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ORIGINAL

Exploring Computer-Aided Environmental Art Design: A Course Overview

Curso de diseño de arte ambiental asistido por ordenador enseñanza de exploración

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ABSTRACT

Introduction: the integration of technology in art education is essential for enhancing student engagement and improving learning outcomes. There is a growing need for innovative methods that supplement traditional teaching practices within environmental art design courses.
Objective: this study aims to introduce an Adaptive Kookaburra Optimized Dynamic Recurrent Neural Network (AKO-DRNN) as a novel approach to transform art education by providing personalized guidance and improving practical skills in environmental art design.
Method: the research explores the application of AKO-DRNN in the context of computer-aided environmental art design. By combining deep learning models with principles of environmental design, the AKO-DRNN utilizes dynamic recurrent networks optimized by a Kookaburra-inspired algorithm to analyze and predict artistic styles and features, offering real-time feedback and customized learning experiences.
Results: implementation of the AKO-DRNN model has shown significant improvements in students' design quality, creativity, and skill acquisition. The adaptive learning paths created by the model successfully cater to individual student needs, enhancing overall learning outcomes and engagement.
Conclusions: the framework established by integrating AKO-DRNN into the art education curriculum presents a robust solution for modernizing environmental design education. It fosters greater innovation and equips students with essential practical skills necessary for success in the field.

Keywords: Environmental Art Design; Computer-Aided Model; Adaptive Kookaburra Optimized Dynamic Recurrent Neural Network (AKO-DRNN); Art Education.

RESUMEN

Introducción: la integración de la tecnología en la educación artística es esencial para aumentar el compromiso estudiantil y mejorar los resultados de aprendizaje. Existe una creciente necesidad de métodos innovadores que complementen las prácticas tradicionales de enseñanza dentro de los cursos de diseño de arte ambiental.
Objetivo: este estudio tiene como objetivo introducir una red neuronal recurrente dinámica optimiadaptkookaburra (AKO-DRNN) como un nuevo enfoque para transformar la educación artística al proporcionar orientación personalizada y mejorar las habilidades prácticas en el diseño de arte ambiental.
Método: la investigación explora la aplicación del AKO-DRNN en el contexto del diseño de arte ambiental asistido por computadora. Mediante la combinación de modelos de aprendizaje profundo con principios de diseño ambiental, el AKO-DRNN utiliza redes dinámicas recurrentes optimipor un algoritmo inspirado en kookaburpara analizar y predecir estilos artísticos y características, ofreciendo retroalimentación en tiempo real y experiencias de aprendizaje personalizadas.
Resultados: la implementación del modelo AKO-DRNN ha mostrado mejoras significativas en la calidad del

diseño, la creatividad y la adquisición de habilidades de los estudiantes. Las vías de aprendizaje adaptativas creadas por el modelo se adaptan con éxito a las necesidades individuales de los estudiantes, mejorando los resultados generales de aprendizaje y la participación.
Conclusiones: el marco establecido al integrar AKO-DRNN en el currículo de educación artística presenta una solución robusta para modernizar la educación ambiental de diseño. Fomenta una mayor innovación y equipa a los estudiantes con las habilidades prácticas esenciales necesarias para el éxito en el campo.

Palabras clave: Diseño de Arte ambiental; Modelo Asistido por Computadora; Adaptive Kookaburra Optimized Dynamic Recurrent Neural Network (AKO-DRNN); Educación Artística.

INTRODUCTION

The integration of computer-assisted technology into environmental art instruction keeps the training fresh and enhances knowledge of the methods used in this field. Computer-assisted environmental architecture guides insights to provide the tools and capabilities to create beautiful, functional, and sustainable spaces among college students using modern software programs and digital design tools.[1] These types combine traditional artistic concepts with high-quality computer techniques, creativity in design and promoting accuracy and performance.[2] Advances in 3-D modelling, virtual reality (VR), and computer-aided layout (CAD) software allow students to visualize and modify their designs in real time, creating environments surroundings are drawn, and spatial structure is tested.[3] This interactive technique encourages deeper engagement, allowing freshmen to explore and refine their imaginative and creative skills while considering environmental and societal needs. Instead of reiterating the route's significance or endorsing CAD over hand-drawn overall performance, itis an innovative method of teaching CAD courses to develop the profession of implementing a more sensible framework for the course.[4]

A lack of certain software operation skills will prevent students from completing the professional design, and the distance between the two courses will result in a poor learning experience.[5] After multiple software classroom courses have concluded, a thorough application of practical engineering training is imperative, but most institutions lack this connection, leading to a long-standing disconnect between professional courses in conducting practical training and software learning and application.[6] To address the demands of forthcoming social and technological advancements, interest-based, problem-oriented, project-driven, and financially supported cross-disciplinary study is incorporated into education, research, and practice to foster the development of highly skilled, thorough individuals possessing an interdisciplinary research vision and the interdisciplinary understanding necessary to tackle increasingly intricate difficulties.[7] A new age in network education has begun with global economic integration. The use of state-of-the-art educational materials in a networked setting is more advanced in developed nations.[8]

The course typically covers foundational topics like design theory, digital drawing, rendering techniques, and environmental sustainability. Through practical projects and collaborations, students gain practical experience in solving real-world environmental design challenges, preparing them for professional practice in architecture, landscape design, urban planning, and related fields.[9] The purpose of this study is to explore the effectiveness of CAD in enhancing the teaching and learning process in environmental art design courses. It aims to evaluate how these technologies can improve students' creative capabilities, design precision, and understanding of sustainable practices.

The growth language of the modern art CAD creative teaching mode in the article is Microsoft's Active Server Pages (ASP) computer-assisted. Network Enabled Technologies (NET) the internet, and it builds the information service creative teaching mode around the Internet Information Services (IIS)server.[10] The environmental design sector in China is growing, and with it, new professional talent is being produced, conventional hand sketching techniques have changed, and CAD technologies like CAD, 3dsmax, and Photoshop[11] are being used more extensively. To satisfy the demands of customers for ever-richer material and cultural products, developed goods must be able to satisfy their internal, unique requirements in addition to being aesthetically pleasing and useful.[12] A high-tech invention that has been widely used in numerous fields, including technological advancements, health, military operations national security, and the arts, is CAD based on virtual reality (VR).[13]

To identify the best scheme, computers are typically utilized in the design process to compute, evaluate, and compare several schemes.[14] The logical scientific meaning and sensuous visual aesthetics of scientific visualization design have made it an efficient means of presenting state-of-the-art science in the setting of integrating technology with art.[15] It examines the need for and drawbacks of art design education in Chinese colleges and universities, as well as the innovative approach to art design education that is supported by computer technology in these institutions.[16] The work examined various improvements and descriptions of art-based design, with a particular emphasis on the technological underpinnings of the art-aided system.

It also incorporates digital technology into the process of creating an artificial intelligence (AI)[17] powered computer-based design system. The teaching of package structure design serves as the backdrop for the revision. Online difficulties in packaging structure teaching are first resolved by analyzing the computer-aided interactive teaching method of the packaging structural design course.[18] The learning effectiveness of a model course focused on three-dimensional printing design for primary school children was examined. Action research was the main method which is used; participant observation and content analysis data were also used.[19] Engineering designers' work methods and interpersonal interactions are changing because of the era. Synchronous collaborative CAD[20] technologies enable designers to work on the same model simultaneously. To experiment and map the experimental center's equipment, address the issues of record confusion, record loss, and complex information associated with tool use.[21]

The aim of this study is to developed an instructional system using the AKO-DRNN model to provide personalized aesthetic guidance, enhance creative exploration, and improve practical skills in environmental art design, thereby transforming art education with advanced algorithms and adaptive learning.

METHOD

This study improved computer-aided environmental artwork design guidance by using an Adaptive Kookaburra Optimized Dynamic Recurrent Neural Network (AKO-DRNN). The algorithm analyzed student inputs and provided real-time personalized feedback. The Kookaburra-inspired algorithm dynamically modified learning routes based on each student's success. The tool became trained to expect artistic styles and aesthetic selections, enhancing creativity and skill acquisition. The version's performance was evaluated through improvements in design, creativity, and student engagement.

Data collection

Records of student overall performance and involvement were accrued for the Computer-Aided Environmental Art Design Course dataset. It facts remarks, challenge submissions, and path fabric. Every access showcases the abilities acquired and effects attained. The dataset allows assessments of pupil involvement and the efficacy of coaching. It encourages the advent of curricula and the development of course services.

Adaptive Kookaburra Optimized Dynamic Recurrent Neural Network (AKO-DRNN)

A progressive neural community design known as the AKO-DRNN uses the Kookaburra Optimization set of rules to beautify the overall performance and versatility of dynamic recurrent neural networks. By integrating optimization techniques stimulated by means of the foraging behaviour of kookaburras, AKO-DRNN dynamically adjusts its parameters to enhance studying effects and version overall performance. This method allows the community to deal with time-series statistics and sequential obligations, making it especially appropriate for packages in fields collectively with speech popularity, herbal language processing, and monetary forecasting.

Environmental art design course teaching using Dynamic Recurrent Neural Network (DRNN)

A neural network (NN) is regularly made of numerous associated neurons, which are nonlinear processing devices. With a traditional neural The DRNN is a 3-layer network structure with nonlinear neurons in the hidden layer and n2 linear neurons in the output layer. Linear neurons are useful in estimating with a specific range, while nonlinear neurons constitute abnormalities within the predicted device. The buried layer features a dynamic self-recurrent connectivity link. NN, each neuron generates an output via adding together its weighted inputs the usage of a nonlinear activation function referred to as a static model. Multi-layered neural networks with a static structure are widely applied in many different sectors these days. As a variant of static neural network topologies, DRNNs were developed by building static neurons and adding state recommendations. DRNN effectively captures and predicts student behavior patterns, adapting teaching methods to individual learning styles. This approach fosters a more personalized and dynamic learning experience, enabling students to better understand and apply environmental design concepts in practical scenarios. DRNN structure and equations (1) to (3) are listed below:

$$O_i^{(2)}(l) = e\left(J_i^{(2)}(l)\right)(i = 1,2,\dots,g) \quad (1)$$

$$J_i^{(2)}(l) = \sum_{j=1}^{m1} x_{ij}^{(1)} w_j\,(l) + \sum_{m=1}^{g} x_{im}^{(2)}\, P_i^{(2)}(l-1) \quad (2)$$

$$J_m^{(n)}(l) = P_n^{(3)}(l) = \sum_{m=1}^{m2} x_{ni}^{(3)}\, P_i^{(2)}(l) \qquad (n = 1,2,\dots m2) \quad (3)$$

Where $w_j(l)$ are input units, $w(l)^S=(\theta_1,\dot{\theta}_1,\ddot{\theta}_1,\theta_2,\dot{\theta}_2,\ddot{\theta}2)$ $x_{ij}^{(1)}$, $x_{im}^{(2)}$, $x_{mi}^{(3)}$ are the dimensions of connections among the input layer as well as the concealed layer, the carrier layer and the concealed layer, and the layer that is concealed and the output layer, and in that order, $J_i^{(2)}(l)$ $O_i^{(2)}(l)$ and $P_n^{(3)}(l)$ represent the hidden layer's

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inputs as well as outputs at a given moment k, k.e(.)e(w)=1,0/(1,0+f^-w^).m1 g and m2 are the quantities of the input layer, outputs layer, and concealed layer, according to order.

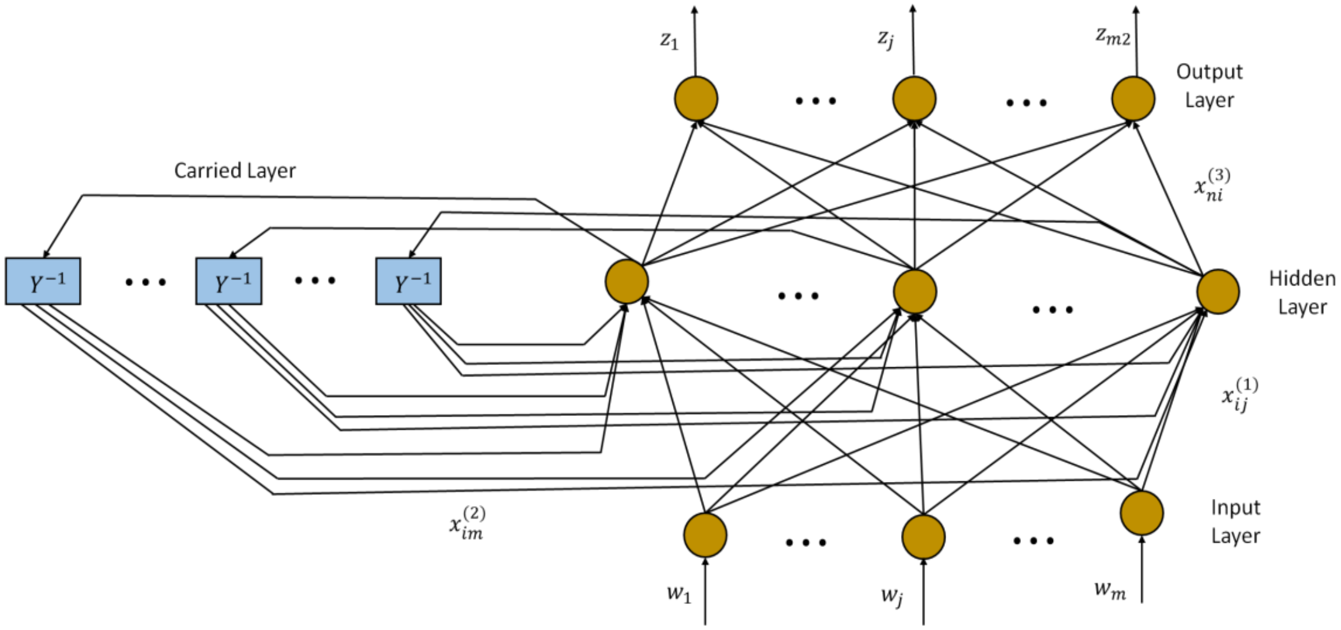

Figure 1. Structure of DRNN

The error function is written as equation (4).

$$I = \frac{1}{2}\sum_{n=1}^{m2} \varepsilon_n^2(l) \qquad (4)$$

Where $\varepsilon_n(l)=v_e^{(n)}(l)-v_m^{(n)}(l)$,m2=2.

Next, using a gradient descent approach, the relationship weights are changed as equations (5) to (8) follow.

$$\frac{\partial I}{\partial x_{ni}^{(3)}} = \varepsilon_n(l)\frac{\partial \varepsilon_n(l)}{\partial x_{ni}^{(3)}} = -\varepsilon_n(l)\frac{\partial P_n^{(3)}(l)}{\partial x_{ni}^{(3)}} = -\varepsilon_n(l)P_I^{(2)}(l) \qquad (5)$$

$$\frac{\partial I}{\partial x_{im}^{(2)}} = \sum_{m=1}^{m2} \varepsilon_n(l)\frac{\partial \varepsilon_n(l)}{\partial x_{im}^{(2)}} = -\sum_{m=1}^{m2} \varepsilon_n(l)\frac{\partial P_n^{(3)}(l)}{\partial x_{im}^{(2)}} = -\sum_{m=1}^{m2}[\varepsilon_n(l)\frac{\partial P_n^{(3)}(l)}{\partial P_i^{(2)}(l)}]\, e'(J_i^{(2)}(l))P_i^{(2)}(l-1) \qquad (6)$$

$$\frac{\partial I}{\partial x_{ij}^{(1)}} = \sum_{m=1}^{m2} \varepsilon_n(l)\frac{\partial \varepsilon_n(l)}{\partial x_{ij}^{(1)}} = -\sum_{m=1}^{m2} \varepsilon_n(l)\frac{\partial P_n^{(3)}(l)}{\partial x_{ij}^{(1)}} = -\sum_{m=1}^{m2}[\varepsilon_n(l)\frac{\partial P_n^{(3)}(l)}{\partial P_I^{(2)}(l)}]\, e'(J_i^{(2)}(l))w_j(l) \qquad (7)$$

$$x(l+1) = x(l) + \alpha(-\frac{\partial I}{\partial x}) \qquad (8)$$

Where e' $(J_i^{(2)}(l))=P_I^{(2)}(l)[1-P_I^{(2)}(l)]$x are the weights $x_{ij}^{(1)}$, $x_{im}^{(2)}$ and $x_{mi}^{(3)}$ of the DRNN and $\propto$ is the educations core.

Environmental art design course teaching using Adaptive Kookaburra Optimized (AKO)

This phase explains the idea and source of proposal for the recommended Adaptive Kookaburra Optimized (AKO) method. It fashions the degrees of execution theoretically in order that they can be implemented to the solution of optimization troubles. AKO aids in developing customized mastering paths with the aid of optimizing teaching methods and aid allocation. This adaptive strategy lets college students to explore diverse environmental artwork ideas, along with sustainable design and spatial aesthetics, with multiplied performance.

Inspiration of AKO: the Kookaburra, a carnivorous fowl from the Dacelo genus, is part of the land-living terrestrial tree kingfisher households Coraciiformes and Alcedininae. Its one-of-a-kind sound, like human laughter, serves as a warning to its predators. The bird's furious look is due to its darkish brown patch behind its eyes and unique head feathers. Kookaburras are predatory birds that consume diverse animals, along with frogs, mice, insects, snakes, and small reptiles. Their beaks are used for diving and searching, with the bird extending its jaws to catch prey earlier than flying back to the tree limb to knock its victim more than once to make certain death. These innate kookaburra inclinations are the basis for the proposed AKO methodology.

Algorithm Initialization: the AKO approach is a population optimizer that uses random searches in the problem-solving space to consistently generate suitable answers for optimization problems. Each kookaburra in the AKO population is constructed based on its location, resulting in every possible vector-based solution to the issue. Equation (9) allows for the modelling of the AKO population matrix, which is composed of kookaburras. At the beginning of the KOA implementation, the locations of the kookaburras are randomly initialized using equation (10).

$$W = \begin{bmatrix} W_1 \\ \vdots \\ W_j \\ \vdots \\ W_M \end{bmatrix}_{M\times n} = \left[\begin{pmatrix} w_{1,1} & \cdots & w_{1,c} & \cdots & w_{1,n} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ w_{j,1} & \cdots & w_{j,c} & \cdots & w_{i,n} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ w_{M,1} & \cdots & w_{M,c} & \cdots & w_{M,n} \end{pmatrix}\right]_{M\times n} \quad (9)$$

$$w_{j,a} = ka_c + q.(va_c - ka_c) \quad (10)$$

Here, X is the AKO the population matrix, w_j is the j^{th} kookaburra, w_j, c is its measurement in investigate space, M is the number of kookaburras, V is a random amount in the interval [0,1], n is the number of decision variables, va_c and ka_c are the less and upper bounds of the c^{th}. Decision variable, respectively in equation (11).

$$E = \begin{bmatrix} E_1 \\ \vdots \\ E_j \\ \vdots \\ E_M \end{bmatrix}_{M\times 1} = \begin{bmatrix} E(W_1) \\ \vdots \\ E(W_j) \\ \vdots \\ E(W_M) \end{bmatrix}_{M\times 1} \quad (11)$$

The container denotes the evaluated purpose occupation based on the kookaburra kooka, with as E_j vector. The objective function's assessed values are used to assess population and potential solutions. The best member has the highest assessed value, while the worst member has the lowest. Iterations update the kookaburras' location, re-evaluate the problem's goal function, and update the best member of the group based on new values.

Mathematical Modelling of AKO: the proposed AKO approach updates kookaburra locations in two phases: mining and exploration, to generate prospective solutions based on the modelling of real-world kookaburra activities. An iterative technique is used to accomplish this. The AKO population update inside the scope of search space follows.

Phase 1: Hunting Strategy

Kookaburras are carnivorous birds that eat mice, frogs, insects, and reptiles. Their robust neck aids in hunting, and their methodical approach involves significant movement in space. This global search concept is embodied in the concept of KOA design, where each kookaburra uses the position of other kookaburras as the prey location to mimic its hunting strategy. As a result, using equation (12) and comparing the values of the objective function, the food set that is accessible for every Kookaburra is determined.

$$CP_j = \{W_l : E_l < E_j \ and \ l \neq j\}, \ where \ j = 1,2,\ldots,M \ and \ l \in \{1,2,\ldots,M\} \quad (12)$$

Here, the kookaburra with a greater purpose meaning value than the kookaburra with a value by W_l, and the set of potential prey for the j^{th} kookaburra is represented by CP_j.

All kookaburras are believed to randomly choose and attack their prey according to the KOA design. Equation (13) is used to determine the kookaburra's new position based on the simulation of its progress toward the prey in the hunting strategy. Equation (14) states that the goal function's value is better at the new location, the appropriate kookaburra's old location will be replaced with the current one.

$$w_{j,c}^{O1} = w_{j,c} + q.\left(SCP_{j,c} - J.w_{j,c}\right), j = 1,2,\ldots,M \ \ and \ c = 1,2,\ldots,n \quad (13)$$

$$W_j = \begin{cases} W_j^{O1}, & E_j^{O1} < E_j \\ W_j, & else \end{cases} \quad (14)$$

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In this case, W_j^{O1} is the newly proposed location of the j^{th} kookaburra based on the first phase of KOA; E_j^{O1} is its objective function value; $w_{j,c}^{O1}$ is its c^{th} dimension; q is a random number with a normal allocation in the range of [0, 1]; *SCPi*, is the d^{th} measurement of particular prey for j^{th} kookaburra; V is a random numeral from set {1, 2}; Nis the numeral of kookaburra and *m* is the number of termination variables.

Phase 2: Making Certain the Prey Is Killed

Kookaburras are known for their aggressive behavior, dragging victims after attacks and striking them against trees. They consume the victim, causing minor shifts in their posture near the hunting area. This behavior is part of the algorithm's ability to provide better solutions near discovered solutions and promising areas. The AKO design uses equation (15) to randomly determine a location, showcasing the behavior of kookaburras based on their movement near the hunting area. In reality, it is assumed that this displacement has a radius equal to (va_c-ka_c) and happens at random in a neighborhood near the center of each kookaburra. This neighborhood's radius is initially set to its maximum value to increase the local search's accuracy, which seeks to converge toward better responses. Its radius is reduced in the next repetitions. The previous position is replaced if each kookaburra's new location improves the value of the target function, as indicated by equation (16).

$$w_{j,c}^{O1} = w_{j,c} + (1-2q).\frac{(va_c - ka_c)}{s}, j = 1,2,\dots M,\ \ c = 1,2,\dots,n \quad (15)$$

$$W_j = \begin{cases} W_{j,c}^{O2},\ W_j^{O2} \\ W_j, \qquad else \end{cases} \quad (16)$$

In this case, $W_{j,c}^{O2}$ is the new location of the j^{th} kookaburra that is proposed based on the 2nd phase of KOA, W_j^{O2}, c is its c^{th} dimension, W_j^{O2} is its object meaning value, s is the algorithm's iteration timer, and S is the greatest numerical of algorithm iterations.

The model adapts to several design duties, along with spatial planning, ecological balance, and aesthetic concerns, imparting college students a device to better visualize and predict the effects of environmental tasks. By the usage of AKO-DRNN, the path introduces computational strategies that permit students to machine complex design styles and environmental data additional accurately, fostering creativity and innovation in their format procedures. This method not only improves problem-solving abilities however, additionally for sustainable, records-driven choices in environmental art tasks. Through actual-time comments and optimization, college students can find out multiple design conditions, leading to more powerful and revolutionary solutions.

RESULTS

The implementation of the Adaptive Kookaburra Optimized Dynamic Recurrent Neural Network (AKO-DRNN) within the CAD artwork layout guides yielded large enhancements for the duration of key general performance metrics. The experiment's setup runs Ubuntu 20.04 with Python 3 for programming, CUDA 10.1 for GPU acceleration, and Kaldi 5.5.636 for English oral pronunciation. An Intel Core i7-7700HQ CPU operating at 2,81 GHz, 8,0 GB of RAM, and a GeForce GTX 1050 Ti GPU are used in the arrangement to improve the efficiency of CAD. The findings underscore the capacity of integrating advanced algorithms in painting education to foster innovation and beautify reading results.

Impact of AKO-DRNN on Art Education Outcomes

The impact of implementing the AKO-DRNN model on key elements in artwork training. Specifically, it compares design excellence, creativity, and ability acquisition before and after the version's integration. Significantly, design exceptional progressed from 65 % to 85 %, creativity from 70 % to 90 %, and skill acquisition from 60 % to 80 %. Each thing showed a significant enhancement of 20 %, highlighting the effectiveness of the AKO-DRNN in fostering an extra engaging and efficient studying environment for college students in environmental art design. Figure 2 and table 1 depict the AKO-DRNN on art education outcomes.

Table 1. Outcomes of Factors

Factors	Before AKO-DRNN (%)	After AKO-DRNN (%)
Design Quality	65	85
Creativity	70	90
Skill Acquisition	60	80

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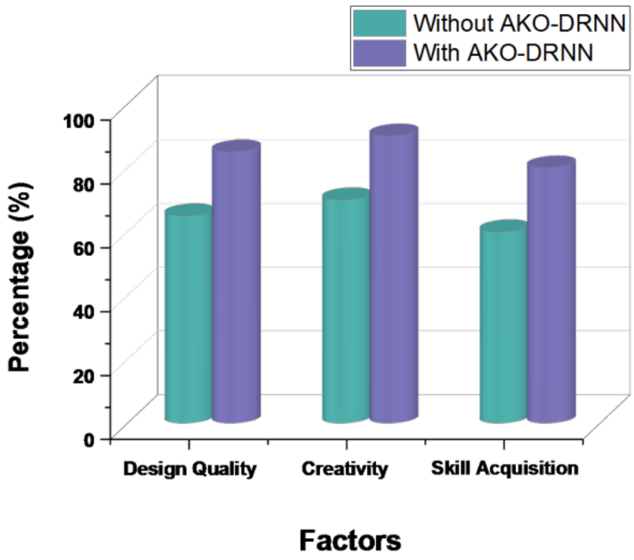

Figure 2. Analysis of Factors

Performance Metrics of the AKO-DRNN Model

The overall performance metrics for the AKO-DRNN and its effectiveness in the context of environmental art layout training. The AKO-DRNN completed an impressive accuracy of 95 %, indicating an excessive level of correct predictions among all instances. In assessment, conventional metrics show a precision of 90 %, reflecting the proportion of authentic high-quality consequences among all advantageous predictions, and a take-into recall of 88 %, demonstrating its potential to discover applicable instances. The f1 score of 77 % shows a balance between precision and recall, but it suggests space for development. Overall, the AKO-DRNN version substantially outperforms the other metrics, underscoring its capacity for reinforcing and gaining knowledge of results in art training. Figure 3 and table 2 depict the performance of AKO-DRNN.

Table 2. Outcomes of the AKO-DRNN Model

Metrics	Percentage (%)
Accuracy	95
Precision	90
Recall	88
F1-Score	77

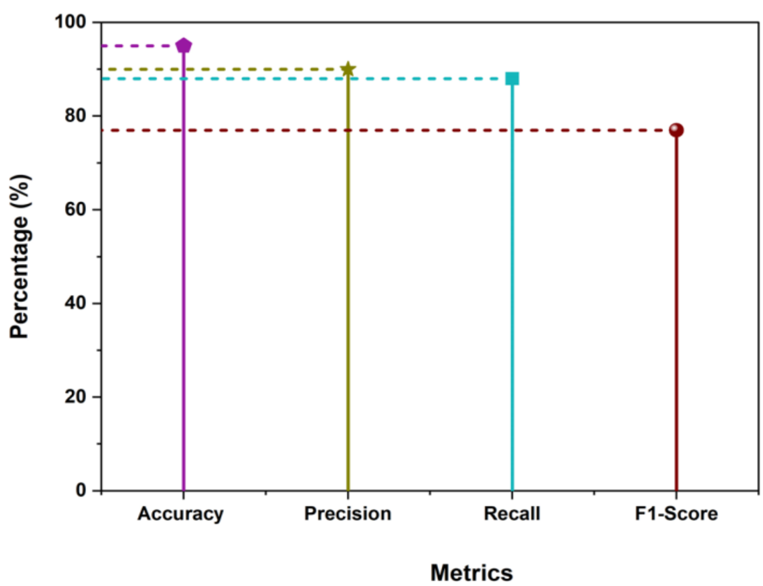

Figure 3. Analysis of the AKO-DRNN Model

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Comparative Analysis of Design Factors with and without CAD

The various factors influencing artwork schooling outcomes with and without CAD tools. Notably, the introduction of CAD substantially enhances design satisfaction, growing from 65 % to 82 %. Creativity also suggests marked development, rising from 70 % to 88 %. Skill acquisition benefits as nicely, with rankings mountain climbing from 60 % to 78 %. Student engagement stages increase dramatically from 55 % to 80 %, indicating an extra immersive getting-to-know-to-enjoy. Figure 4 and table 3 depict the performance of factors with and without CAD.

Table 3. Outcomes of with and without CAD

Factors	Percentage (%)	
	Without CAD	With CAD
Design Quality	65	82
Creativity	70	88
Skill Acquisition	60	78
Student Engagement Level	55	80
Real-Time Feedback Effectiveness	75	90
Adaptive Learning Path Efficiency	50	75

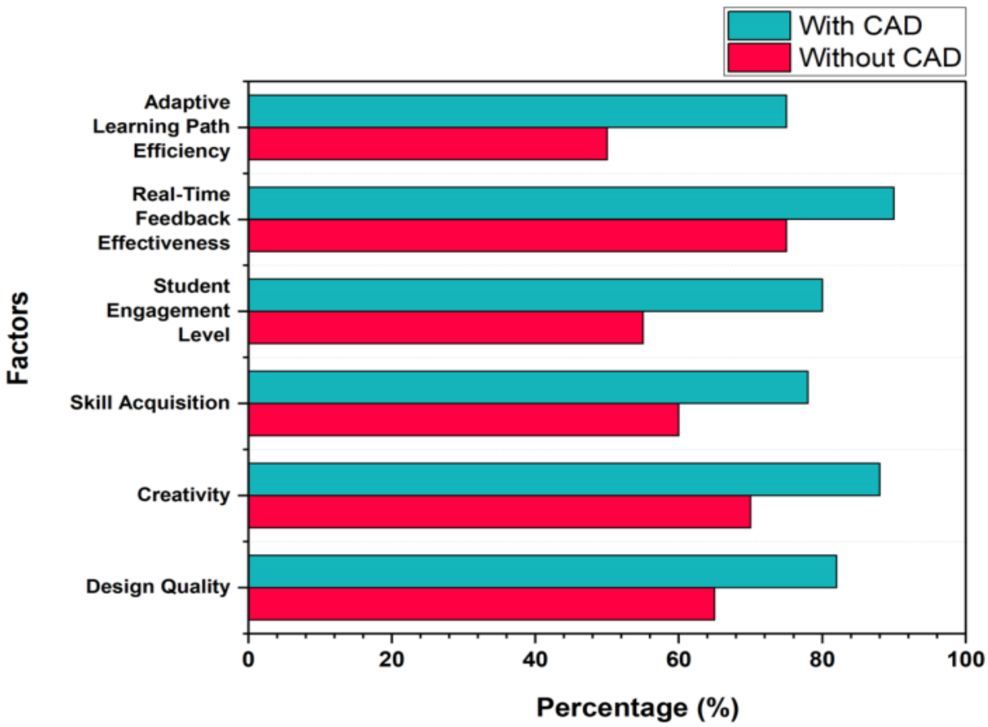

Figure 4. Analysis of with and without CAD

Additionally, the effectiveness of actual-time feedback improves from 75 % to 90 %, even as the performance of adaptive studying paths will increase from 50 % to 75 %. Overall, these metrics highlight the full-size impact of CAD on diverse dimensions of art education.

The examination was completed with longer time limits, which can be able to determine the long-term impact of the AKO-DRNN on college students' involvement and ability levels. Research on additional AKO-DRNN elements, including adding user feedback mechanisms or augmented reality equipment, to further improve the learning experience.

DISCUSSION

The Impact of AKO-DRNN on Art Education Outcomes Before implementing AKO-DRNN, art education outcomes faced challenges in personalized feedback, real-time tracking, and adaptive content delivery. After AKO-DRNN, it showed better real-time adaptability, personalized feedback, and dynamic content delivery. The performance metrics of the AKO-DRNN model indicate strong overall effectiveness, demonstrating high accuracy and precision in classification tasks. The F1-score has improvement in balancing false positives and false negatives, which impacts model reliability. The CAD improves design quality, creativity, and engagement compared to traditional methods. The with CAD include the need for technical skills, potential for over-reliance on tools, and initial setup time. Without CAD, design has slower, with fewer real-time adjustments and a less efficient learning path, but it fasters creativity and skill development through manual processes.

CONCLUSIONS

The integration of the Adaptive Kookaburra Optimized Dynamic Recurrent Neural Network (AKO-DRNN) into PC-aided environmental artwork design courses marks a huge advancement in artwork training. This study demonstrates that the use of superior algorithms can transform traditional coaching techniques, enhancing student engagement and mastering outcomes. The results suggest outstanding enhancements in design, creativity, and talent acquisition, highlighting the effectiveness of real-time feedback and customized learning paths. As artwork training continues to conform, incorporating innovative technologies like AKO-DRNN offers a strong framework for fostering creativity and sensible talents among students. The adaptive nature of the version not only supports individualized mastering reports but additionally encourages exploration and experimentation in environmental layout. The findings advise in addition exploration of computational techniques in instructional settings, aiming to create extra engaging and effective knowledge of environments in the arts. The examination was completed with longer time limits, which can be able to determine the long-term impact of the AKO-DRNN on college students' involvement and ability levels. Research on additional AKO-DRNN elements, including adding user feedback mechanisms or augmented reality equipment, to further improve the learning experience.

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