the Python working platform. The performance of the proposed MDEACUI-MSNN-SBOA approach attains 23.52%, 21.72%, and 24.92%higher accuracy; 23.52%, 22.72%, and 21.92%higher Precision; and 20.74%, 28.01% and 23.28%higher recall compared with existing methods such as Quantitative Enhancement of University Students' Employability Deep Learning Digital Era (QEUEDDE-DFNN), Entrepreneurship education computer-aided instruction for college Music using convolution neural network (EECIC-CNN) and Application of Art in Colleges and Universities Based on BP Neural Network Algorithm (AACU-BPNN) respectively.

Keywords: Art Education, College, University, Students, Privacy Preserving Distributed Kalman Filtering, Mix Style Neural Networks, Secretary Bird Optimization Algorithm.

I. INTRODUCTION

(a) Back ground

Art education is the complete development of pupils' capacities to locate, recognise, and create beauty via a variety of educational activities, such as painting production and appreciation [1, 2]. In addition to teaching pupils painting theories and methods, colleges and institutions should teach them how to identify and appreciate spiritual substance in art. Within the context of college and university art education reform, art education should completely stress its qualities, using the model of art education as a guide, instruct pupils in drawing techniques and art knowledge, and fully use the distinctive art education efficacy of art [3, 4]. The Internet and numerous industries have achieved integrated development, resulting in a tremendous volume of data. As a result, database design and management can increase work efficiency [5, 6]. In order to achieve the educational objective of bolstering students' art literacy and drawing skills, methodical activities in art education are conducted for students to improve their autonomous integration as well as to conduct art practice and research [7, 8]. Institutions of higher learning should approach art instruction with an eye towards resolving issues with traditional art education in accordance with the optimised art teaching mode in order to meet the needs of contemporary students' artistic development and to guarantee that the usefulness and efficacy of art education are recognised [9].

(b) Literature Review

Meng et al. [10] have suggested The method of quantitatively enhancing college students' job and entrepreneurial capacities in the digital era is investigated and studied through the application of deep learning. The deep learning questionnaire was created, and it was classed using exploratory factor analyses to lessen dimensionality. The deep learning questionnaire's particular indicators and elements with a scientific implication were determined.

Liang et al. [11] New media technology has also been widely used in college education, revolutionising the old single teaching approach and enhancing the curriculum. Art education is significant in higher education and has

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historically been an essential component of our country's quality education. WeChat has had a significant impact on the subject of art education. This study classifies the technical features of art works.

Cao [12] has utilized second, the CNN weight sharing and local perception were used to construct the Computer-aided Instruction (CAI) model, which involves both the teacher and the student. Lastly, an evaluation of the “CNN-based CAI model's performance” was conducted. Meanwhile, it examines experience with the proposed CAI paradigm using a case study of Music Majors at Xi'an Conservatory of Music.

Aydoğdu [13] made use of Students' usage of the learning management system was not given priority; instead, artificial neural networks were used to anticipate performance based on student results. This study set out to forecast, using artificial neural networks, the performance of 3518 university students studying and actively engaged in a learning management system based on variables such as content score, gender, time spent on the content, homework score, number of attendance to archived courses ,quantity of people that attended live sessions , amount of hours spent in live sessions overall, quantity of content entries and time allotted to courses that have been archived.

Li et al. [14] have suggested that the improved thinking skills technique is an educational strategy that uses practical, experiential learning activities to help students build critical reasoning, ability to make decisions and problem-solving. Although LAL has shown positive impacts on children's cognitive development, it has a number of challenges, including the need for personalized instruction and the difficulty of tracking progress. The DNN-LALM model is offered by the current work as a viable remedy for the aforementioned issues.

Tato and Nkambou [15] have developed that a hybrid design that combines DNN topologies, including Long Short-Term Memory andCNN, with expert knowledge for user modeling. The proposed technique employs the attention mechanism to integrate expert information into the DNN. There is less data on pupils who properly answered questions about challenging skills vs those who erroneously answered questions about simple skills.

Zhuang and Zhu [16] have developed that The goal of universities' "Internet Plus, Innovative Entrepreneurship Practice Education Pattern" is to help students become more independently innovative and proficient in basic reading. IEPEP's lone practice education pattern does not include any practical tasks; it just provides theoretical teaching. There was insufficient professional teaching personnel and a majority of part-time teachers delivering IE courses. The IEPEP evaluation standard was the written evaluation. The evaluation approach is imprecise due to the absence of real exercises.

c) Research Gaps and Motivation

The literature reveals several endeavors aimed at improving aspects of college education in the digital age. While some researchers advocate for deep learning approaches to enhance students' employability and entrepreneurial skills, others explore the impact of new media technologies like WeChat on art education. Additionally, studies have examined the integration of CNN into CAI to enhance learning experiences, and the use of artificial neural networks to predict student presentation based on various factors. Challenges persist, however, particularly in fostering critical thinking skills and addressing the limitations of existing educational models. Efforts to develop hybrid architectures combining Deep Neural Networks with expert knowledge aim to overcome these challenges, yet gaps remain in understanding the effectiveness of such approaches. Seek to enhance students' innovation abilities but face obstacles such as a lack of practical exercises and insufficient teaching resources. Moreover, initiatives like innovative the proposed MDEACUI-MSNN-SBOA the proposed predicts the performance of the students. Based on the performance the teachers should gives practice to individual student’s ability enhanced. These findings underscore the need for further research to address gaps in understanding and effectively implementing educational interventions in higher education contexts.

d) Challenges

Most colleges and universities' art education has been plagued by issues like insufficient investment in art education, unreasonable curriculum, outdated educational ideas, insufficient educational mechanisms, and instructional impacts that require further improvement. Some students lack a sufficient enthusiasm in art and are unmotivated to study after attending university, resulting in poor art professional quality. This has an impact on the quality of art instruction at colleges and universities. Meanwhile, certain colleges and institutions' syllabuses have not kept up with the emergence of new media, which has an impact on the effectiveness of art education. Some students nowadays view computers as tools for entertainment and daily life, but they do not make the connection between technology and learning, nor do they properly use new media. Predicting student success with artificial neural networks poses issues in effectively analyzing numerous elements influencing learning outcomes, such as gender, content engagement, and participation metrics inside learning management systems.

e) Contribution

- In this research, MDEACUI-MSNN-SBOA is proposed.
- The aim of the work is to develop student's imagination, artistic creativity, aesthetic ability, promote their overall development and improve their artistic quality.
- Develop aPP-DKFbased preprocessing method for the noise removal and pixel normalization of the collected image.
- MSNN is constructed for the prediction of chickpea disease and classification. forecasting the grades of art and painting students in colleges and universities based on the internet plus.
- Propose a secretary bird optimization algorithm (SBOA) to optimize the Mix Style Neural Networks (MSNN) weight parameters.
- The proposed model's effectiveness is evaluated using current techniques, including as QEUEDDE-DFNN, AACU-BPNN and EECIC-CNN respectively.

f) Organization

Following is the arrangement of the remaining manuscripts: Part 2 explains the proposed methodology, Part 3 proves the result with discussion and Part 4 concludes this paper .

II. PROPOSED METHODOLOGY

In this section describe the proposed methodology of MDEACUI-MSNN-SBOA. The input images gathered from Art Images: Drawing/Painting/Sculptures/Engravings data set. PP-DKF filtering is used at the pre-processing stage to reduce noise and enhance image clarity. The output of the pre-processing step is sent to the predict stage, where the Mix Style Neural Networks (MSNN) forecasting the grades of art and painting students in colleges and universities based on the internet plus. Art may be distributed to a larger audience with the aid of the Internet. Digital art education's superiority should be widely acknowledged by instructors and students of art in colleges and universities. The SBOA is employed to enhance the prediction of MSNN by optimizing the weight parameter of the MSNN. Block diagram illustrating the proposed strategy depicts in Figure 1

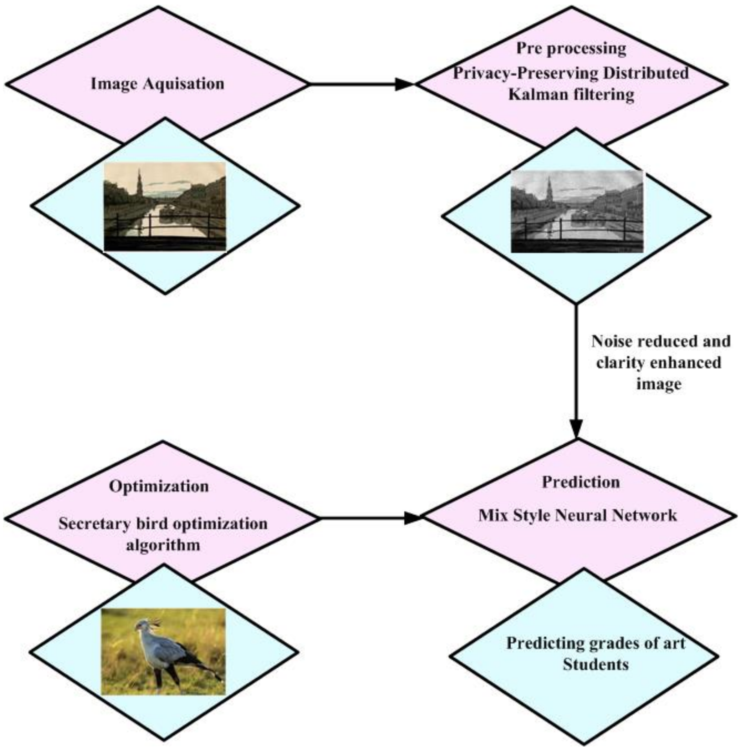

Figure 1: Block diagram illustrating the proposed strategy

A. Development of the Practical Ability Enhancement based on Internet Plus

Computer software takes the place of conventional art education's pen, paper, ink, and ink tones in internet-based art education and training, which facilitates the preservation of art pieces [17]. The Internet allows for the wider dissemination of works of art. College art teachers should completely realize the dominance of internet education and teaching approaches and incorporate them into their regular teaching practices. The internet has made it easier to share information than ever before. Students can readily submit their work. The "Internet+" art education platform is used to develop the practical abilities of art students through professional training in colleges and institutions. The internet server is the focus of the students' activities, and it is the internet server that manages the system to provide quick access to the database. The complex and varied management material that the system contains calls for efficient processing of operations like updating, removing, and querying. in order to finally make sure that students' performance is in line with the expectations of education and to further enhance the generation of information on students, instructors, colleges, and management, among other things, using the database server.

B. Image Acquisition

In this section, input images are gathered from the Art Images: Painting/Sculptures/ Drawing \Engravings Dataset. Approximately 9000 images in a dataset representing five categories of art [18]. College art students' performance data based on images are essential aspects influencing their learning outcomes. This system should be used for both the system performance test and the performance prediction of online learning behaviour for college art students.

C. Pre-Processing using Privacy-Preserving Distributed Kalman Filtering (PP-DKF)

In this segment, PP-DKF [19] technique is utilized which used to remove the noise, and normalize the pixel from the collected input images. The noise in images is effectively reduced and pixel normalization and image resizing by the filter, which can help improve the precision of algorithms used to predict the art student performance.

$$\hat{X}_{i,q|q-1} = A\hat{X}_{i,q-1|q-1} \tag{1}$$

Where $\hat{X}_{i,q}$ represents the predicted state vector for the i th entity at time step $n-1$ the state vector typically includes parameters representing the current state of the system, such as position, velocity, etc. A The system's evolution from one time step to the next is depicted in the state transition matrix.

$$\mathrm{M}_{\mathrm{i,q|q\text{-}1}} = \mathrm{AM}_{\mathrm{i,q\text{-}1|q\text{-}1}} A^{T} + C_{v_q} \tag{2}$$

Where $M_{i,q}$ denotes the predicted error covariance matrix for the ith entity at time step $q-1$. The error covariance matrix represents the uncertainty associated with the estimated state vector. The A state transition matrix depicts how the system's state changes from one time step to the next and reflects our level of uncertainty about each component of the state vector. V It is alleged that the process noise at each time step is zero mean Gaussian noise with covariance matrix C. It depicts the real process noise. It expresses our level of uncertainty about every component of the state vector. The evolution of the system's state from one time step to the next is shown in a state transition matrix. V alleged to be zero mean Gaussian noise with covariance matrix C, it depicts the real process noise at each time step.

$$G_{i,q} = NM_{i,q|q} H_i^T C_{w_{i,q}}^{-1} \tag{3}$$

Where $G_{i,q}$ calculates the correction to the anticipated state depending on the difference between the pixel-based actual measurement and the predicted measurement. N is denoted as the observation matrix. It relates the state vector to the measurements obtained from sensors. It's used to predict what measurements would be expected based on the current state H is measurement matrix. Similar to the observation matrix, it maps the state space onto the measurement space. It's used to relate the predicted state to the actual measurements of the pixel obtained from images.

$$\frac{1}{2}(\alpha_{i,q}(0)+\beta_{i,q}(0)) = r_{i,q} \tag{4}$$

Where $(\alpha_{i,q}(0)+\beta_{i,q}(0))$ both elements a summation or combination that results in r_n^i Without further information about the specisic calculations involved.

$$\hat{x}_{i,q}|_q = \alpha_{i,q}(k)\ \forall i \in Q \tag{5}$$

By processing PP-DKF method the noises removed, pixel normalized and image resized are done from the input image. Then the pre-processed images are fed to prediction phase.

D. Prediction by using Mix Style Neural Networks (MSNN)

In order to produce high-caliber artists for colleges and universities, this piece focus on building and improving a college art and painting student practical ability prediction based on a neural network prediction model [20]. The practical performance data of college art students and the major factors disturbing their performance of learning form the basis of the prediction algorithm. This system should be used for both the system performance test and the performance prediction of online learning behaviour for college art students. In order to support the effective growth of college art education, the efficiency of pertinent educational development strategies should be discussed and evaluated. $IN\ (s) = \gamma\,\Theta\ \frac{s-\mu(s)}{\sigma(s)} + \beta$ (5)

Where $IN(s)$ This likely represents an input to a neural network layer, where the input features γ this is a parameter to the "scale" or "gamma" parameter. It's used to scale the normalized input. The performance data analyses model for the art education platform will be built by the suggested MSNN. The data layer houses test-related data, learning behaviour suggestion data, and student data-based visuals. Θ This symbol typically denotes an element-wise multiplication or Hadamard product. s isan input feature. $\mu(s)$ This is the means the input feature s, which could be calculated across a batch or channel dimension. $\sigma(s)$ This represents the standard deviation of the input features s, also typically calculated across a batch or channel dimension. β This is a parameter referred to as "beta" parameter.

$$\gamma_{\min} = \lambda\sigma\ (s) + (1-\lambda)\ \ \sigma(s') \tag{6}$$

Where $\gamma_{\min}$ This likely represents a parameter related to mixing or combining scaling sectors. λ This is a weight or mixing coefficient typically ranging between 0 and 1, used to blend the two terms. $\sigma(s)$ This indicates the standard deviation input images s'. σ(s'): This likely indicates the standard deviation of another input feature 's' prime, possibly from source or distribution. $\sigma(s')$ This likely represents the standard deviation another input feature s' prime, possibly a source or distribution.

$$\beta_{\min} = \lambda\mu\ (s) + (1-\lambda)\,\mu(s') \tag{7}$$

Where $\beta_{\min}$ represents a parameter related to mixing. Where λ is a weight or mixing coefficient, typically ranging between 0 and 1, $\mu(s)$ this indicates the mean the input feature s'. $\mu(s')$ This likely indicates the mean another input feature s' prime, possibly source or distribution.

$$Mixstyle(s,s') = \gamma_{mix}\ \Theta\ \frac{s-\mu(s)}{\sigma(s)} + \beta_{mix} \tag{8}$$

$Mixstyle(s,s')$ This function likely represents a method or operation for mixing or blending style information from two input features, s and s' prime. γ_{mix} This is a parameter related to scaling or modifying the combined style features. It's computed using a weighted combination of standard deviations from both input features. This indicates the input feature. $\mu(s)$ This is the mean of the input feature s', representing its average value. $\sigma(s)$ This indicates the SD of the input feature’s’, indicating the spread or variability of its values. β_{mix} This is a parameter related to shifting" and "modifying the combined style features. Where, α and β is denoted as the weight parameter of the MSNN. It's computed using a weighted combination of means from both input features.

$$\mu(s)_c = \frac{1}{HW}\sum_{h=1}^{H}\sum_{w=1}^{W} s_{c,h,w} \tag{9}$$

Where, $\mu(s)_c$ this likely represents the mean activation value of a specific feature map's' in a convolutional neural network (CNN), corresponding to channel 'c'. It indicates the average value of activations across the spatial dimensions (height and width) for a particular feature map and channel. 1 This represents the reciprocal or inverse of the product of the spatial dimensions (height and width) of the feature map. HW This indicates the spatial dimensions of the feature map, typically denoting height (H) and width (W). H This represents the height of the feature map. $h=1$ It denotes the index for iterating over the height dimension, starting from 1. $w=1$ This denotes the index for iterating over the width dimension, starting from 1. $s_{c,h,w}$ This represents the activation value at a spatial location. Hence c is denoted as the channel of the s -The feature map. Both the final output data and the MSNN for grade prediction are shown immediately on the browser side. The MSNN predicts grades based the practical performance through the internet. The accuracy of the prediction is improved by using SBOA.

E. Optimization Using Secretary Bird Optimization Algorithm (SBOA)

The proposed SBOA is explained, and the secretary bird's behaviour is mathematically represented. SBOA [21] The SBOA method falls under the category of population-based metaheuristic techniques , with each "Secretary Bird" considered a member of the methods 's population. One of Secretary Birds' most remarkable abilities is that they can fight snakes, which makes them a formidable foe to these animals. The Secretary Bird is incredibly intelligent when it comes to snake hunting. Optimizing the weight parameter of MSNN improves prediction accuracy. The schematic diagram is displayed in Figure 2.

Step 1: Initialization

Initialize the input parameter such as the weight parameter α and β of the MSNN.

Step 2: Random generation

The initialised parameters are generated randomly in a matrix format.

$$X = \begin{bmatrix} X_1 \\ . \\ X_i \\ . \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,m} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,m} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{N,1} & \cdots & x_{N,j} & \cdots & x_{N,m} \end{bmatrix}_{N\times m} \tag{10}$$

Here N indicates the count of population members, m indicates the count of problem variables, X_i indicates the ith suggested solution, $x_{i,j}, x_{i,j}$ indicates the jth variable's value as supplied by the ith proposed solution, and X is the said secretary bird group.

Step 3: Fitness Function

The fitness is evaluated which is described by,

$$F = Optimization\ (\alpha\ and\ \beta) \tag{11}$$

Step 4: Hunting strategy

The secretary birds normally go through three stages when hunting snakes: seeking for prey, devouring victim, and assaulting the victim. The biological statistics of the hunting phases and their associated durations in the secretary bird allowed us to partition the total hunting activity into three equal time intervals. Finding the global optimum is more likely since people can look at different parts of the solution space. Therefore, Eqns. (12) and (13), which update the position of the secretary bird during the Searching for Prey stage, may be used to describe the information analytically.

$$WhileT < \frac{1}{3}t, X_{I,J}^{NEWp1} = X_{I,J} + \left(X_{Random\_1} - X_{Random\_2}\right) \times r_1 \tag{12}$$

$$X_I = \begin{Bmatrix} x_I^{New,p1} & if\ f_I^{New,P1} < 1 \\ x_j, & else \end{Bmatrix} \tag{13}$$

Here , X_{Random_2} and X_{Random_1} indicates the arbitrary candidate solutions during the initial iteration , t specifies the maximum iteration count, T is a specifies the current iteration count, and $x_1^{New,p1}$ specifies the the initial phase of the noval state of the I Secretary Bird. r_1 is specifies a an array of dimensions created at random. $X_{I,J}^{New,p1}$ specifies its value of the J dimension, and $f_I^{NEW,p1}$1 i specifies its goal function's fitness value.

Step 5: Exploration phase

In order to improve algorithm performance, avoid premature convergence, accelerate convergence, and strike a better balance between exploitation and exploration , SBOA should be made more adaptable and flexible during the optimisation process. $\left(1-\frac{T}{t}\right)\left(2\times\frac{T}{t}\right)$ is the nonlinear perturbation factor that we introduce. Therefore, Eqns. (14) and (15) may be used to mathematically simulate updating the position of the secretary bird during the Attacking Prey stage.

$$WhileT > \frac{2}{3}t, X_{I,J}^{NEWp1} = X_{Best} + \left(\left(1-\frac{T}{t}\right) \wedge \left(2\times\frac{T}{t}\right)\right) \times \alpha \times rl \tag{14}$$

$$x_I = \begin{Bmatrix} x_I^{New,p1} & if\ \alpha < f_I \\ x_I, else & \end{Bmatrix} \tag{15}$$

Step 6: Exploitation phase

When secretary birds notice the presence of a predator, they first seek out a good camouflage habitat. If they cannot find an appropriate and safe disguise environment nearby, they must fight or flee. To increase amativeness and flexibility, introduce a nonlinear perturbation factor represented by a weight parameter. Adjusting these elements allows you to raise the level of exploitation or exploration at different phases. In conclusion, Eqn. (16) may be utilised to quantitatively represent the escape strategies used by secretary birds, and Eqn. (17) can be used to define this updated condition.

$$x_{I,J}^{nEW,p2} = \begin{Bmatrix} c_1 : X_{Best} + (2\times rb - 1)\times\left(1-\frac{t}{T}\right)^2 \times \beta,\ if\ R\,and < R_I \\ c_2 : X_{I,J} + r_2 \times \left(X_{Random} - k \times X_{I,J}\right), else \end{Bmatrix} \tag{16}$$

$$x_I = \begin{Bmatrix} x_I^{New,P2}, if\ \beta < f_I \\ x_I, else \end{Bmatrix} \tag{17}$$

In this case, $R = 0.5$, r_2 stands for arbitrary dimension generation from the normal distribution. The arbitrary candidate solution for the current iteration is shown by X_{Ramdom}. and k indicates the arbitrary selection of integer one or two, which can be calculated by Eqn. (18).

$$k = Round(1 + rand(1,1)) \tag{18}$$

$rand(1,1)$ now refers to the casual generation of a number between 0 and 1. This may involve exploiting the current best solutions while also exploring nearby regions to improve accuracy and convergence speed.

Step 7: Termination

In this action, the weight parameters values, from MSNN are optimized with the help of SBOA have iteratively repeated the step 3 until the halting criteria is met. Lastly MSNN predicts accurately each grades of the art students using internet plus with higher accuracy lower processing time and error.

MSNN enhances the model's capacity to understand complex artistic concepts and nuances, thereby improving the accuracy of performance predictions. Moreover, the flexibility of MSNN allows for continuous learning and adaptation to evolving artistic trends and teaching methodologies, contributing to the sustainable development of art education practices.

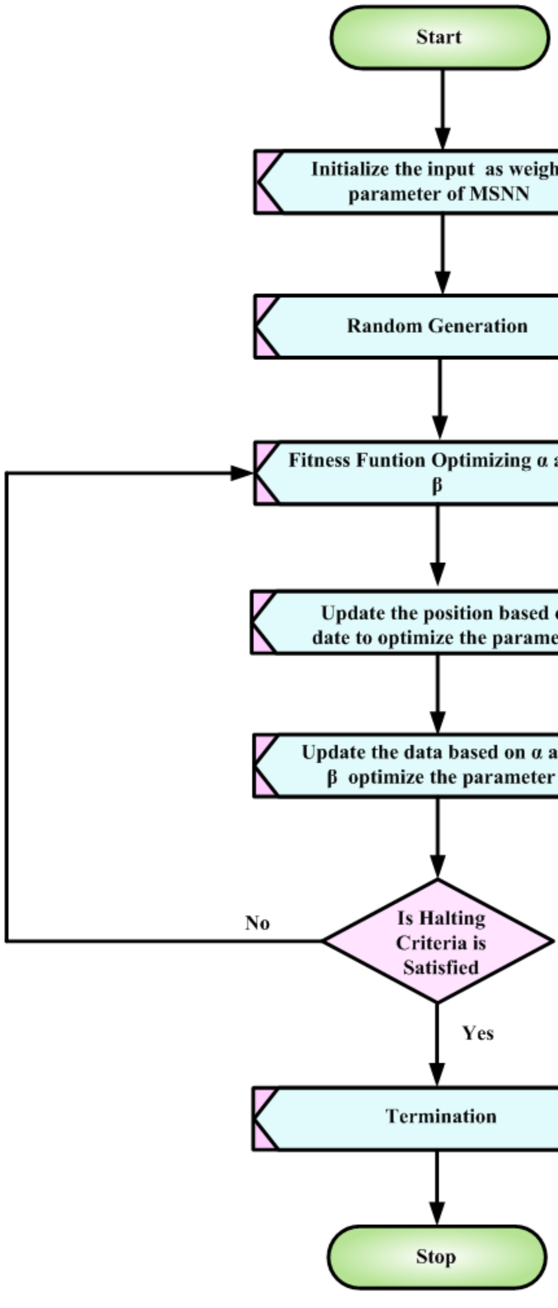

Figure 2: Flowchart of secretary bird optimization algorithm (SBOA)

MSNN models typically require large amounts of diverse data for training. Obtaining and curating such datasets can be challenging and may raise concerns related to data privacy and bias. SBOA is intended to efficiently explore the search space and converge on optimal solutions. SBOA may not be suitable for all types of optimization problems. The combination of MSNN-SBOA can be applied to optimize curriculum design for art education. MSNN-SBOA can facilitate cross-disciplinary collaboration between art and technology domains.

III. RESULT WITH DISCUSSION

The simulated results of suggested technique is discussed this section. The suggested technique is then replicated in Python using the mentioned act indicators. The proposed MDEACUI-MSNN-SBOAapproach is implemented in Python. The obtained outcome of the proposed MDEACUI-MSNN-SBOAapproach is analyzed with existing systems like QEUEDDE-DFNN, AACU-BPNN and EECIC-CNNrespectively. Table 1 shows the output of the Proposed MDEACUI-MSNN-SBOA method

Table 1: The output of the Proposed MDEACUI-MSNN-SBOA method

Input-Image	**Pre-Processed Image**
	
	
	
	

A. Performance measures

This is a crucial step in choosing the best classifier. The following performance metrics are assessed: Computation Time, Accuracy, Recall, Precision, Sensitivity, and Specificity. To scale the performance metrics, the performance metric is deemed. To In order to increase the performance metric's scale, the TP, FN, TN, and FP samples are needed.

- True Negative (TN): The amount of instances that are not required class in reality, and they are properly recognized.
- True Positive (TP): The amount of instances that have a place to required class and are properly recognized by the classifier.
- False Positive (FP): The amount of instances that do not have a place to required class but mistakenly recognized as the needed class.
- False Negative (FN): The amount of instances that have a place to required class but wrongly classified.

1) Accuracy

The amount of samples (positives and negatives) other than the total count of samples is measured by accuracy, which is provided by Equation (19).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (19)$$

2) Precision

Precision is a statistic used to assess the effectiveness of machine learning techniques; it gauges how well the model produces good forecasts. Equation (20) illustrates that precision may be computed by dividing the entire count of positive forecasts by the fraction of genuine positives.

$$\Pr ecision = \frac{TP}{TP + FP} \quad (20)$$

3) Recall

The proportion of data samples that a machine learning technique correctlyidentifies as being part of the class of interest is called recall, or TPR. To measure it, use Equation (21).

$$\mathrm{Re}call = \frac{TP}{TP + FN} \quad (21)$$

4) Sensitivity

Sensitivity is represented as in Eqn. (22),

$$Sensitivity = \frac{TP}{TN + FN} \quad (22)$$

5) Specificity

The metric used to determine a model's specificity is its ability to predict true negatives for each group that is provided. These metrics are applicable to all specific models. It is given in Eqn. (23).

$$Specificity = \frac{TN}{TN + FP} \quad (23)$$

6) Computation Time

Computation time is represented as in Eqn. (24),

$$ComputationTime = \frac{Instructioncount * CPI}{Clock\,rate} \quad (24)$$

B. Performance Analysis

Figure 3 to 8 illutraties the simulation outcome of proposedMDEACUI-MSNN-SBOA method. Then, the proposed MDEACUI-MSNN-SBOAmethod is likened with present methodsQEUEDDE-DFNN, AACU-BPNN and EECIC-CNN respectively.

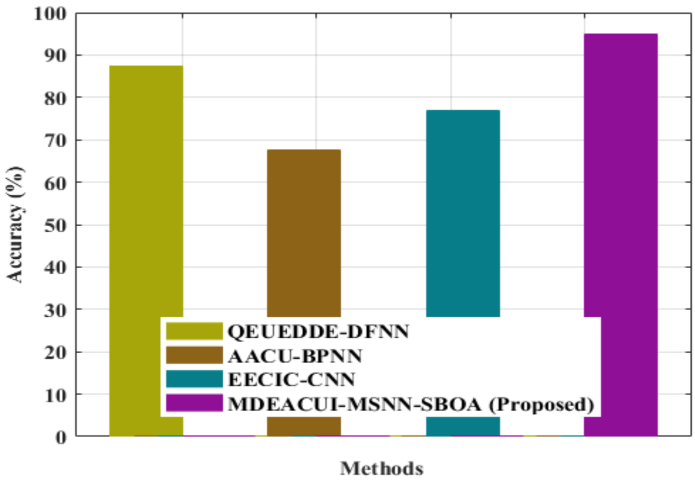

Figure 3: Performance Analysis of Accuracy

The performance analysis of accuracy is depicted in figure 3. Several models are probably compared to one another in the accuracy performance comparison graph for the art student's practical ability enhancement by predicting their performance. Higher accuracy values on the graph show how well the proposed MDEACUI-MSNN-SBOA a model can predicts the performance that helps to the teachers and art training faculties provide practices to enhance student creativity, artistic imagination aesthetic aptitude, , raise their artistic quality, the in the college and university by using internet plus. The proposed MDEACUI-MSNN-SBOA attains higher accuracy 23.52%, 21.72%, and 24.92% higher accuracy as contrasted with current techniques such as QEUEDDE-DFNN, AACU-BPNN and EECIC-CNNrespectively.

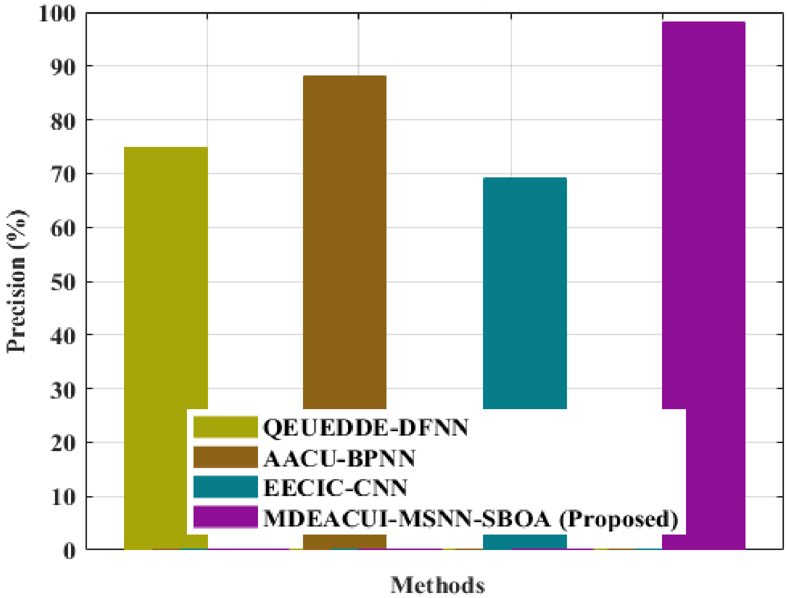

Figure 4: Performance Analyses of Precision

The performance analyses of Precision is depicted in figure 4.Precision emphasizes the accuracy of art student's practical performance by measuring the percentage of true positive predictions among all positive predictions; the proposed method MDEACUI-MSNN-SBOAsuccessfully detects disease patterns inside the plants. The proposed MDEACUI-MSNN-SBOA attains higher Precision23.52%, 22.72%, and 21.92%compared with existing methods such as QEUEDDE-DFNN, AACU-BPNN and EECIC-CNNrespectively.

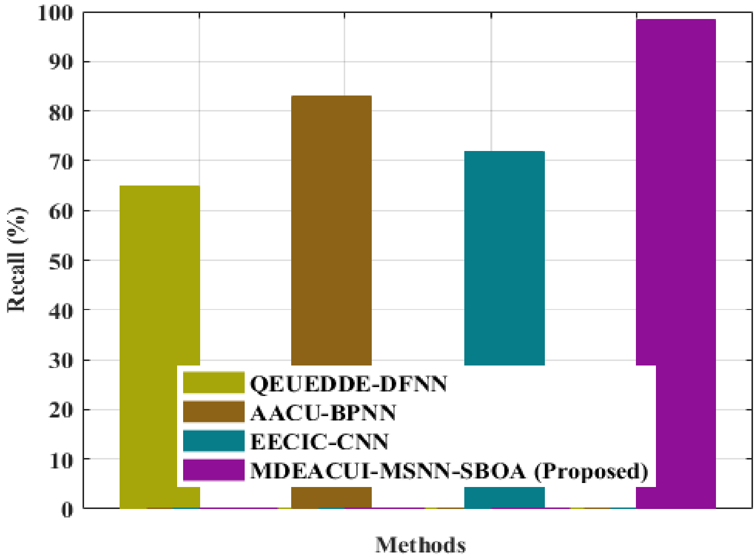

Figure 5: Performance Analyses of Recall

The performance analyses of Recall is depicted in figure 5. Recall is a metric that quantifies the percentage of true positive occurrences that the proposed MDEACUI-MSNN-SBOA method properly identifies in prediction. When assessing a proposed MDEACUI-MSNN-SBOA method performance, recall is a critical statistic, particularly in situations when finding positive instances is essential. A high recall rate means that the majority of the positive occurrences in the dataset are being accurately captured by the proposed MDEACUI-MSNN-

SBOA method.The proposed MDEACUI-MSNN-SBOA attains 20.74%, 28.01% and 23.28% higher Recall as contrasted with current techniques like QEUEDDE-DFNN, AACU-BPNN and EECIC-CNNrespectively.

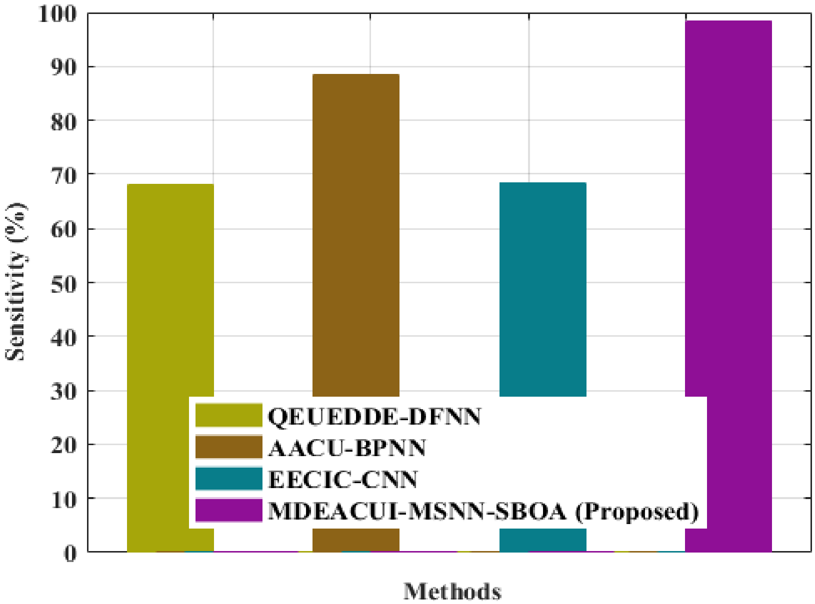

Figure 6: Performance Analyses of Sensitivity

The performance analyses of sensitivity is depicted in figure 6. The sensitivity graph based on the grades of practical performance prediction explains the proposed method MDEACUI-MSNN-SBOAcapacity to correctly identify performance in the college and university students. A high sensitivity rating is indicative of the model's ability of prediction, which is important for the development of art work quality. The proposed attains MDEACUI-MSNN-SBOA 21.04%, 27.51% and 22.18% higher sensitivity as contrasted with current techniques such as QEUEDDE-DFNN, AACU-BPNN and EECIC-CNNrespectively.

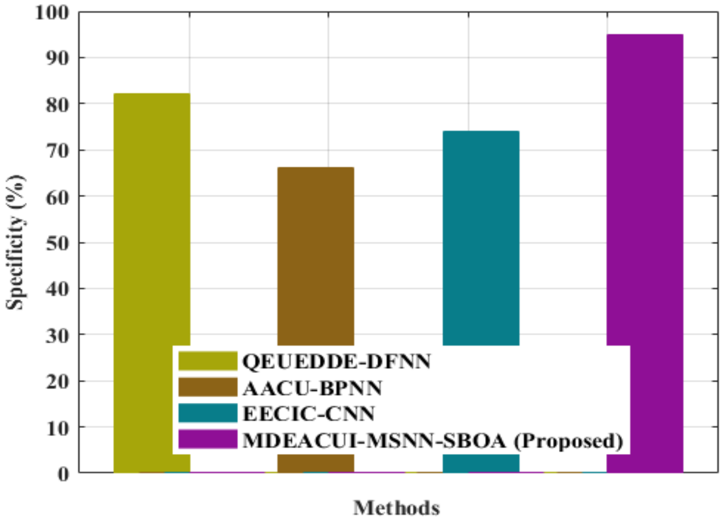

Figure 7: Performance Analyses of Specificity

The performance analyses of Specificity is depicted in figure 7. The specificity graph based on the grades of practical performance prediction explains the proposed method MDEACUI-MSNN-SBOAcapacity to correctly identify performance in the college and university students. This graph shows the percentage of true negatives that are correctly detected. A high specificity rating is indicative of the model's ability of prediction, which are important for student practical performance diagnosis and the development of art work quality. The proposed attains MDEACUI-MSNN-SBOA 20.04%, 27.51% and 22.08% higher specificity contrasted with present techniques such as QEUEDDE-DFNN, AACU-BPNN and EECIC-CNNrespectively.

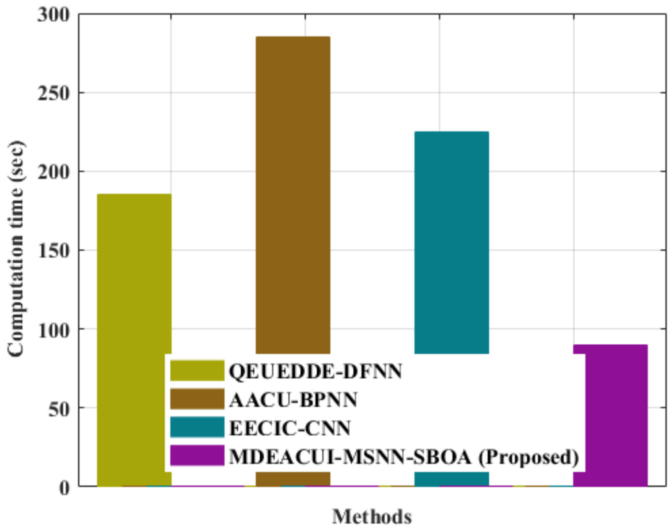

Figure 8: Performance Analyses of Computation Time

The performance analyses of CT is depicted by figure 8. The computation time graph art student's grades prediction shows the proposed method MDEACUI-MSNN-SBOA effectiveness at various processing stages. It shows how long it takes to complete various activities, including inference, validation, model training, and data preprocessing. Researchers can find bottlenecks and maximize computational resources for quicker and more precise performance prediction by examining the graph. The proposed MDEACUI-MSNN-SBOA attains 26.14%, 24.01% and 22.08% lower Computation Time compared with existing methods such as QEUEDDE-DFNN, AACU-BPNN and EECIC-CNNmethods respectively.

C. Discussion

The discussion outlines a comprehensive performance analysis of the proposed MDEACUI-MSNN-SBOA model compared to existing methods in predicting art students' practical ability enhancement. The analysis covers various metrics including accuracy, precision, recall, sensitivity, computation time and specificity each depicted in separate figures. Higher accuracy values demonstrate the model's proficiency in predicting student performance, aiding teachers and art training faculties in enhancing students' imaginative, aesthetic, and creative abilities. The MDEACUI-MSNN-SBOA model consistently outperforms existing methods across all metrics, showcasing its superiority in predicting practical performance and reducing computation time, thereby offering a more efficient solution for assessing and improving artistic quality in college and university settings.

IV. CONCLUSION

In conclusion, this paper suggests mechanism of the practical ability enhancement mechanism for art students in colleges and universities depends on internet plus were successfully implemented. Using the internet to transform and teach talent nurturing methods for art education courses in colleges and universities. The proposed MDEACUI-MSNN-SBOA proposed is executed on the Python working site. The proposed approach is analysed under different metrics like precision, computation time, , sensitivity, accuracy, ,specificity, and recall.The performance of proposed MDEACUI-MSNN-SBOA approach containsMDEACUI-MSNN-SBOA methodcover21.04%, 27.51% and 22.18% higher sensitivity; 20.04%, 27.51% and 22.08% higher Precision; 21.71% higher specificity and 26.14%, 24.01% and 22.08% lower computational time than the current techniques such as QEUEDDE-DFNN,AACU-BPNN and EECIC-CNN respectively. Implementing Internet Plus mechanisms assumes a certain level of digital. However, not all students may be proficient in using digital tools or navigating online resources effectively, which could hinder the success of the initiative. Develop thorough programmes for digital literacy to help pupils become more adept at using digital devices and navigating the internet. These programs could be integrated into the curriculum or offered as extracurricular activities.

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