J. Electrical Systems 20-7s (2024): 3190-3200

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Intelligent Assistant System for Graphic Design Creation Process: Research on Creative Inspiration Extraction and Visualization Tools

Journal of Electrical Systems

***Abstract:* -** In graphic design, words, images, and creativity are combined to create a primarily "visual" medium for communication and expression. Design thinking and a variety of methodologies are also utilized to recreate the symbols, images, and words that are used in visual art to communicate ideas and information. When choosing design elements, a designer must make sure that the elements' contexts match the semantics provided by the product image and that the elements' visual styles such as their colors, forms, and sizes are perfectly harmonious. To address these challenges, a methodology for developing an intelligent assistant for graphic design creation is described in this manuscript. The images are collected fromImp1k dataset. The collected data are fed to pre-processing. Designs with skewed aspect ratios, few numbers of elements, or outliers within their design class were filtered out using the Adaptive Multi-scale Improved Differential Filter during pre-processing. The pre-processed data is then sent to Multi-scale Hypergraph-based Feature Alignment Network for classification. The image design categories infographics, mobile-UI, movie posters and webpages are successfully classified using MHFAN. The Elk Herd Optimizer (EHO) is used to optimize the weight parameters of MHFAN. The proposed IAGDC-MHFAN-EHO method is executed on the Python working platform. Performance metrics like F1-score, accuracy sensitivity , precision and computation time are examined. The gained outcomes of the proposed IAGDC-MHFAN-EHO method attains higher accuracy of 16.71%, 18.82%, and 17.93%, higher sensitivity of 16.37%, 12.25%, and 18.51% and higher precision of 14.93%, 16.79%, and 18.18%. The proposed IAGDC-MHFAN-EHO method is contracted with the present technique like DoGDAS-AI-DL, TADD-AIAD, and DAIAFDS-StyleGAN2 models respectively.

Keywords: Graphic Design, Artificial Intelligence, Inspiration, Creative Process, Filter, Classification Network, Intelligent Assistant System.

I. INTRODUCTION

a) Background

Professional graphic design expertise is in high demand since it is necessary for graphic designers to produce visually appealing work. Through design discussion forums, live streams, and how-to videos, graphic artists actively impart their skills to others [1]. Additionally, as digital design tools are used for the majority of graphic design work these days, it is possible to monitor the activities a designer does within a design tool and the resulting output. This suggests that experienced designers can impart their comprehensive procedures to beginners so they can learn from them [2, 3].The placement of a poster or commercial can reveal if the design effectively conveys its message to the spectator or if the visitor overlooks crucial features or concepts [4]. It is true that many businesses provide eye tracking assessments of graphic designs that shed light on the design's efficacy, however these studies usually require a different eye tracking research for each design. It is a typical responsibility for designers to establish a visual hierarchy and importance for their elements, ideally leading the reader from elements of greater to lesser relevance [5, 6].The capacity to generate and refine ideas is creativity. It entails developing novel strategies for solving issues, creative ways to resolve conflicts, or novel insights from datasets. The quantity of fresh concepts a designer may come up with for a certain design challenge has frequently been equated with creativity [7]. Fixation is the term used to describe the difficulty designers frequently face in expanding upon previously encountered ideas. Because of this effect, designers are unable to consider more than their initial concepts or to include the structure and/or functionality of other things into their design solutions [8, 9]. Also, it is essential to fully comprehend and look into the existence of tacit knowledge in graphic design in order to improve the transfer of design knowledge from people having it to others who do not [10].

b) Literature Review

Several research works were suggested in the literature related to intelligent assistant system for graphic design. Some of them are provided below:

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Liu [11] suggested the expansion of an artificial intelligence system based on deep learning theory. Technology advancements have made graphic designers' tools more and more sophisticated, enabling them to create the designs of their dreams, produce a greater variety of special effects, and broaden their conceptual options. The graphic design sector might grow as a result of the use of numerous novel technologies in the field.
Artificial intelligence (AI) has overtaken traditional graphic design in terms of layout design. The class variance was used by the DL theory to segment the image. A two-dimensional (2D) model's voxelized image matrix was sent into a CAE as input data. The CAE's convolution layer, which mostly finishes the feature mapping, was the first layer that the input data flow through.
Peuteret al. [12] suggested rethinking how artificial intelligence (AI)assists designers.AI should complement and capitalize on designers' creativity and problem-solving skills in order to cooperate rather than automate. The difficulty for such AI was to deduce the intentions of designers and then assist them without unduly disturbing them. Presented a novel framework for developing AI-assisted design, which was based on generative user models and enables the system to infer and adjust to the objectives, logic, and skills of designers.
Choiet al. [13] suggested that artificial intelligence is being used in the garment creation system in a number of ways, both in fashion and the academia industry, as a result of its recent expansion into the creative domain. A number of IT businesses have created and acquired AI-based technologies for clothing design that use StyleGAN2 to convert images. They aren't used very often in the fashion industry, though. Fashion companies need to create a lot of designs in order to provide new clothing lines for at least two seasons a year, therefore one way to increase productivity is to use AI-based garment design generating technology.
Sunet al. [14] developed SmartPaint, a generative adversarial networks (GANs)-based co-creative drawing system that permits a human and a machine to work together to paint cartoon landscapes. The majority of people only has the ability to sketch out their ideas quickly and was not skilled enough to finish beautiful paintings. Current AI techniques have not been able to preserve the semantic concepts of a wide range of user sketches while transforming them into exquisite paintings. Using triples of cartoon images, their related semantic label maps, and edge detection maps, the SmartPaint trains a GAN. The machine can then concurrently comprehend the semantics and cartoon style of the visuals, as well as the spatial relationships between the items in the landscape. For consistent handling of a variety of sketches, the trained system automatically synthesizes its edge map after receiving a sketch as an input for a semantic label map.
Kim and Maher [15] investigated the impact on design ideation of an AI-based co-creative design tool that offers inspiration based on conceptual similarities. It was suggested that conceptually related inspirations, as opposed to chance inspirations, have a bigger impact on design ideation. The CIP system was created in order to study how an AI model for conceptual similarity affects ideation in a design project. Inspired graphics based on conceptual resemblance were provided via the co-creative design approach known as CIP.
Son et al. [16] built a thorough set of attributes related to tacit knowledge by use of a literature review. The tacit nature of design prevents information exchange, even in spite of the increasing need for professional graphic design skills. On the other hand, little was known about the traits and applications of tacit knowledge in graphic design.Ten expert graphic designers were interviewed, leading to the collection of 123 instances of tacit knowledge and the labeling of their attributes. Through qualitative coding of the cases, the salient features, behaviors, and objectives of tacit knowledge were determined. A comprehensive evaluation of previous system support for graphic design literature was created in order to determine which instances have received the least attention.
Liu et al. [17] presented the innovative function-structure concept network construction technique, which integrates structural and functional information by combining word/phrase extraction with sentence parsing. The swift expansion of data and the necessity for designers to monitor vast amounts of data in order to derive creative inspirations have presented obstacles for conceptual design, thereby encouraging the advancement of data-driven design. Additionally, a network analysis approach was put forth to investigate linkages in design information that combine explicit and implicit relationships, and in doing so, to simultaneously suggest these associations to designers as sources of inspiration to aid in the ideation process. This method can improve designers' capacity to create connections between design elements, generate fresh concepts during conceptual design, and boost their creativity when addressing design challenges.

c) Research Gap and Motivation

The generic review of the recent research work shows that intelligent assistant system for graphic design is important. Due to cognitive limitations shown by studies on design cognition and insufficient problem information, human designers nearly never display optimal behavior. Designers may have biases in their thinking since they rely on "fast and frugal" choice heuristics. An example of an anchoring bias in design was when a designer becomes obsessed with little changes to a well-known solution to a design challenge. Additionally, due to the limitations of human long-term memory, people may become obsessed on ideas and be unable to come up with new potential solutions. These were really unique factors. The extremely problem-specific nature of the drawings in the AI-assisted design approach was a drawback. As a result, it is challenging to transfer methods between design domains. Even though GAN models were an essential tool for picture production, the quality of the dataset has an impact on how well garment designs were generated when utilizing GANs. Consequently, the data source needs to be acquired in a way that makes it possible to learn designs under different circumstances. This restriction makes it difficult for designers to work with and manipulate the images. There aren't many approach-based publications in the literature that address this issue; these shortcomings and issues were what motivated the research work.

d) Challenges

A number of design judgments on various design components are made during the intricate and abstract design process. It needs a method to turn this design process into a machine learning model that records important design phases and frequent arrangement of design components. When choosing design elements, a designer must make sure that the elements' contexts match the semantics provided by the product image and that the elements' visual styles such as their colors, forms, and sizes are perfectly harmonious. The way that design elements are arranged can influence how people view a product. A perfect arrangement should achieve specific aesthetic objectives and highlight the product image. In the lack of quantitative guidelines, designers find it challenging to define fashion trends. Designers may identify a particular style differently from other designers because they typically define the style of their brands on their own. A further issue for designers is the lack of quantifiable standards. To stay on top of fashion trends, designers often consult trend reports provided by independent fashion companies. It is challenging for designers to get a full and all-encompassing picture of style trends throughout several seasons, though, because these trend reports concentrate on detecting trends within a single season. Also the intelligent system process is time consuming and another challenge is when determining the number of conceptual instances. When it comes to tacit knowledge, it is difficult to adequately convey a designer's expertise within a design tool and to share that information with others. To address these challenges, a hybrid approach is proposed in this work.

e) Contribution

The following are this manuscript's primary contributions:

- The images used in this study are sourced from the Imp1k dataset, which encompasses a broad collection of 1000 annotated designs spanning various categories.
- With the help of Adaptive Multi-scale Improved Differential Filter, designs with skewed aspect ratios, few numbers of elements, or outliers within their design class were filtered out.
- The pre-processed design images are fed to Multi-scale Hypergraph-based Feature Alignment Network where it is classified into infographics, mobile-UI, movie posters and webpages.
- Then the weight parameters of MHFAN are optimized using Elk Herd Optimizer.
- The proposed IAGDC-MHFAN-EHO method is employed on the Python working platform and performance metrics like accuracy, F1-score, precision ,sensitivity and computation time are examined.

f) Organization

The rest of the manuscript is structured as follows: segment 2 discusses the proposed methodology of the manuscript and then segment 3 provides results and discussion. Lastly, segment 4 concludes the paper.

II. PROPOSED METHODOLOGY

In this segment, delve into the discussion of the proposed hybrid method-based intelligent assistant system for graphic design creation. Block Schematic for Proposed Approach is illustrated in Figure 1. This system comprises four distinct stages: image acquisition, preprocessing, classification, and optimization. Each stage plays a pivotal role in the seamless operation of the overall system, facilitating the efficient generation of high-quality graphic designs through the integration of advanced artificial intelligence techniques.

Figure 1: Block Schematic for Proposed Approach

A. Image Acquisition

The images utilized in this study are sourced from the Imp1k dataset [18], which comprises a comprehensive collection of 1000 annotated designs spanning diverse categories. These designs have been meticulously curated from existing research datasets, ensuring a rich and varied pool of stimuli and annotations that can be readily shared with the wider research community. To annotate the importance of each design within the Imp1k dataset, the ImportAnnots user interface (UI) was employed. This interface facilitates the systematic evaluation and annotation of the significance attributed to each of the 1000 designs, providing valuable insights into their respective importance levels. Subsequently, the acquired image dataset undergoes pre-processing using the AMIDIF framework to prepare it for further analysis.

B. Preprocessing usingAdaptive Multi-scale Improved Differential Filter

Multi-scale approaches have been used to mine fault features more precisely[19].For image filtering, AMIDIF is capable of acquiring bidirectional impulses within the image signals, thereby improving fault feature extraction and mitigating background noise. Here, introduced a weighted reconstruction algorithm grounded in correlation analyses. This algorithm calculates weight coefficients to accentuate valuable filtered signals derived from MIDIF and diminish ineffective ones. Through this approach, AMIDIF enhances the clarity of images by emphasizing relevant details while minimizing irrelevant noise. The AMIDIF is used to filter out the designs that don’t match the research requirement. The scale ζ can be articulated as

$$\zeta G = G \oplus G \oplus \ldots \oplus G = ((G \oplus \ldots \oplus G) \oplus G) \oplus G \qquad (1)$$

Here , G denote the SE unit.

Basic morphological operators on several scales can be articulated as:

$$(P \oplus \zeta \oplus G)(n) = P \oplus (G \oplus G \oplus \ldots \oplus G) \qquad (2)$$

$$(P \Theta \zeta \Theta G)(n) = P \Theta (G \Theta G \Theta \ldots \Theta G)$$

(3)

$$(P \circ \zeta G)(n) = ((F \Theta \zeta G) \oplus \zeta G)(n) \qquad (4)$$

$$(P \bullet \zeta G)(n) = ((P \oplus \zeta G) \Theta \zeta G)(n) \qquad (5)$$

The following is an additional definition of the multi-scale black top-hat (MBTH) and multi-scale white top-hat (MWTH):

$$MBTH(P(n)_{\zeta G}) = (P \bullet \zeta G)(n) - P(n)$$

$$MWTH(P(n)_{\zeta G}) = P(n) - (P \circ \zeta G)(n) \tag{6}$$

Accordingly, positive impulses are obtained by applying the MWTH, and negative impulses are extracted using the MBTH. Given that the original signal had bidirectional impulses, the MIDIF can be written as follows:

$$MIDIF(P(n)_{\zeta G}) = MWTH(P(n)_{\zeta G}) - MBTH(P(n)_{\zeta G}) = 2P(n) - (P \circ \zeta G)(n) - (P \bullet \zeta G)(n) \tag{7}$$

The weighted average of the filter is given as

$$MIDIF(P(n)) = \sum_{\zeta=1}^{\zeta_{\max}} (\omega_{\zeta} \cdot MIDIF(P(n)_{\zeta G}))$$

(8)

Where, ω_{ζ} denote the weighted co-efficient under different scales.

Aside from being outliers within their design class, designs with skewed aspect ratios or with low number of elements were removed during pre-processing using AMIDIF. The pre-processed images are then sent to MHFAN for classification.

C. Classification by Multi-scale Hypergraph-based Feature Alignment Network

The 'Multi-scale Hypergraph-based Feature Alignment Network' is an advanced computational framework designed for enhancing feature alignment tasks across multiple scales within complex datasets [20].The image design categories infographics, mobile-UI, movie posters and webpagesare successfully classified using MHFAN. Leveraging hypergraph theory, MHFAN effectively captures intricate relationships among features, facilitating robust alignment across diverse contexts. By incorporating multiple scales, MHFAN accommodates the heterogeneous nature of data, enabling comprehensive feature representation and alignment. This approach ensures that both local and global characteristics of the data are effectively captured, leading to improved performance in various applications such as image recognition, natural language processing, and biomedical data analysis. MHFAN stands out for its ability to adaptively adjust to different data structures, making it a versatile tool for addressing feature alignment challenges across a wide range of domains.The feature map, represented by $F \in R^{C \times H \times W}$ is divided into nodes, or $C \times 1 \times 1$pixel blocks. Building on earlier research, enable the model to independently discover commonalities between node attributes in order to enhance its capacity to depict the interaction between cells and their surroundings. The following formula is used to calculate the learnable cosine similarity:

$$Sim(g_i, g_j) = \frac{(g_i w_i)(g_j w_j)^T}{\|g_i w_i\|_2 . \|g_j w_j\|_2} \tag{9}$$

Here , g_i indicates feature vector of V_i, and $\| \ . \ \|_2$ 2 indicates the L_2 norm w_i and w_j are learnable weights .The process of combining the learnable cosine similarity with the Euclidean distance to determine how similar the attributes of nodes is M_{sim} .However, that the different similarity measurements of node features might cause a disproportionately big discrepancy between M_{sim} and M_{dis}, It may cause one or both sides to lose the weighting effect. The use of Softmax function to normalize m_{dis} and m_{sim} in order to solve this problem. More precisely, turn both matrices into probability distributions by normalizing each row. This guarantees that the weighting effect of any matrix is maintained and that both matrices have the same value domain. Lastly, use the following formula to combine the normalised matrices and get the correlation matrix Co_Mat :

$$Co\_Mat = \mu \times m_{dis} + \nu \times m_{sim} \tag{10}$$

Where μ and ν are hyper parameters utilized to modify the distance matrix to similarity matrix ratio, as will be covered in subsection. After calculating the correlation matrix Co_Mat at, provide a construction process for a multi-scale hypergraph that records feature connections at different scales. Using convolutional approaches, this method connects each node's features to those of its neighbors by hyper edge connections. As a result, it modifies the multi-scale feature aggregation and creates new node features. Ultimately, the optimization of features by the dwHGCN tends to induce excessive smoothness, resulting in a notable decline in feature discriminability.

Use hypergraph convolutional architectures to transmit features within hypergraphs of various sizes. This technique combines the characteristics of each node with those of its neighbours to provide adaptive multi-scale feature aggregation and unique node features through the use of convolutional algorithms and hyperedge connections. This method enhances the model's interpretability and generalization capabilities. In particular, the hypergraph-optimized features are used as attention to optimize the original features. Here is an illustration of the process:

$$x^{out} = Sigmoid(MH(x^{in})) \cdot x^{in}$$

(11)

The MHFAN accurately classifies the image design categories as infographics, mobile-UI, movie posters and webpages. MHFAN typically does not offer the optimization methods needed to determine the best variables to validate a precise detection. In order for the optimization process to maximize the MHFAN weight parameters, it is necessary..

D. Optimization Using Elk Herd Optimizer

The EHO is theoretically modelled in the context of optimisation in this section. Generation after generation, the elks are bred to create a stronger herd capable of overcoming obstacles in their natural habitat[21]. This section maps optimization principles to the breeding process. The EHO is used to optimize the weight parameter of MHFAN.To connect the elk herds' breeding cycle with the optimization framework, seven procedural stages are suggested in the EHO mathematical model. We will go over these processes in detail. Figure 2 provides the EHO flowchart.

Step 1: Initialization

Initialize the input parameter which is the weight parameters of MHFAN which are denoted as W_i and W_j.

Step 2: Random Generation

The input parameter of a matrix is generated randomly.

$$EH = \begin{bmatrix} y_1^1 & y_2^1 & \cdots & y_m^1 \\ y_1^2 & y_2^2 & \cdots & y_m^2 \\ \cdots & \cdots & \cdots & \cdots \\ y_1^{EHS} & y_2^{EHS} & \cdots & y_m^{EHS} \end{bmatrix} \quad (12)$$

Where, y is the population of elk herd.

Step 3: Fitness Calculation

The fitness value is calculated by

$$Fitness\ function = Optimizing(w_i, w_j) \quad (13)$$

Where, w_i and w_j are the weight parametres of MHFAN.

Step 4: Rutting Season

Based on the bull rate during the rutting season, elk families are simulated to form. First, the overall count of families is ascertained. Next, grade the bulls in the Elk Herd according to their fitness values, placing the best-fitting elks (shown by numbing B) at the top of the Elk Hierarchy. The goal of this selection procedure is to replicate the difficulties of battling supremacy in the wild, where the strongest elks are given preference and are given more responsibility for leading harems within the herd..

$$\beta = \arg \min_{n \in (1,2,\ldots,d)} f(y^n) \quad (14)$$

Where, β is the set of bulls and d is the bull number.

The bulls y^n in β shall be given a selection probability and k_m determined by dividing its fitness value by the total of all bulls' fitness values.

$$k_m = \frac{f(y^n)}{\sum_{l=1}^{d} f(y^l)} \tag{15}$$

Step 5: Calving Season

During the calving season, the focus is on the calving season to facilitate the reproduction of calves within each elk family. This procedure is mostly dependent on characteristics that they got from their mother harem and father bull. When a calf shares the same index as its bull father within the family, a specific reproduction mechanism, as outlined in Eq. (16), is employed to ensure the accurate propagation of desired genetic traits.

$$y_m^n(t+1) = y_m^n(t) + \alpha \cdot (y_m^l(t) - y_m^n(t)) \tag{16}$$

Where, α denotes a random value in range of [0, 1]. Note that a higher value of α increases the chance that random components will be involved in the new calf, which improves diversification.If the calf's index matches that of its mother, it inherits the characteristics of its father, a bull, and its mother, a harem, as stated in Eq.(17).

$$y_m^n(t+1) = y_m^n(t) + \beta(y_m^{u_n}(t) - y_m^n(t)) + \gamma(y_m^r(t) - y_m^n(t)) \tag{17}$$

Where, r denotes the random bull in the current set ,the u_n is the bull of the harem and $y_m^n(t+1)$ denotes the attribute m of the calf n at iteration $t+1$,. Also, β and γ denote random values in the range [0, 2].

Step 6: Update the Best Solution

The process is finished if the best result is achieved.

Step 7: Termination

If the solution is the best, the procedure will terminate; if not, it will loop back to the step 3 fitness calculation and continue processing the subsequent levels until a solution is found.

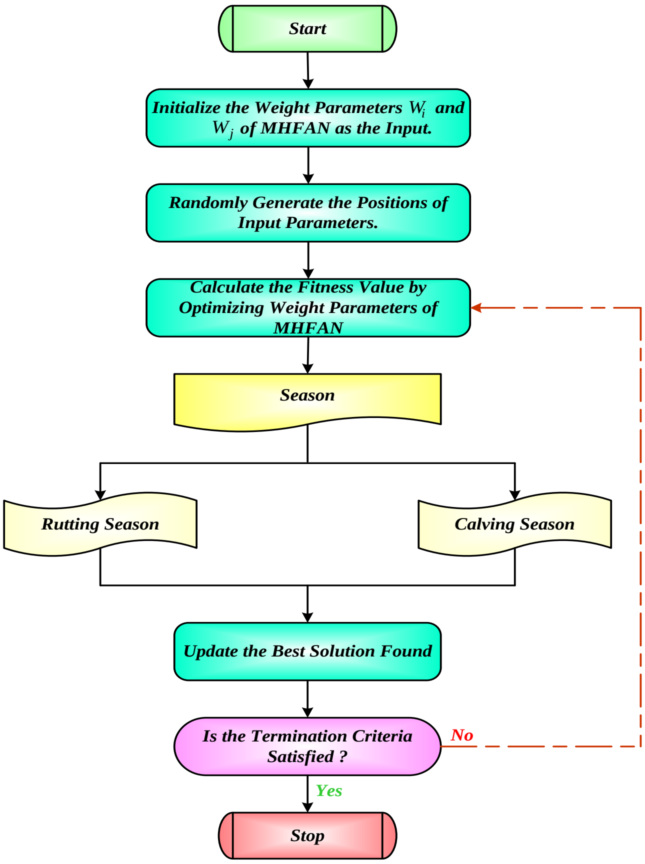

Figure 2: Flowchart of EHO

III. RESULTS AND DISCUSSION

The experimental result of intelligent assistant for graphic design creation using MHFAN-EHO method is discussed in this session. A Python working platform is used to replicate the suggested approach under various performance criteria. Outcome of IAGDC-MHFAN-EHO is compared with present techniques such as DoGDAS-AI-DL, TADD-AIAD, and DAIAFDS-StyleGAN2.

A. Performance Measures

The confusion matrix is determined in order to scale the performance metrics, which include accuracy, F1-score, sensitivity, precision and computation time. The True Positive (TP), True Negative (TN), False Negative (FN) and False Positive (FP) ,values are required in order to scale the confusion matrix.

1) Accuracy

It is the ratio of the entire count of predictions generated for a dataset to the count of exact forecasts. It is measured through equation (18).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{18}$$

2) F1-Score

F1-score is a metric used to analyze the performance of proposed IAGDC-MHFAN-EHO technique. It is computed in equation (19).

$$F1score = \frac{TP}{TP + \frac{1}{2}[FP + FN]} \tag{19}$$

3) Precision

A statistic called precision (P) counts the number of correctly produced positive predictions. This is computed via following equation (20).

$$P = \frac{TP}{TP + FP} \tag{20}$$

4) Sensitivity

A statistic called sensitivity (S) compares the overall count of correct positive forecasts to the overall count of correct positive forecasts. It is measured by following equation(21).

$$S = \frac{TP}{TP + FN} \tag{21}$$

B. Performance Analysis

Figure 3 to 7 shows the simulation outcomes of IAGDC-MHFAN-EHO. The findings are contracted with present DoGDAS-AI-DL, TADD-AIAD, and DAIAFDS-StyleGAN2 methods.

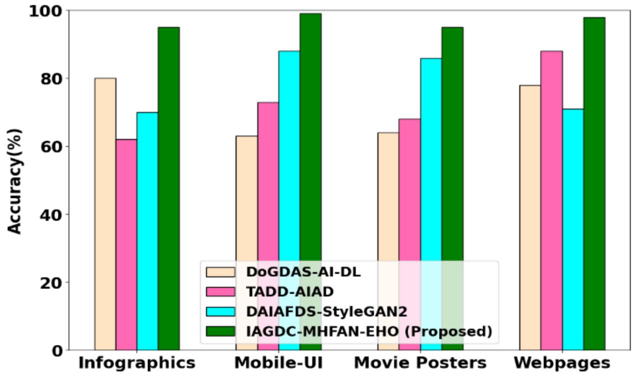

Figure 3: Comparison of accuracy between proposed and existing methods

The comparison of accuracy value between proposed and existing methods is displayed in Figure 3. The performance of the proposed technique results in accuracy that are 50.57%, 20.81%, 35.88% higher for the classification of infographics, 20.41%, 35.59%, 23.48% higher for the classification of mobile-UI, 21.44%, 30.73%, 18.41% higher for the classification of movie posters and 21.45%, 30.90%, 15.41% higher for the classification of webpages when evaluated to the existing DoGDAS-AI-DL, TADD-AIAD, and DAIAFDS-StyleGAN2 methods respectively.

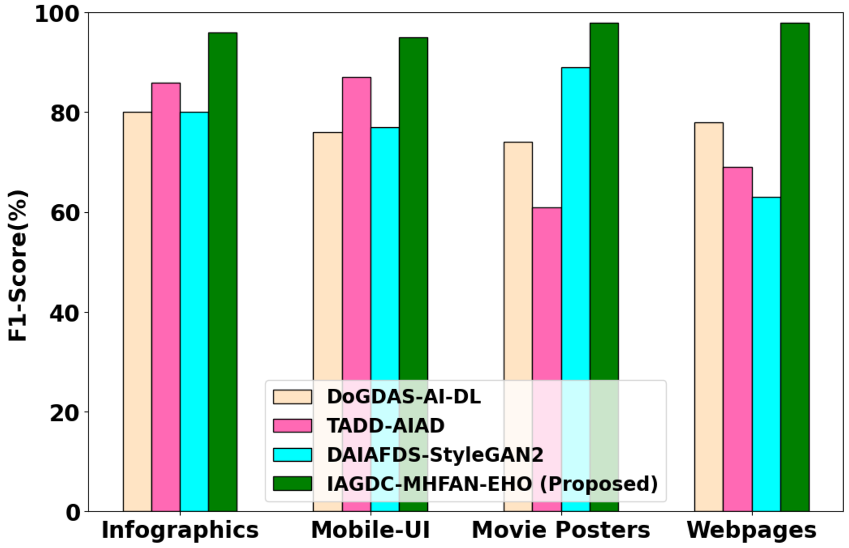

Figure 4: Comparison of F1-Score between proposed and existing methods

The comparison of F1-score value between proposed and existing methods is displayed in Figure 4. The performance of the proposed technique results in f1-score that are 22.47%, 21.76%, 33.97%, higher for the classification of infographics, 21.52%, 33.61%, 23.53% higher for the classification of mobile-UI, 21.49%, 30.70%, 18.37% higher for the classification of movie posters, and 20.48%, 30.84%, 15.44% higher for the classification of webpages when evaluated to the existing DoGDAS-AI-DL, TADD-AIAD, and DAIAFDS-StyleGAN2 methods respectively.

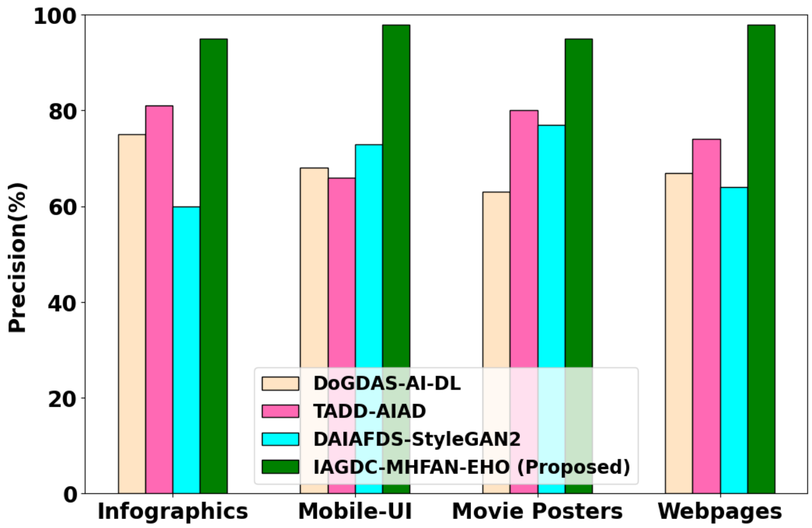

Figure 5: Comparison of precision between proposed and existing methods

The comparison of precision value between proposed and existing methods is displayed in Figure 5. Here, a direct comparison with existing methods is offered to show how the proposed method's precision is higher. The proposed method provides for a more extensive analysis and has higher precision than existing methods due to its wider consideration of factors. The performance of the proposed technique results in precision that are 30.58%, 21.71%, 35.86% higher for the classification of infographics, 21.48%, 33.57%, 23.53% higher for the classification of mobile-UI, 21.39%, 30.68%, 18.42% higher for the classification of movie posters, and 20.49%, 30.79%, 15.42% higher for the classification of webpages when evaluated to the existing DoGDAS-AI-DL, TADD-AIAD, and DAIAFDS-StyleGAN2 methods respectively.

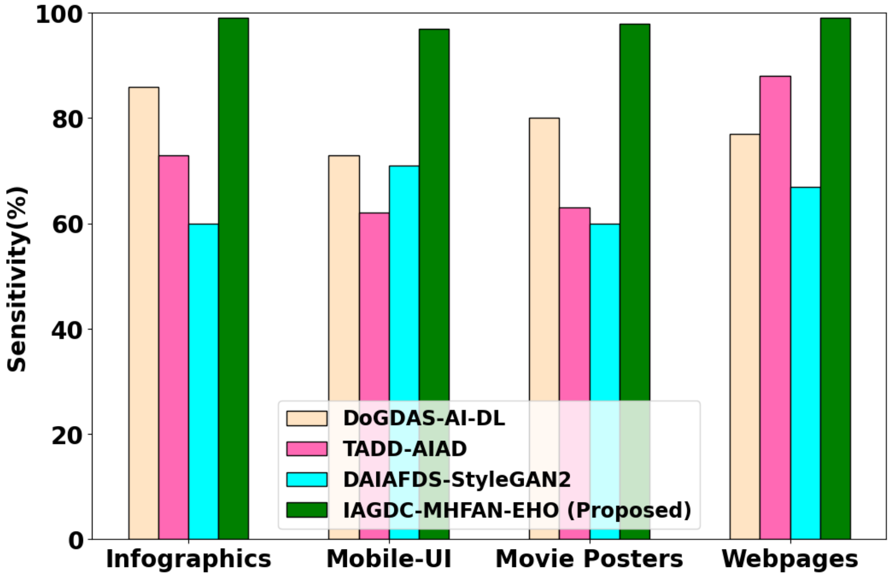

Figure 6: Comparison of sensitivity between proposed and existing methods

The comparison of sensitivity between proposed and existing system is displayed in Figure 6. The performance of the proposed technique results in sensitivity that are 23.48%, 22.75%, 31.88% higher for the classification of infographics, 22.38%, 31.63%, 22.55% higher for the classification of mobile-UI, 22.43%, 29.69%, 17.48% higher for the classification of movie posters, and 19.52%, 29.86%, 14.40% higher for the classification of webpages when evaluated to the existing ECTT-RNN, ECTT-DNN, and ECTT-MLPNN methods respectively.

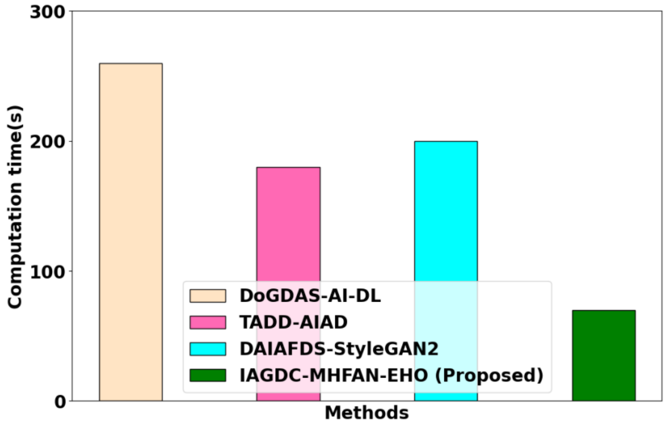

Figure 7: Comparison of computation time between proposed and existing methods.

The comparison of computation time between proposed and existing methods is displayed in Figure 7. The performance of the proposed technique results in computation time those are 38.96%,34.13%and 37.81% lower when constracted with present technique like DoGDAS-AI-DL, TADD-AIAD, and DAIAFDS-StyleGAN2 respectively.

IV. CONCLUSION

In conclusion, this research harnesses the Multi-scale Hypergraph-based Feature Alignment Network to develop an intelligent assistant for graphic design creation. An intelligent first step is data collection where the images are acquired from Imp1k dataset. During pre-processing, the Imp1k dataset is processed using the Adaptive Multi-scale Improved Differential Filter. The pre-processed data is fed to the classification where the Imp1k data is classified using Multi-scale Hypergraph-based Feature Alignment Network into infographics, mobile-UI, movie posters and webpages. The proposed technique is evaluated in python working platform and is compared to existing methods. The suggested approach is examined in a variety of scenarios, including those involving computing time, sensitivity, accuracy, precision, and F1-score.Future works encompass extending the technology's capabilities to generate intricate graphic designs, such as infographics, by integrating advanced algorithms for data visualization and layout optimization. Additionally, efforts will focus on addressing current limitations regarding diversity in design elements and fontface options, exploring techniques like style transfer and font synthesis to broaden the range of design possibilities and enhance creative expression.

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