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DISTRIBUTED SYSTEMS FOR EVALUATING AND OPTIMIZING ENVIRONMENTAL ART DESIGN USING IMAGE PROCESSING

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Abstract. Improving the visual appeal and practicality of areas is a major function of environmental art design. Nevertheless, conventional techniques for assessing and improving such designs are frequently arbitrary and ineffective. In order to assess and improve environmental art design, this study suggests a distributed system that makes use of Generative Adversarial Networks (GANs) and sophisticated image processing methods based on the characteristics of Computer-aided design (CAD). The methodology is based on distributed demand-side management in intelligent energy systems and emphasizes the decentralization of computational resources for increased flexibility and effectiveness.In order to model different design situations and improve based on aesthetic characteristics like color balancing, spatial arrangement, and visual balance, the system uses GANs for creating images and design transmission. This method's implementation in a distributed framework speeds up the assessment procedure and allows for continuous improvement and real-time feedback. A comparative examination of the findings from the experiment highlights the remarkable quality and effectiveness of the strategy presented in this study, which performs better than alternative strategies when it comes to of precision, recall, and F1 score. The results validate the superior performance of the suggested approach in relation to component extraction and recognition in CAD environmental artwork design. It is expected that this will support strong evidence for real-world applications and further research advancements in relevant sectors.

Key words: Distributed Systems, Optimization, Environmental Art Design, Image Processing, Deep Learning

1. Introduction. Computer vision's primary responsibilities include interpreting, evaluating, and comprehending images. An essential duty in the domains of planning for cities, sustainability, and growth of tourism is assessing the overall condition of the environment. Manually observation and scoring are frequently used in conventional landscape evaluation techniques, yet this approach is unreliable and subjective[12]. It is frequently used in evaluations of landscape quality. Utilizing the pixel data of the street view pictures, deep learning-based image segmentation methods are able to divide images into numerous areas and recognize the objects and scenes that belong to each zone[17]. This method offers robust support for evaluating the beauty of landscapes by extracting rich visual data from photos.

With the application of AI technology in visual communication design, the viewer may get involved in the creation process, which not only piques their attention but also helps them connect emotionally with the artist [2]. The singular connection among artistic items and conventional design for visual communication has fundamentally changed due to AI virtual art's communication, opening up a variety of potential sensory experiences.Artificial intelligence has elevated visual perception to a considerable degree. It is an artistic and technological fusion that disrupts the conventional display and opens up new possibilities. People would be treated to a novel creative moment upon its arrival [19].The effective enhancement of art design's job efficiency has emerged as a crucial subject in the discipline of smart art creation.

In recent years, as technological and scientific developments have advanced, pictures have been employed in numerous facets of people's life, including web page image material, face recognition, license plate recognition, and mobile phone imaging. Extensive study on pictures can enhance people's standard of life, alter people's way of life, and improve their living conditions [22, 13]. Numerous disciplines are involved in processing images, such as division, improvement, pairing, reconstruction, change, and categorization. The primary applications of image processing technology include image enhancement and reconstruction, image storage and coding, picture segmentation, image alignment, and picture classification [23]. Among these applications, there are numerous restorations of image, imaging segmentation, and visual distribution-related issues that require optimization.

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Key design features can be extracted from these photos through processing and analysis using deep learning techniques. In order to give architects more thorough and in-depth design references, the author [31] included geography, water bodies, plant species, and other elements in photographs.Connection and interaction among many factors are critical for ecological design for landscaping.By examining geographical element correlations and comprehending the connections and interactions among elements, deep indication learning technology can offer designers more precise design guidance [18, 9, 6, 25]. One of the most important links to ecological landscape architecture is structural design. Engineers can receive technical assistance, particularly analysis of structures and optimizing, from computer-assisted building and construction [6, 26]. It is possible to more precisely assess the stability and safety of structures by using machine learning construction and facilities which gives architects more dependable design options.

In the modern world where art has gained prominence, creating designs that can not only complement the space but also allow for fluid interactions with the said design and the space it is in, become the need of the hour. On the downside, design assessment approaches to date tend to be subjective, slow, and non-scalable. Irrespective of the impressive features provided by the current approach, it is becoming increasingly clear that modern design challenges require new data-driven solutions. Taking into consideration the increasing potential of artificial intelligence, one can anticipate dramatic changes in this area.

Design evaluation and generation are the fields where Generative Adversarial Networks can demonstrate the best results in addressing these challenges. GANs are primed to provide a comprehensive set of variants for each design and then CAD offers a great deal of organized approaches needed for the integration. The goal of the research is to make use of these technologies within the distributed systems framework allowing for the outsourcing of computational power to allow flexibility and constant scaling along with near-instantaneous feedback. Extending the applications of demand-side management in intelligent energy systems, aid is provided in the form of efficient resource allocation and redesigning of environmental arts.

The main contribution of proposed method is given below:

1. The distributed system architecture presented in this work decentralizes computing resources for environmental art design evaluation and optimization. Designing possibilities are created, modeled, and transferred using Generative Adversarial Networks (GANs).
2. This allows the framework to improve visual harmony, color balance, and spatial layout—all important aspects of natural art creation. GANs retain computing efficiency while improving the overall quality of design variants.
3. The study makes use of advanced image processing techniques designed for CAD-based design of environmental components.
4. A thorough experimental assessment is carried out, which shows that in regards to precision, recall, and F1 score, the suggested system performs better than conventional image processing and design assessment methods. This confirms the program's exceptional ability to gather and identify design components from environmental artwork created using CAD.

The rest of our research article is written as follows: Section 2 discusses the related work on various Distributed Systems, Optimization, Environmental Art Design and Image Processing, Deep Learning. Section 3 shows the algorithm process and general working methodology of proposed work. Section 4 evaluates the implementation and results of the proposed method. Section 5 concludes the work and discusses the result evaluation.

2. Related Works. The conventional techniques of designing landscapes typically lack accuracy and impartiality because they rely too much on the expertise and intuition of the designers. More thorough and in-depth design guides are made available to designers with the progressive implementation of landscape design. Within the field of landscape design, the author [20, 28, 24] investigated the use of neural network-assisted intelligence and CAD vision technologies. Environmental design features can be precisely measured and modeled using CAD visual technological advances, and they can be intelligently analyzed and optimized with the use of neural networks and intelligent technology [21, 5, 10, 16]. Various components must be recognized and categorized in designing landscapes. Automatic detection and categorization of these components is possible using CAD visual technological advances, increasing design efficiency and accuracy.

An all-encompassing design approach that blends design, creativity, and environment is called environmental art development [14]. Designers of environmental art must separate out from the crowd and incorporate into their designs the components that have aesthetic value. Conventional approaches, on the other hand, lack objectivity and precision because they frequently rely on the experience and intuition of the creator to determine artistic and creative components [11]. The technique of identifying environment design and artistic components was examined by the author [3]. It explains how to create and apply an algorithm and how to use it to recognize design features and works of environmental art. Large-scale datasets can be used to train and deduce the method despite the need to formally describe the geographical distribution of the information.

The field of visual communication is now at the forefront of modern art design due to a shift in people's aesthetic sensibility, and a lot of pieces are constantly in the public eye. Over time, interest has also grown in the creative visual communication design. In [4] the author provided an example of how digital equipment is used in the production of art for digital media as well as how it might improve artistic practice in connection to digital media. By examining the features of ornamental paintings instruction in every aspect of graphic layout, the author talked about the ways to update the curriculum, instructional strategies, and instructional ideas[15, 8, 30]. A significant part of the human past and cultural legacy is the cultural environment, which includes both natural and man-made environments.

Modern technological methods are required for recording and presenting this priceless historical treasure so that it can be better preserved and passed down to future generations [1]. A reliable and accurate method for measuring and modeling that can be utilized to capture comprehensive data on cultural landscapes is point cloud 3D modeling. Using a case study of a garden, the author [29] presented the technique of using point cloud three-dimensional models to document cultural environments and illustrated the use of spatial integration technologies in landscape architecture. The dimensions, form, substance, and other details associated with cultural settings can be adequately represented by this representation, offering solid backing for later planning and preservation [27, 7]. An essential source for guidance for landscape designers is geographic data. Geospatial data and 3D models can be integrated via geographic integration technology to give designers deeper and more thorough design guidelines [18]. Geographic integrating the internet, for instance, may be employed to gather data on elevation, plant transportation, environment, etc.

In spite of the desire to create eye-catching artistic designs, the evaluation and optimization of those designs remain a considerable challenge. Conventional methods of design and detail orientation are predominantly subjective and rely on guesswork which often leads to contradictions and ineffective scenes. Archcad drawings often disregard the changing nature of such aesthetic aspects as their arrangement and scale. Although some progress has been made, for instance, CAD tools enable accurate design, many of them still struggle to encapsulate a wide range of design aspects like integration of color and balance in space. The use of computing technologies for image processing in environmental art design is still largely undeveloped particularly the use of jot GANs of these methodologies in other fields has proven to be very effective in creating a wide range of designs.

3. Proposed Methodology. The proposed methodology for Evaluating and Optimizing Environmental Art Design Using Image Processing in Distributed Systems based onGenerative Adversarial Network (GAN) and the characteristics of CAD. In this work, initially the data is collected and stored in distributed networks. The collected data is used for pre-processing and then the feature is extracted. Finally, the GAN is used for training and optimizing the dataset. In figure 3.1 shows the architecture of proposed method.

The recognition and extraction of components is essential in enhancing the accuracy and productivity of CAD in the rendering of environmental designs. These methods consist of the analysis of the overall design by breaking it down into its components and features such as shape, pattern, texture, and even the structural components, for further detail, modification, and enhancement. Thus, if certain features are extracted, the designers of the project can devote their energy to circling single parts without changing the complete structure. For example, it is possible to detail a texture or a geometric pattern that has been removed from the general design for modifications. Components in CAD systems should be presented as independent elements of design to be further examined for features such as materials, structural, or decorating purposes. This isolation of elements makes it relatively easy to assess the design as a whole and within elements of design so that there is a fast modification of the design in consideration of the less time taken to evaluate an element within a design.

3.1. Data Pre-processing. The recognition and extraction method is presented automatically in this piece. This technique makes extensive use of GAN, pattern recognition, image processing, and other techniques

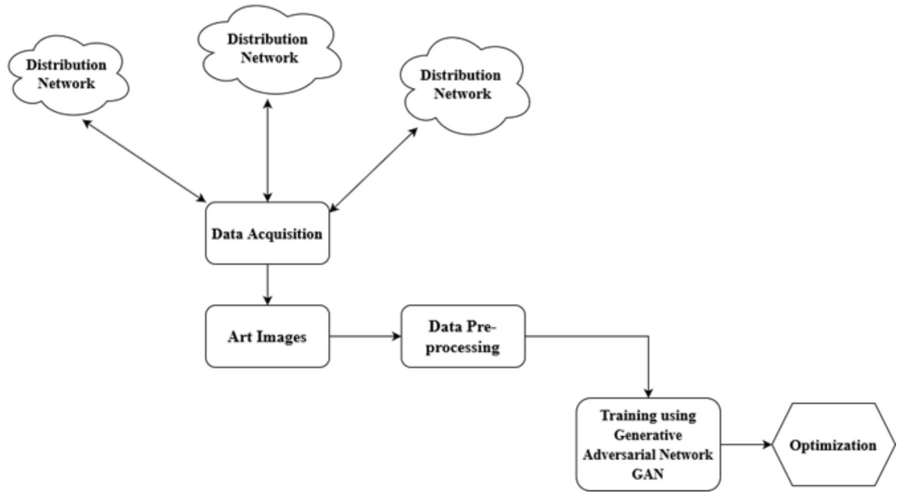

Fig. 3.1: Architecture of Proposed Method

to extract and identify design aspects automatically, hence increasing the effectiveness and caliber of the creation procedure.For recognition and extraction techniques to be accurate and effective, preparing the data is essential. The term complexity, which variation, and huge dimensions are common features of original data in CAD environment designs. In order to guarantee that the data supplied to GAN is precise and consistent, information cleaning—the main preprocessing task—aims to eliminate any superfluous, redundant, or incorrect components from the initial information. Duplicate drawings of designs or features may arise throughout the data collection or organization procedure.

For this reason, duplicate data is found and eliminated using the appropriate methods or tools in this article. Furthermore, certain information may lack specific design features or characteristics, which will result in data that is insufficient.In this situation, it can be handled by interpolation, deletion, or estimation using associated information. Furthermore, faults or other factors related to the acquisition procedure could introduce noise or anomalous values into the data. These parameters will negatively affect the model's learning. It is possible to effectively remove outliers as well as noise from these data by employing filters, statistical approaches, or other noise removal strategies.

3.2. Training and Optimization using GAN. The creation of realistic data has allowed Generative Adversarial Networks (GANs) to transform a number of machine learning disciplines. In this work, GANs are used in conjunction with image processing methods to maximize environmental art design. Two neural networks, the Generator (G) and the Discriminator (D), which cooperate within a min-max gaming structure, make up the GAN design.

The Generator is in charge of creating artificial visuals that mimic aspects of real-world layout, like aesthetic harmony, color balance, and spatial organization. In order to provide fresh design examples, it learns how to map points from a latent space (random noise). At the other side, the Discriminator's job is to differentiate among actual design examples and those generated by the Generator. The Generator gains the capacity to create images that are more realistic as it trains, while the Discriminator keeps getting better at telling actual photos from produced ones.

A min-max game among the two networks can be used to illustrate the main objective of the GAN development procedure:

$$\min_{G}\max_{D} V\left(D,G\right)=\mathbb{E}_{x\sim P_{d}(x)}\left[logD\left(x\right)\right]+\mathbb{E}_{rnv\sim P_{rnv}(rnv)}[\log?(1-D(G(rnv)))] \tag{3.1}$$

In this formula, the Discriminator optimizes its incentive by successfully detecting genuine samples from the dataset and differentiating them from produced samples, while the Generator aims to limit the Discriminator's

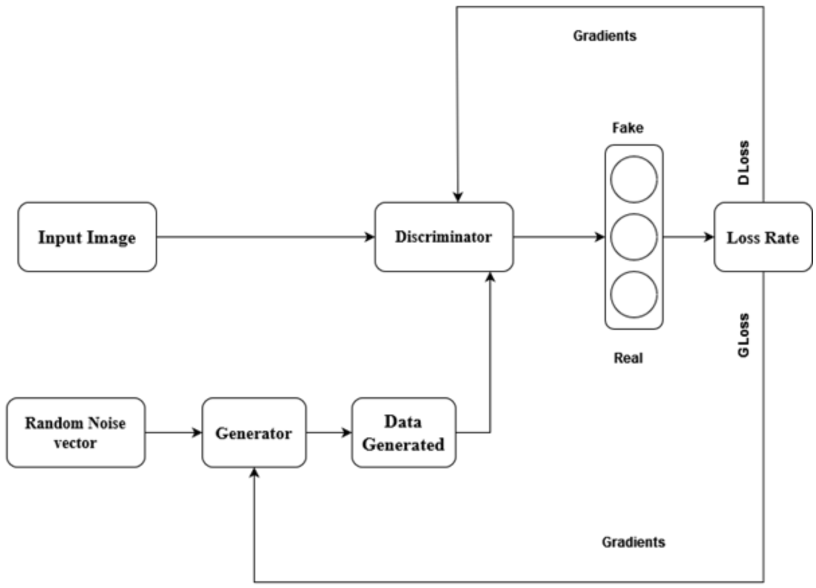

Fig. 3.2: Structure of GAN

capacity to do so. The Generator generates synthetic samples G(z) using the random noise variable $P_z(z)$, and the Discriminator assesses the probability that each sample is created $D(G(z))$ or real $D(x)$.

The Generator is tuned to generate incredibly lifelike artistic creations that imitate actual training instances as the system goes through its iterative learning procedure. As this is going on, the Discriminator gets better at differentiating real photographs from fake ones, making it harder and harder to tell both of them apart.

The Generator makes use of a deep neural network with numerous convolution layers to produce high-quality images that capture the creative elements that comprise environmental layouts. The input photographs are edited to match the design of the Generator after being shrunk to 128 × 128 × 3 pixels. Four convolution layers combined with ReLU activations produce aesthetically pleasing and incredibly intricately designed pictures.Through information sharing among the encoder and the discriminator, the discriminator integrates an encoder to improve feature extraction. Although the encoder makes sure the created images retain the visual integrity needed for environmental artwork, the discriminator focuses on differentiating between actual and produced pictures.

The following is a representation of the loss function for reconstruction for this process:

$$\mathcal{L}_{recons}^{pix} = \mathbb{E}_{q \sim D_{encoder}(x), x \sim I_{real}} [| \, |\kappa\,(q) - \tau\,(x)| \, |] \tag{3.2}$$

In this case, $\tau(x)$ indicates the discriminator's feature map, while $\kappa(q)$reflects the decoder's operations on real image characteristics IrealIreal. In order to guarantee that the created designs closely resemble the visual traits of actual environmental art, the aim is to reduce this reconstruction loss.This method guarantees that the Generator generates high-quality synthetic design pictures that match the visual and spatial qualities pertinent to ecological art design, in addition to deceiving the Discriminator.In figure 3.2 shows the structure of GAN architecture.

The first challenge is the deployment of the system requires particular strategies for maintaining the effectiveness and efficiency of the system while managing resource allocation, latency, data synchronization, and scalability across different environments. The allocation of resources to nodes in the distributed system was one of the major challenges. Working with computational tasks which include running Generative Adversarial networks (GANs) or processing digital models based on complex CAD data, achieving balanced workloads was vital. This was handled by demand-side management approaches where resources were dynamically reallocated

Table 4.1: Dataset Description [12]

Dataset	Design element category	Number training samples of set	Number verification samples of set	Number test samples of set
Dataset A	Material selection, color coordination, and space layout	5000	1000	2000
Dataset B	Space organization, color coordination, material choice, and lighting	8000	2000	3000
Dataset C	Space planning, color coordination, material choice, lighting configuration, furnishings, and decoration	10000	3000	4000

as per task priority and node constraints. Advanced scheduling algorithms were employed to evenly distribute computational loads and avert bottlenecks. Another difficulty involved the restriction of latency in the real time feedbacks and the iterative processes of continuous improvements. It is fair to assume that high latency could cause a disturbance to the iterative approach of design evaluation. To solve such a problem, parallel processing and predictive caching techniques were used to retrieve frequently accessed data and allow for the execution of multiple tasks at the same time. Furthermore, the implementation of edge computing was used to localise the tasks and thus reduce the dependency on the central nodes and improve the response time. Also, data synchronization between geographically distributed nodes was also a challenge.

4. Result Analysis. Large multi-core CPUs, GPUs, or TPUs that have the capability of running the GANs or performing demanding image processing tasks are the main computational resources for the suggested distributed framework. These resources should be able to provide efficient handling of large databases as well as allow real time interaction within the system. However, due to the large amount of data that is created when evaluating and optimizing designs of the environmental art, distributed storage systems are necessary for data management. Furthermore, a network infrastructure that is bandwidth-intensive is also paramount so as to enable effective inter-node communication within the distributed system. To overcome the problem of scalability, cloud resources and distributed computing concepts are utilized which makes it possible for such workload and or dataset size to increase without limits. The system applies adverse management techniques and therefore achieves better resource efficiency by ensuring that all tasks with computational requirements are distributed across available nodes in a dynamic manner. As a result, the latencies are somewhat controlled and bottlenecks are avoided, which makes the systems useful in real life large scale applications like urban planning for architecture.

Numerous simulation tests have been carried out as part of this inquiry in order to validate the effectiveness of the suggested method for the recognition and extraction of design elements. Following this, a thorough study and explanation of the results have been conducted. Here is the setup for the test: This part uses TensorFlow, a Python-based GAN structure, to conduct the study. Three public CAD environment creative design information sets—Dataset A, Dataset B, and Dataset C—are used in this study's training and evaluation of the model. The labeling information for these three sets of data covers a variety of design features, including choosing materials, matching of colors, and spatial design. Learning is done on the training set, and optimisation is done using the aforementioned techniques. In order to monitor the model's training environment, its precision and loss are documented throughout the training phase. The model's variables are saved and evaluated on the test set once the model reaches its maximum efficiency on the validation set. Table 4.1 shows the dataset description.

It appears that the loss numbers for the various tests fluctuate, suggesting that the model's performance changes with each iteration.It's possible that there is inconsistency in the optimization process or that the algorithms are still learning and altering parameters because none of the tests appear to show a continuously decreasing loss.Although the behavior of each test varies, overall, throughout the course of the 10 repetitions, the loss values lie between 0.1 and 0.7. The four tests are distinguished by their corresponding colors in the description on the left. Every test seems like a study or a model that is being optimized, and the legend makes

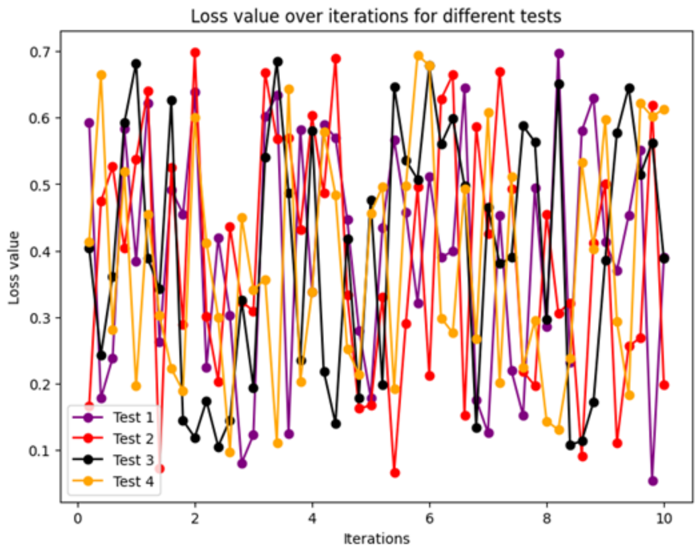

Fig. 4.1: Loss Value over Iterations

Table 4.2: Experimental Result of Accuracy, Recall, and F1-score

Dataset	Design element category	Accuracy rate	Recall rate	F1 value
Dataset A	Space Layout	93.3%	90.6%	92.7%
	Colour matching	88.5%	86.3%	87.2%
	Material selection	91.2%	88.4%	89.8%
Dataset B	Space Layout	93.8%	91.1%	92.5%
	Colour matching	90.3%	93.7%	92.7%
	Material selection	94.9%	89.7%	93.5%
	Lighting setting	93.3%	91.2%	93.7%
Dataset C	Space Layout	95.7%	92.1%	95.7%
	Colour matching	89.5%	94.7%	90.9%
	Material selection	90.4%	90.6%	90.2%
	Lighting setting	92.7%	90.4%	92.1%
	Decoration and furnishings	93.8%	92.6%	93.1%

it easier to figure out which line goes with which test. Figure 4.1 shows the result of Loss Value.

This section presents the detection and extraction outcomes of the suggested method on several data sets, following a series of trials. Table 4.2 displays particular outcomes indicators.

The most inconsistent and lowest accuracy rates are displayed by the Traditional Image Processing Methods, suggesting that this approach may not be the best fit for the given task.Although the RNN technique outperforms the old technique, it still exhibits significant accuracy fluctuations, suggesting that further tuning or stability in the learning process may be necessary for the model.The highest performance is shown by the Proposed Method , which maintains a high degree of accuracy with comparatively less volatility, indicating that it is more robust or effective for the task at hand.

This graphic 4.2 shows that the accuracy of the Proposed Method constantly beats that of the other two methods (conventional and RNN) over the course of the iterations. This implies that the suggested approach has a more successful model architecture or is more adept at learning from the data.Significant instability is shown by the traditional image methods of processing, which may indicate that these techniques are out of date or not task-specifically tuned.The RNN Method performs moderately, indicating that it has promise but

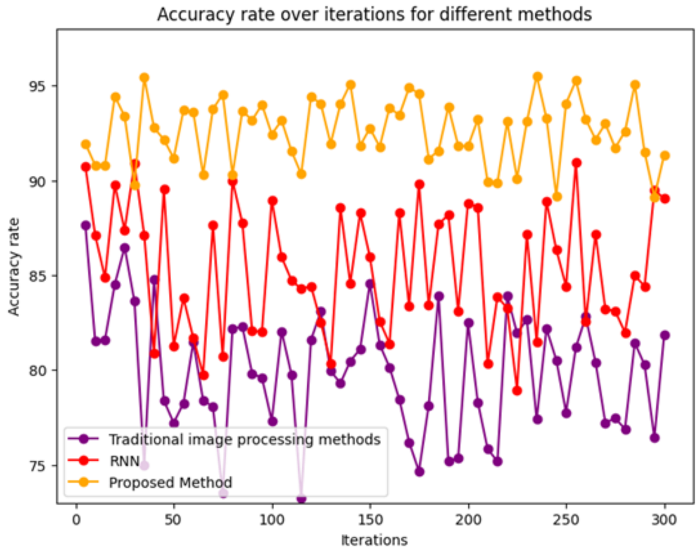

Fig. 4.2: Accuracy

might require more improvement. The Proposed Method gets the best and most stable accuracy, following by the RNN, with the Traditional Image Processing Methods trailing behind. The plot, which compares all three approaches over numerous iterations, illustrates this.

Traditional image processing techniques: This technique performs the worst in terms of recall rate, ranging from about 75 to 85. The line has several changes and is rather unpredictable.RNN: This approach outperforms the conventional techniques, with recall rates ranging from 80 to 90. While variable, it continues to be higher than the conventional approach.Proposed strategy: With a recall rate that hovers around 90 to 95, this strategy is the most effective on a regular basis. More stability is indicated by the significantly smaller volatility.Recall rate is a continuous advantage of the Proposed Method over both the RNN and the Traditional Image Processing Methods.The two alternative methods perform better in recall, but the traditional image processing methods show a lot of instability.Though it is still fewer reliable and successful than the suggested method, the RNN outperforms more conventional approaches. In figure 4.3 result of Recall.

In terms of F1 value, the Proposed Method reliably performs better than the RNN and Traditional Image Processing Methods respectively.The F1 values of the Traditional Methods drop noticeably after numerous iterations, resulting in poor performance and instability.Although RNN outperforms conventional techniques, its performance is inconsistent and frequently varies greatly.With the highest F1 values and the most stability, the Proposed Method is probably the best solution for the given situation because it effectively balances precision and recall. In figure 4.4 shows the result of F1-score.

5. Conclusion. Enhancing spaces' aesthetic appeal and usefulness is one of environmental art design's main goals. However, traditional methods for evaluating and enhancing such designs are often arbitrary and unproductive. This study proposes a distributed system that utilizes advanced image processing techniques based on computer-aided design (CAD) features and Generative Adversarial Networks (GANs) to evaluate and enhance environmental art design. The methodology stresses the decentralization of computational resources for enhanced flexibility and efficacy. It is based on distributed demand-side management in intelligent energy systems. The system uses GANs for image creation and design transmission in order to simulate various design scenarios and improve depending on aesthetic qualities including color balancing, spatial arrangement, and visual balance. The use of this technique in a distributed system facilitates real-time feedback, continuous improvement, and expedites the evaluation process. An analysis of the experiment's results in comparison reveals the exceptional quality and efficacy of the method described in this study, outperforming other techniques

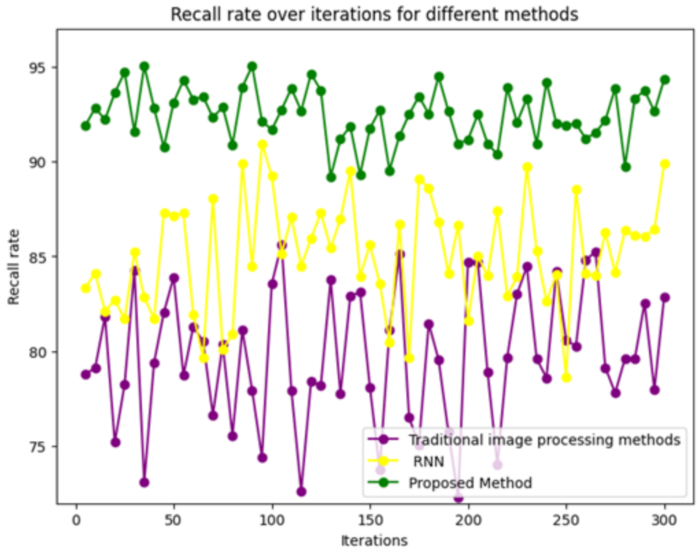

Fig. 4.3: Recall Rate

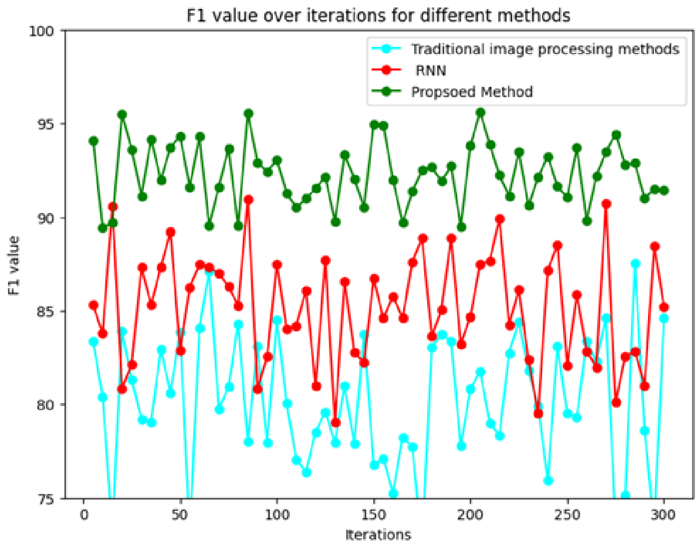

Fig. 4.4: F1-Score

in terms of precision, recall, and F1 score. The outcomes confirm that the recommended method performs better when it comes to component extraction and recognition in CAD environmental artwork design.

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