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Wei Du[1*]

Exploring the Development of Intelligent Designer Assistance System Using Deep Reinforcement Learning

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Abstract: - While Artificial Intelligence (AI) models have the ability to provide intelligent designer support, there are drawbacks as well. These include the possibility of homogenizing design outcomes, overreliance on predefined design parameters, difficulties in accommodating changing user needs, and potential limitations in capturing nuanced design preferences. In this research, exploring the Development of Intelligent Designer Assistance System Using Deep Reinforcement Learning (ED-IDAS-DRL-DKNN) is proposed. Initially the input data is collected from the UrbanScene3Ddataset.The input data's are fed to pre-processing using Low-Pass Virtual Filtering (LPVF).LPVF is used to clean the data. Then, the pre-processed data is fed to Deep Kronecker Neural Networks (DKNN) as it improves the efficiency of architectural space design and reduces the cost. In order to improve the efficiency and reduce the cost accurately Deep Kronecker Neural Networks is optimized using the Golden Search Optimization (GSO). The proposed method is implemented in Python. The efficiency of the proposed ED-IDAS-DRL-DKNN approach is evaluated using a number of performance criteria including Accuracy, precision, design error and model fitting degree. The proposed ED-IDAS-DRL-DKNN methods attains 16.33%, 35.42% and 28.27% higher precision, 19.36%, 23.42% and 35.42% higher accuracy compared with existing methods such as "Towards intelligent design": An AI-based fashion designer using generative adversarial networks assisted by sketch and rendering generators (AIFD-SRG-GAN), "Exploration of the intelligent-auxiliary design of architectural space using artificial intelligence model" (IADAS-AIM-ANN), and "Intelligent designs in Nano photonics from optimisation towards inverse creation" (IDNP-OTIC-DNN), respectively.

Keywords: Deep Kronecker Neural Networks, Design, Golden Search Optimization, Low-Pass Virtual Filtering, Python, UrbanScene3D.

I. INTRODUCTION

The current state of AI and technology represents a significant advancement. Neural networks and design do not, however, intersect very much; instead, they are primarily concerned with the scientific technology of design. This opens up the Possibilities of combining AI with design [1]. Therefore, fusing modern artificial intelligence with conventional design will open up new development possibilities [2]. In the AI era, dialogue and communication amongst designers are critical means of fostering creativity, which is essential to raising the required level of designing intelligence space. The present state of technological advancement demonstrates that the successful fusion of AI and design can satisfy the varying design requirements of humans [3-5]. With the growth of the AI sector and its many uses in recent years, AI technology has greatly influenced design and encouraged the advancement of the designing [6], AI supports theoretical models that are both academic and practical, fosters technical innovation, and helps to generate architectural intention and form. All of these factors contribute to the design industry's increased design efficiency [7, 8]. Every designer can attain design independence with the help of AI. In addition, it may finish the related task more quickly and effectively using AI's assistance [9]. Artificial intelligence (AI) technology generates a range of design schemes automatically by modifying and optimising phrases. In order to advance AI design, designers may select the plan that best suits their needs based on area, design idea, and other practical considerations from the set of options generated by AI learning. For designers, sketching up a design is usually the initial stage in the process [10-12]. In this work, we describe an AI-driven design technique that should aid designers in automatically producing initial drawings so that this procedure may be replicated. Even in the information era, designers may still utilise traditional tools as AutoCAD and Photoshop, which help with the laborious drawing process, are based on standard three-dimensional (3D) rendering pipelines [13–15]. These conventional technologies can produce beautiful graphics when used by skilled designers, but they cannot help designers automatically generate accurate preliminary context-sensitive designs that satisfy users [16]. The majority of recent research in the design focuses mostly on image synthesis through the use of generative models and deep learning, which are effective techniques for creating stylish images. In this work, we develop a unique strategy to address the issues previously addressed [17, 18]. More specifically, we decompose our suggested design approach into two modules: renderer development and sketch generation. The goal of the sketch-generation module is to produce a variety of

[1] [1]School of International Communication and Arts, Hainan University, Haikou, Hainan, China, 570100
[*]Corresponding author e-mail: 995085@hainanu.edu.cn

drawings. A sketch-generation network is meant to produce several and varied painting sketch seeds from the latent space, taking use of the unpredictable nature of latent space in noise [19].
It is anticipated that our AI-driven design approach will help designers create more intricate interactive designs with clients, enabling them to create more specialised designs based on user requirements [20].
ANNs are resource-intensive and may be expensive to implement since they frequently need large amounts of data and computer power. Moreover, overfitting is a problem that affects ANNs and limits their generalizability by making when training with data that is uncertain, the model performs poorly. Furthermore, the intricacy of ANNs may make it difficult to comprehend and analyze the underlying decision-making procedures, which would reduce architectural design's openness and accountability. Whereas Generative Adversarial Networks (GANs) bring novel opportunities for fashion design, there are limitations, such as difficulties maintaining correct representation and controlling output quality. Mode collapse may be a problem for GANs, leading to unrealistic or repeating designs. Furthermore, scalability and accessibility in fashion design applications may be restricted by the need for massive datasets and computational resources for GAN training. Whereas Deep Neural Networks (DNNs) improve Nano photonic designs, there are certain disadvantages, such as possible model fitting flaws and design mistakes. These restrictions make it difficult to achieve the accuracy and dependability needed for complex Nano photonic applications, which makes it difficult to fully utilize DNNs in this area.
The creation of an intelligent system to aid designers was the goal of this project. AI can help designers save time and personnel throughout the design process by using various techniques to develop and test models. AI has the potential to both increase productivity in the engineering sector and foster design advancement.
Significant contribution made by this work, which includes;

- In this research work, exploring the Development of Intelligent Designer Assistance System Using Deep Reinforcement Learning (ED-IDAS-DRL-DKNN) is proposed.
- By utilizing Deep Kronecker Neural Networks techniques to provide effective representation learning, scalability, and interpretability when integrated into Intelligent Designer Assistance (IDA) systems.
- The realization of adaptive adjustment and optimization within the environment through the development of an intelligent algorithm model.
- The obtained results of proposed ED-IDAS-DRL-DKNN algorithm are compared to the existing methods such as IADAS-AIM-ANN, AIFD-SRG-GAN and IDNP-OTIC-DNN methods respectively

The remaining manuscript is organized as follows: Part 2 outlines the Literature Survey, Part 3 Displays the proposed technique, Part 4 presents the results with discussions, and Part 5 concludes the manuscript.

II. LITERATURE SURVEY

Several research projects were recommended in the literature pertaining to Intelligent Designer Assistant based on Deep Learning. A few current works were reviewed here;
Li, et.al, [21] have presented examination of intelligent-auxiliary architectural space design based on artificial intelligence models. The study's findings demonstrate that the degree of model fitting on the training and test data sets decreases with an increase of network nodes. The superiority of the AI-based intelligent architectural space design scheme over the traditional architectural design scheme is demonstrated by the fitting curve of the entire model. The intelligent score for temperature and humidity in space will keep rising as more nodes are added to the network connection layer. The most intelligent auxiliary impact on architectural space could come from the model. The study offers potential applications in the real world for encouraging the digital and intelligent transformation of architectural space design. It offers both low precision and great accuracy.
Yan, et.al, [22] have presented an AI-based fashion designer who uses sketch and rendering generators in conjunction with generative adversarial networks. This article offers a brand-new framework for fashion design that was based on artificial intelligence (AI). Using this architecture, a latent space-based sketch-generation module was initially presented for creating different kinds of sketches. Second, in order to finish the fashion design work, there was also a rendering-generation module available, which can map drawings to textures. The rendering-generation model develops a multi-conditional feature interaction module to successfully synthesise semantically aware textures on drawings. Additionally, two distinct training techniques were shown in order to maximize the performance of the renderer generation module as well as the sketch generation module. It provides high model fitting degree and it provides low accuracy.

Wang, et.al, [23] have presented clever ideas in nanophotonics: from inverse creation to optimisation. It presents a comprehensive analysis of the latest developments in intelligence-algorithm-designed Nano photonic components, highlighting a shift in research from performance optimizations to inversely generated new designs. In order to demonstrate the connection between two domains, this article first discusses the various applications of algorithm operational principles among a number of well-known meta-elements, utilising meta-atom spectrum modification as a case study.AI and photonics. This article addresses algorithm-assisted Nano photonic designs to explore their mutual benefits, ranging from levels of individual optimized component to feasible system. It also discusses a number of open-ended issues, such as algorithm benchmarking, costlier data issues, and appropriate uses of sophisticated algorithms. In general, it sees mounting photonic-focused techniques to significantly advance functional artificial meta-devices for the benefit of both domains. It provides lowdesign error, and it provides low model fitting degree.

Janiesch, et.al, [24] have presented Deep learning and machine learning, In order to provide readers a deeper grasp of the systematic foundation of contemporary intelligent systems, this article presents an overview of the key concepts of both machine learning and deep learning. It does this by providing definitions for important words and ideas, outlining the process by which automated analytical models were built with machine learning and deep learning. and discussing the challenges associated with implementing these intelligent systems in the context of electronic markets and networked commerce. These highlight issues with artificial intelligence servitization and human-machine interaction, which are intrinsically transcendental to technical reasons. It provides high precision, and it provides low accuracy.

Popova, et.al, [25] have shown the use of deep reinforcement learning to create drugs from start. In order to produce chemically valid SMILES strings, generative models were trained in this paper utilising a stack-augmented memory network. Next, in order to forecast the required characteristics of the molecules that were synthesised, predictive models were developed. A supervised learning technique wasused to train the generative and predictive models independently in the first stage of the process. Using the reinforcement learning approach, both models were jointly trained in the second stage. The objective was to bias the formation of new chemical structures towards those that had the required physical and/or biological attributes. It provides high accuracy, and it provides high design error.

Chen and L. Chen, [26] have presented Investigating the Use of Reinforcement Learning in Adaptive Environment Design in CAD Environment. This article analyze the complexities and variances present in the design of CAD environments, highlighting the importance of flexibility and investigating RL's potential to improve CAD intelligence. This results show that the RL-driven adaptive design method effortlessly modifies the setups and parameters of the CAD environment to conform to giving the best possible design support while adapting design challenges. Compared to conventional CAD settings, this adaptive method significantly increases design efficiency, reduces errors, and increases the level of user happiness. By using this approach, the development of intelligent CAD environments enters a new era and opens the door to technological improvements in engineering design. Its conclusions provide practitioners and academics with insightful advice that encourages further innovation in CAD environmental design technology. It provides high precision, and it provides low model fitting degree.

Tang, et.al, [27] have presented Reinforcement learning: Creating Visualisations of Expressive Storylines. In order to train an artificial intelligence agent that assists users in swiftly exploring the design space and producing the best stories, this paper presents a reinforcement learning framework. We now introduce Plot Thread, a writing tool built on the framework that includes a variety of flexible interactions to make it easier to modify story visualisations. It uses a mixed-initiative approach to smoothly integrate the AI agent into the authoring process, whereby designers and the AI agent work together on the same canvas to promote collaborative narrative design. Through a number of use scenarios, this shows you how to use Plot Thread and conduct both qualitative and quantitative research to assess the reinforcement learning model. It provides high model fitting degree and it provides high design error.

III. PROPOSED METHODOLOGY

In this sector, exploring the Development of Intelligent Designer Assistance System Using Deep Reinforcement Learning (ED-IDAS-DRL-DKNN) is proposed. This process consists of four steps: Data acquisition, Pre-processing, Prediction and optimization. Data were collected and pre-processed to prepare them for further analysis. The final step involves employing a Deep Kronecker Neural Networks for Prediction, with the feature vector serving as input. The GSO method is used to optimise the DKNN's weight parameter. The block diagram of proposed ED-IDAS-DRL-DKNN approach is represented in Fig 1. Accordingly, detailed description of all step given as below,

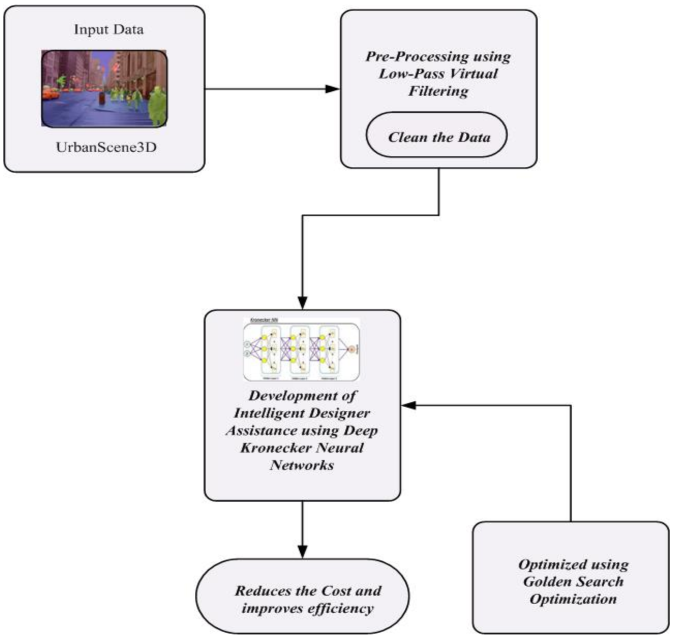

Figure 1: Block Diagram of ED-IDAS-DRL-DKNN methods

A. Data Acquisition

Originally, UrbanScene3D [28] is where the input data are gathered, was predicting Development of Intelligent Designer Assistance. It offers three download options—Google Drive, Drop box, and Baidu Cloud—and offers a classified download along with a description of pertinent UrbanScene3D data. Next, in order to understand and manage 3D data, a data-driven method called 3D Deep Learning is needed. Applied deep learning is more challenging for 3D data than for 2D data. Matrix data, for example, may be easily created from 2D photos, but processing 3D data becomes more challenging. As a result, choosing the 3D data expression form is essential. In modelling, objects having depth channels that specify spatial data features are represented by photographs taken from various perspectives.

B. Pre-Processing using Low-Pass Virtual Filtering (LPVF)

In this section, Pre-Processing using Low-Pass Virtual Filtering (LPVF) [29] is discussed. A LPVF method is used to clean the data. Deep Reinforcement Learning (DRL)-based Intelligent Designer Assistance System (IDAS) is improved by using Low-Pass Virtual Filtering. By lowering noise, it provides the agent with clearer signals, promoting stability and quicker convergence. It improves generalization and robustness by concentrating on pertinent data, allowing for efficient operation in a variety of settings. By optimizing computational resources, the filtered input encourages resource efficiency. To sum up, Low-Pass Virtual Filtering strengthens IDAS by improving input signals, enabling more seamless learning, and enabling the system to make better decisions, all of which increase the system's usefulness in challenging design tasks. Using Deep Reinforcement Learning (DRL), the integration of Low-Pass Virtual Filtering into an Intelligent Designer Assistance System (IDAS) aims to improve convergence speed, noise reduction, and stability. It also seeks to enhance robustness, generality, and resource efficiency, which will ultimately allow for more efficient support for intricate design tasks. This is given in equation (1),

$$S_b(\lambda) = x_2\lambda^2 + x_1\lambda + x_0 \quad (1)$$

Where S_b represents the second order polynomial of λ, constant coefficients are represented by x_0 x_1 x_2 $S_{b\max}(\lambda)$.Equation (2) gives the nonlinear function of the power coefficient S_b with relation to the tip speed ratio (λ).

$$gS_b(\lambda)\big/g\lambda = 2x_2\lambda_{opt} + x_1 = 0$$

(2)

Where d denotes the pitch angle, λ_{opt} represents the polynomial optimization, g represents the attenuation factor this is essential to the pace of convergence process. Therefore the polynomial optimization is given in equation (3) as

$$\lambda_{opt} = \frac{x_1}{2x_2} \tag{3}$$

In these types of design systems, the instability mechanism is provided and a stability-constrained coefficient is constructed to guarantee the stable functioning of artificial neuron layer. Therefore, the $B_{\max}$ that can be obtained from the design is given in equation (4),

$$B_{\max}(\omega_{nopt}) = \frac{8(x_1^2 - 4x_2x_0)\pi\rho U^5 x_2^2}{b^3 x_1^3 x_d^3}\,\omega_{nopt}^3 = x_{opt}\omega_{nopt}^3 \tag{4}$$

Where b denotes the network parameter, ω_{nopt} represents the speed, $B_{\max}$ denotes the transfer coefficient, U denotes the neural spectrum, x_{opt} denotes the optimal coefficient. The data validation is given in equation (5) as

$$\dot{\omega}_n = \frac{1}{2F_G}\left(L_y - L_c - X_G\omega_n\right) \tag{5}$$

Where X_G represents the gram matrix, L_y represents the mean, L_c represents the variance, F_G represents the spatial down sampling function. Here Low Pass Virtual Filtering (LPVF) have cleaned the data. Next, DKNN receives the preprocessed data.

C. Development of Intelligent Designer Assistance using Deep Kronecker Neural Networks (DKNN)

In this section, Deep Kronecker Neural Networks (DKNN) [30] is discussed. DKNN is proposed for Development of Intelligent Designer Assistance and it lowers costs and increases the effectiveness of architectural space design. Deep Kronecker Neural Networks (DKNNs) provide effective representation learning, scalability, and interpretability when integrated into Intelligent Designer Assistance (IDA) systems. Increasing productivity, sharpening judgment, speeding up iterations, encouraging innovation, and producing better design results with astute support are among the objectives. The affine transformation is given in equation (6),

$$K_k\left(x^{k-1}\right) \stackrel{\Delta}{=} M^k x^{k-1} + a^k \tag{6}$$

Where M^k denotes the weight matrix, a^k denotes the bias vector connected to layer k, x^{k-1} denotes the composition of hidden layer K_k represents the affine transformation, An output layer is followed by the activation function, sometimes referred to as the identity function. Consequently, equation (7) provides the final representation of a neural network.

$$n^{LL}(x) = \left(K_g \circ \phi_1 \circ K_{g-1} \circ \ldots \circ \phi_1 \circ K_1\right)(x) \tag{7}$$

In the network represented by equation (8), the trainable parameters are denoted by n^{LL}, the nonlinear activation function by ϕ_1, and the composition operator by $\circ$.

$$x^k = \left(1_{F\times F} \otimes M^k\right)\vec{\phi}\left(x^{k-1}\right) + 1_{F\times 1} \otimes a^k \tag{8}$$

Here $\vec{\phi}$ denotes the block activation function, F denotes the fixed positive integer, $\otimes$ is the Kronecker product, M^k denotes the block weight matrix, We introduce the scaling parameters to properly scale the block weight matrices and block bias vectors. It is shown in equation (9),

$$x^k := \tilde{K}_g\left(x^{k-1}\right) = \tilde{M}^1 x^{k-1} + \tilde{a}^1 \tag{9}$$

Here $\tilde{K}_g$ denotes the Kronecker network Parametric ReLU activation, $\tilde{a}$ denotes the block bias vectors, $\tilde{M}^1$ denotes the block weight matrices, a feed-forward neural network is created from the Kronecker network by using layer-wise locally adaptive activation algorithms. DKNN improves the efficiency and reduces the cost in the following equation (10),

$$n_{\Theta}^{F}(x) = \left(\tilde{K}_G \circ \vec{\phi} \circ \vec{K}_{G-1} \circ ... \circ \vec{\phi} \circ \tilde{K}_1\right)\left(1_{F\times 1} \otimes x\right) \tag{10}$$

Where $n_{\Theta}^{F}(x)$ represents the Kronecker neural network, while F, Θ are the network parameters, $\vec{K}_{G-1}$ represents the standard network. Moreover, the Kronecker network may be understood as a novel class of neural networks that, in particular, generalise a class of feed-forward neural networks currently available through adaptive activation functions. Ultimately, DKNN has decreased costs and increased architectural space design efficiency. In this work, GSO is employed to optimize the DKNN network parameters F and Θ .

D. Optimized using Golden Search Optimization (GSO)

In this section, the Optimization using Golden Search Optimization (GSO) [31] is discussed. The DKNN network parameters F and Θ is optimized by GSO. The incorporation of Golden Section Search Optimization into the Deep Reinforcement Learning (DRL) Intelligent Designer Assistance System (IDAS) development process enhances parameter tuning's effectiveness and resilience. By identifying the ideal values, this method effectively traverses the complicated parameter space and improves the system's performance. Golden Section Search has a strong track record of resilience against noise and non-smooth objective functions, which makes it an invaluable tool for improving the complex dynamics of DRL-based IDAS. This optimization strategy is seamlessly compatible with DRL methodologies and guarantees rapid training and fine-tuning of the system, enabling it to provide intelligent design help with reliability and efficiency. The objectives are to use DRL to incorporate Golden Section Search Optimization into an IDAS, optimize complex functions robustly, optimize parameters efficiently, and improve system performance and reliability.

Step 1: Initialization

Initialize the input parameter, here the input parameter of DKNN which is denoted as F and Θ . It is given in equation (11)

$$Q_i = \begin{bmatrix} I_1 & \cdots & I_b \\ I_2 & \cdots & I_c \\ . & . & . \\ I_N & \cdots & I_N \end{bmatrix} \tag{11}$$

Where I_N represents the updated feature vector of the node, Q_i signifies the position of items within the search area, I_b means the predicted grades, I_c represent the count of solutions. In a neural network, each connection between neurons has an associated weight parameter.

Step 2: Random Generation

According to the following equation, GSO begins the search with a set of randomly generated objects (possible solutions) in the search space.

Step 3: Fitness Function

Using initialised variables, the fitness function generates a random solution. It calculated using optimizing parameter. Thus it is shown in equation (12),

$$FitnessFunction = optimizing[F, \Theta] \tag{12}$$

Where, F represents the increasing accuracy and Θ represents the lowering Design error.

Step 4: Exploration Phase $[F]$

At this stage, the exploration phase of the GSO is examined. Multimodal benchmark functions with numerous local optima are typically taken into consideration while evaluating the ability of an optimisation method to efficiently search the search space. From the perspective of standard deviation, which shows the stability of the algorithm, the outcomes demonstrate that, in contrast to the other approaches, GSO is a more stable method. It is shown in equation (13)

$$S = 100 \times \exp(-20 \times \frac{F}{f_{\max}}) \tag{13}$$

Where S represents the transfer operator, which, in order to improve search efficiency and regulate the proportion of global search in previous iterations to local search in subsequent rounds, shifts the focus of search from exploration to exploitation, F denotes the network parameter of neural network, $f_{\max}$ represents the distance between current position and best position

Step 5: Exploitation phase for optimizing $[\Theta]$

Exploitation is main criteria for any metaheuristic optimization algorithms, the variable which is random and ranges from 0 to 1. It implies the new algorithm has a bigger potential search space than the existing optimisation techniques.

It should be mentioned that the efficient position update method of GSO is the reason for its strong exploitative capability. Then it is shown in equation (14)

$$Qf_{\max} = 0.1 \times \left(nd_l - id_l\right) + \Theta \tag{14}$$

Where $Qf_{\max}$ denotes the allowed maximum movement which defines the most modification that an object's positional coordinates can go through in a single loop, d_l represents the dimensions. GSO could provide a better solution which is shown in the equation (14).

Step 6: Termination Condition

The network parameters from Deep Kronecker neural network is enhanced with the use of GSO, iteratively repeating step 3 until the halting condition $Q = Q + 1$ is satisfied. Then DKNN has managed the Intelligent Assistant Designer System by assessment with higher accuracy. Flowchart of GSO for optimizing DKNN parameter is shown in figure 2.

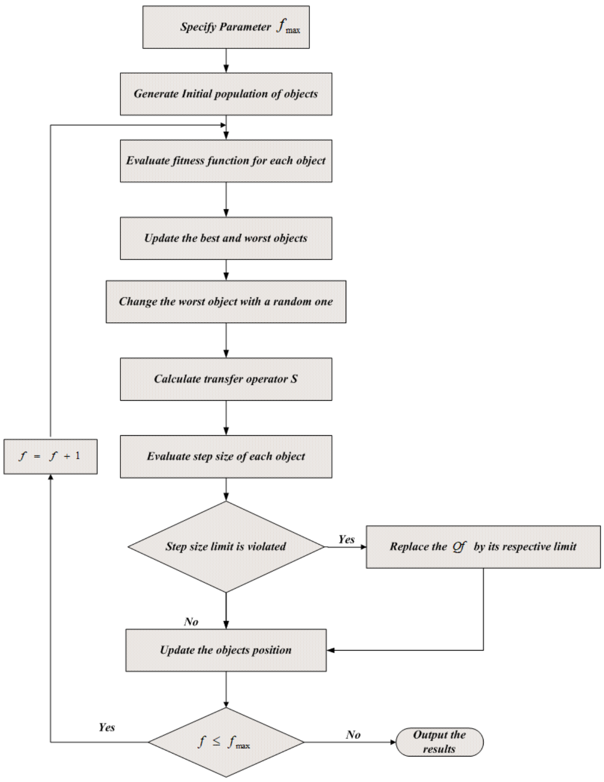

Figure 2: Flowchart of GSO for optimizing DKNN parameter

IV. RESULT AND DISCUSSION

Intelligent Designer Assistance System is one of the experimental results of the proposed ED-IDAS-DRL-DKNN approach. In Implementation work was carried Python and evaluated by using several performance analysing metrics like accuracy, precision, design error and model fitting degree are analysed. The results of the proposed ED-IDAS-DRL-DKNN technique are likened to the existing methods such as IADAS-AIM-ANN, AIFD-SRG-GAN and IDNP-OTIC-DNN.

A. Performance Measures

Performance measures include accuracy, precision, design error and model fitting degree. The confusion matrix will used to scale the performance parameters, it is decided.

- True Positive (TP) : Perfectly predictive Intelligent Designer assistance system into positive class.
- True Negative (TN): Perfectly predictive Intelligent Designer assistance system into negative class.
- False Positive (FP): Imperfectly predictive Intelligent Designer assistance system into positive class.
- False Negative (FN): Imperfectly predictive Intelligent Designer assistance system into negative class.

1) Accuracy

Accuracy is the capacity to measure an exact value. A performance statistic known as accuracy may be used to describe the model's functionality across all classes. The following equation (15) quantifies it.

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{15}$$

2) Precision

Precision, or how well a machine learning model generates positive predictions, is one indicator of the algorithm's efficacy. The following stated equation (16) is used to measure it.

$$\Pr ecision = \frac{TP}{(TP + FP)} \tag{16}$$

3) Design Error

Design error is the difference between the planned or ideal design specifications and the actual result; it is frequently quantified in terms of errors, inefficiencies, or fails to reach predetermined goals or standards.. It is quantified by the following equation (17)

$$D.E = \frac{FP + FN}{TP + FP + FN + TN} \tag{17}$$

B. Performance Analysis

The simulation outcomes of the proposed ED-IDAS-DRL-DKNN technique are shown in Figure 3 to 6.The proposed ED-IDAS-DRL-DKNN techniques linked to the IADAS-AIM-ANN, AIFD-SRG-GAN and IDNP-OTIC-DNN techniques, in that order.

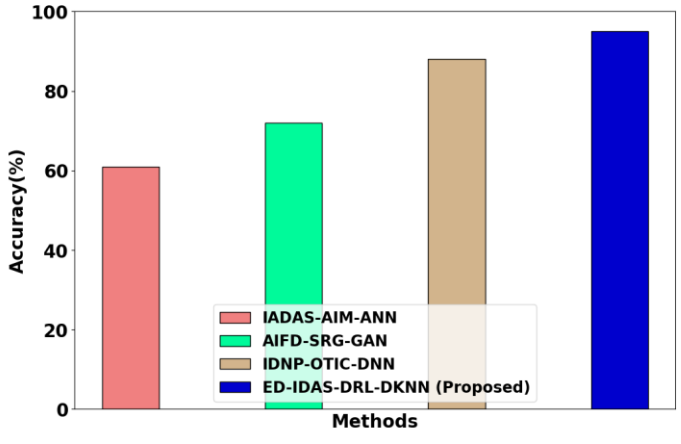

Figure 3: Performance analysis of Accuracy

Figure 3 displays Performance analysis of accuracy. The figure illustrates the significant improvement in accuracy that the suggested ED-IDAS-DRL-DKNN method within intelligent designer support systems achieves. It shows remarkable increases over well-known techniques like IADAS-AIM-ANN, AIFD-SRG-GAN, and IDNP-OTIC-DNN, with accuracy rates increase rapidly at 19.36%, 23.42%, and 35.42%, respectively. These results highlight the method's effectiveness in streamlining decision-making procedures in a variety of fields. The graphic representation highlights the possibility for more accurate and dependable results while also demonstrating the scope of these developments, establishing ED-IDAS-DRL-DKNN as a formidable competitor in the field of intelligent design aid systems.

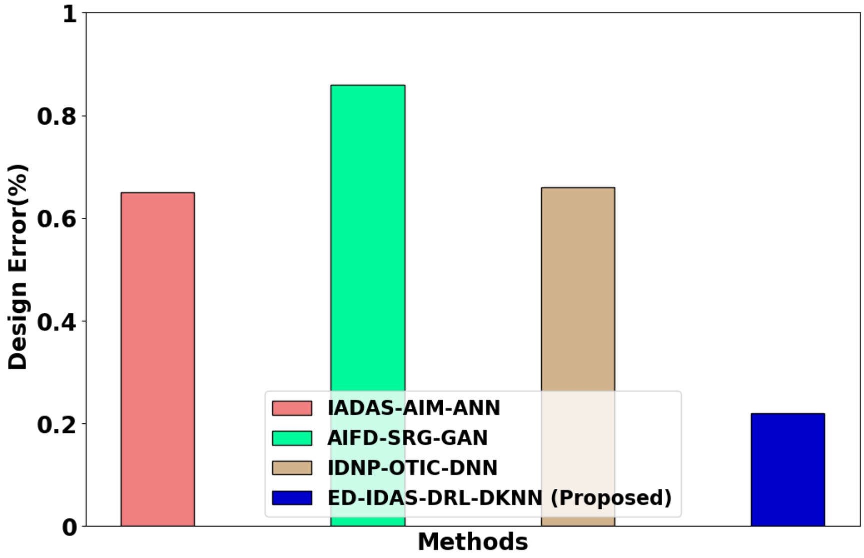

Figure 4: Performance analysis of Design error

Figure 4 displays Performance analysis of Design error. The graphic representation reveals significant decreases in design error enabled by the ED-IDAS-DRL-DKNN method in intelligent designer support systems. It demonstrates the technique's ability to refine design processes with a range of 26.36%, 35.42%, and 28.27% lower error rates compared to existing approaches like IADAS-AIM-ANN, AIFD-SRG-GAN, and IDNP-OTIC-DNN, respectively. These results highlight its ability to reduce errors and improve accuracy in a variety of fields. The graph highlights the concrete advantages of using ED-IDAS-DRL-DKNN by graphically illustrating the extent of error reduction, establishing it as a useful tool for increasing dependability and efficiency in intelligent design support systems.

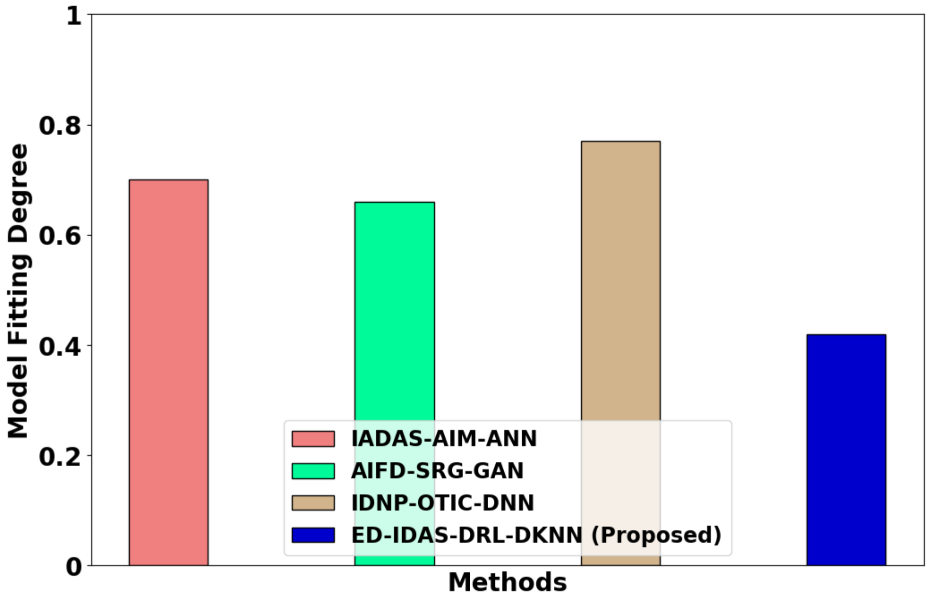

Figure 5: Performance analysis of Model Fitting Degree

Figure 5 shows Performance analysis of Model Fitting Degree.The graphical representation clearly shows how the ED-IDAS-DRL-DKNN technique in intelligent designer assistance systems significantly reduces the model fitting degree. Reductions of 28.27%, 19.36%, and 23.42%, respectively, when compared to well-established techniques such as IADAS-AIM-ANN, AIFD-SRG-GAN, and IDNP-OTIC-DNN demonstrate the technique's ability to improve model alignment and accuracy. These results highlight its ability to optimize the fitting procedure, reducing inconsistencies and improving the overall performance of the model in various domains. The graph, which illustrates the degree of improvement, highlights the concrete advantages of integrating ED-IDAS-DRL-DKNN and establishes it as a key instrument for increasing dependability and efficiency in intelligent design support systems.

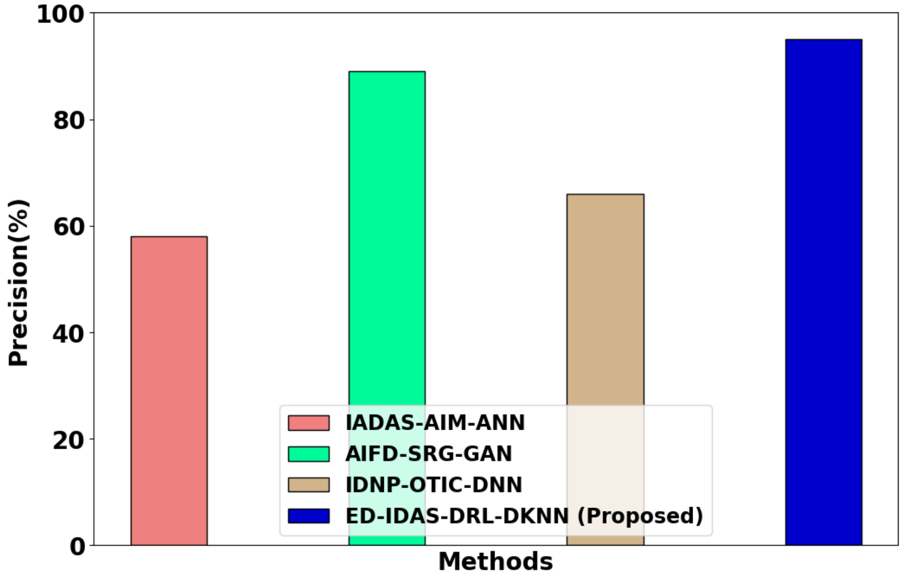

Figure 6: Performance Analysis of Precision

Figure 6 shows Performance analysis of Precision. The figure illustrates the impressive accuracy gains made possible by the ED-IDAS-DRL-DKNN method in intelligent designer support systems. It highlights the technique's effectiveness in improving decision-making processes with increases of 16.33%, 35.42%, and 28.27% in comparison to well-established approaches like IADAS-AIM-ANN, AIFD-SRG-GAN, and IDNP-OTIC-DNN, respectively. These results demonstrate its capacity to produce more dependable and precise results, which is crucial for intricate design work in a variety of areas. The graph highlights the concrete advantages of implementing ED-IDAS-DRL-DKNN by graphically illustrating the extent of precision improvement. This helps to establish ED-IDAS-DRL-DKNN as a useful for increasing effectiveness and efficiency in intelligent design assistance systems, which in turn promotes innovation and process optimization.

C. Discussion

Even though several countries are currently developing AI technology, not much is known about how AI and designer assistants work together. The path of the intelligent designer aid system is examined in this study. This study develops the ED-IDAS-DRL-DKNN model's initial step toward Development of intelligent designer assistance system. It is improved by using Low-Pass Virtual Filtering, which cleans the data. DKNN is proposed for improving the efficiency and reducing the cost. DKNN parameters are optimized using Golden Section Search which has a strong track record of resilience against noise and non-smooth objective functions. Using various assessment metrics, the results confirmed the proposed method's outstanding performance and the exploitation and exploration stages of the traditional GSO have been enhanced, indicating that the suggested GSO performs much better than the traditional GSO. As a result, from an economic perspective, the proposed technique is less costly than the comparison procedures.

V. CONCLUSION

In this paper, exploring the Development of Intelligent Designer Assistance System Using Deep Reinforcement Learning (ED-IDAS-DRL-DKNN)was successfully implemented. Here, UrbanScene3D dataset were used in thorough evaluation tests to assess the presented technique. The proposed ED-IDAS-DRL-DKNN method is executed in Python. The presentation of proposed ED-IDAS-DRL-DKNN method attains 26.36%, 35.42% and 28.27% lower design error and 28.27%, 19.36% and 23.42% lower model fitting degree compared with existing IADAS-AIM-ANN,AIFD-SRG-GAN and IDNP-OTIC-DNN methods. Future studies must extend the semantic network's information structure database and use the hybrid deep learning model to better optimise the intelligent designer support system.

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