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RESEARCH ARTICLE

AI Knows Aesthetics: AI-Generated Interior Design Identification Using Deep Learning Algorithms

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ABSTRACT The integration of Artificial Intelligence (AI) in interior design has revolutionized how spaces are conceptualized, visualized, and classified. As digital tools and generative design models become increasingly sophisticated, distinguishing between AI-generated and real-world interior design images has emerged as a critical challenge. This classification is essential for ensuring authenticity in design visualization, improving recommendation systems, and enhancing virtual and augmented reality applications in architectural planning. Convolutional Neural Networks (CNNs) have proven to be highly effective in image classification tasks due to their ability to learn complex spatial hierarchies, making them particularly well-suited for differentiating between AI-rendered and real interior spaces. However, recent advancements in deep learning, including hybrid AI models and transformer-based vision networks, have further enhanced classification accuracy by integrating multimodal learning techniques. This study explores the use of advanced pre-trained CNN models, including DenseNet, RegNet, and SqueezeNet architecture, to classify interior design images. By leveraging a proprietary dataset composed of diverse AI-generated and real-world interior designs, our model achieved a peak classification accuracy of 97%, demonstrating superior performance compared to traditional deep learning techniques. Additionally, we introduce a novel image preprocessing technique that enhances feature extraction by adjusting lighting, texture, and noise levels, thereby reducing discrepancies between AI-rendered and real images. The results indicate that AI approaches, CNNs, hold immense potential for further improving classification robustness. This study contributes to the growing field of AI-driven interior design classification by presenting a high-accuracy model capable of distinguishing between real and AI-generated environments with unprecedented precision.

INDEX TERMS Artificial intelligence, classification, convolutional neural network, deep learning, feature extraction, interior design.

I. INTRODUCTION

The advent of artificial intelligence (AI) has revolutionized numerous industries, with the field of interior design being no exception. AI-based technologies, particularly those employing convolutional neural networks (CNNs), are now at the forefront of classifying and analyzing interior design images [1]. This process involves determining whether images of interior spaces are digitally rendered or photographed from real-life scenarios [2]. Such classification helps in numerous aspects, including the validation of design authenticity, enhancement of design recommendation systems, and the improvement of virtual reality (VR) experiences in interior design planning [3].

Multi-faceted is the significance of lying in classifying the interior design images using the AI. In such an image intensive industry, the ability to differentiate between real and AI generated image is critical to prevent the decisions from being taken based on inaccurate visual information by designers, stakeholders and clients [4]. In addition, this

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classification assists in the creation of more advanced AI tools for generating effective interior design renderings that are not very distinguishable from the original photographs [5]. It is this capability that professionals relying on making designs visual and revising before actual implementation will need to use to cut down time, resources, and get client approvals [6]. Deep neural networks are chosen well for image recognition tasks as they process data on a grid, which is the way it is defined in an image [7]. CNNs are used for visual information analysis and training unique features based on large interior image datasets that they can use to identify accurate interiors as either real or not [8]. Not only does this add further reliability to digital assets found in design portfolios, but it also adds to the analytical skill of designers regarding the understanding of and application of design trends [9].

In the digital age, the interior design trends have taken a bright forward not only as a tool but as a part of the design process itself, as shown in figure 1. Advancements in 3D modeling and virtual reality allow designers to currently create and show more sophisticated and customized designs to match in fashion and requirements of recent clients [10]. High end design aesthetics have democratized themselves AI powered tools, they can be reached out by anyone. The accessibility on this site encourages the continuous evolution of design styles that are fed from global trends and learned cultural nuances to the AI analytics [11]. The latest advancements in this field are only becoming more and more heightened as technology continues to expand [12]. These classification and simulation are still far from being accurate and realistic, however, given that they continue to enhance their AI algorithms, they may soon become more accurate and realistic [13]. Such progress could change how designers and clients create space, and one that more is immersive and interactive. [14] Additionally, AI's involvement in the creative fields such as interior design is unlikely to stop soon as the digital creations will increasingly lead into actual life applications, blurring the line even more between the digital and real world [15].

In this study, our main aim is to classify interior design images to determine whether the ideas and work presented are generated by AI-based tools or derived from real-world environments. To achieve this, we utilize our proprietary dataset, which comprises a diverse collection of interior design images. This data set serves as the foundational element for training and validating our approach, which leverages advanced pre-trained models of CNN. By applying these sophisticated AI models, we intend to accurately identify and differentiate between AI-generated and real interior design images, thus providing a reliable tool for industry professionals and researchers alike.

- Examined an advanced CNN architectures for interior design image classification, we adopted an innovative CNN model and a hybrid architecture – using a CNN model and the ablation SqueezeNet. Evaluation based on DenseNet and RegNet were implemented to compare the strength on what can do in complex image classification tasks.
- Using CNN model, we able to achieve 97% accuracy compared to traditional architecture. And this shows how powerful modern deep learning techniques can solve the problem of interior designing image classification to improve the ability and speed of classification

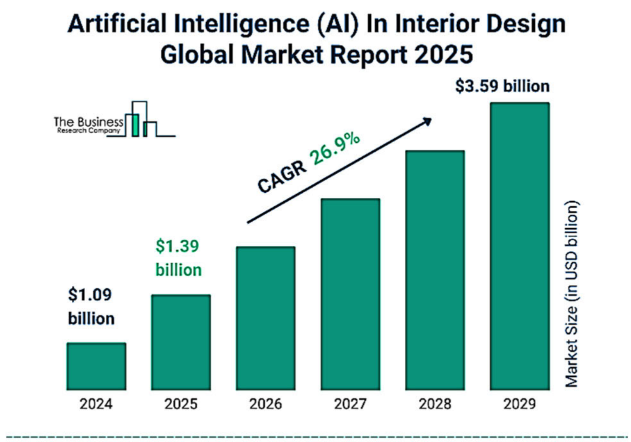

FIGURE 1. Analysis of AI-based interior design trend[1].

II. RELATED WORK

Recently, due to the growth of machine learning, deep learning, and transformer vision, classification of the interior design images has been a hot topic. Various research on different methods to improve the accuracy and efficiency of such classifications.

A. DEEP LEARNING

Theories of such a method using the Generative Adversarial Networks (GANs), Spatial Transformer Networks for replacing the virtual furniture in the interior design images have been proposed by Vijaykumar et. al [16] proposed model demonstrated enhanced visual accuracy, which was used by the designers to render real interiors. Vo and Nguyen [17] introduced a transformer-based framework to classify interior style from textual and visual information found that transformer architectures are superior to the conventional machine learning algorithms such as CNN networks, when we are working on image classification. Multi modal fusion evaluation mechanism based on deep learning in interior design assessment is then presented by Fan et al. [18]. Specifically, they used transformer encoder – decoder to process both textual and visual data and achieved better classification accuracy. In the same way, Elbadrawy [19] also explored the indoor scene synthesis using transformer models and gives

[1] https://www.thebusinessresearchcompany.com/report/artificial-intelligence-ai-in-interior -design-global-market-report

TABLE 1. Summary of deep learning based models.

Ref	Year	Model	Dataset	Classes	Research Area	Limitation	Result Acc (%)
[16]	2024	GAN + Transformer	Virtual furniture dataset	2	Virtual Furniture Replacement	Limited dataset diversity	92.5
[17]	2024	Transformer-based framework	Interior style dataset	5	Interior Style Classification	Requires large computational power	94.8
[18]	2024	Transformer Encoder-Decoder	Multi-modal interior dataset	3	Interior Design Evaluation	Limited real-world testing	90.7
[19]	2021	Transformer-based Scene Synthesis	Synthetic interior images	4	Scene Synthesis	Synthetic data realism issues	89.3
[20]	2024	CNN	Interior design image set	2	Design Recognition	High dependence on training data	93.6
[21]	2023	Vision Transformer	AEC vision dataset	3	AEC Industry Applications	Transformer models require large datasets	91.2
[22]	2024	Fine-tuned ML Model	User-preference style dataset	4	Spatial Visualization	User bias in dataset	95.1
[23]	2024	Vision Transformer Segmentation	Floor plan dataset	5	Floor Plan Analysis	Complexity in segmentation tasks	90.5
[24]	2022	DNN, DenseNet	Urban & indoor space images	3	Sentiment Analysis	Sentiment accuracy variability	88.7
[25]	2024	GAN + Transformer	Multimodal interior dataset	6	Scene Generation & Recognition	High training time and data requirement	96.3

a new solution for generating realistic interior design that benefit architects, interior designers.

For interior design recognition, Lee et al. [20] used high-performance image recognition models. In their study, they pointed out that advanced classification methods are required to improve design evaluation. In [21], Rane goes on to explore the use of vision transformers in architecture, engineering, and construction, in object detection and automated design evaluation. Lee et al. [22] address the spatial visualizations by fine tuning interior design style models based on user's preference. In architectural design processing, automatic floor plan analysis using a vision transformer as an advancement over the previous method led by Goonathilake and Thanuja [23] to be more efficient. In this work, 2D urban and indoor space images are performed to analyze sentiments using deep learning architectures, following Chatzistavros et al. [24]. They demonstrated how transformer models can learn what users prefer and what aesthetics are good for. Finally, Kassab et al. [25] construct a multimodal dataset (MMIS) for interior scene visual generation and recognition through GANs and transformer models in the purpose of enhancing machine learning applications for interior design. Table 1 defines the deeper understanding of existing studies to highlight the research gaps.

B. HYBRID LEARNING BASED APPROACHES

Advancements in artificial intelligence have made interior design more influenced recently and it is done through hybrid AI ambits that mesh deep hijacking, machine learning. Table 2 defines the deeper analysis of existing studies for deeper insights.

Sonpol and Khalifa [26] gave a comprehensive and review of AI based tools for generating alternative interior space design using accuracy improvements of classification and regression based on smart designing applications. As in Ko et al. [27], hybrid AI approaches are investigated into architectural spatial layout planning, which tries to train complex kitchen layouts to optimize interior planning using AI based models. Moreover, how ecological ideas can be embedded into smart interior environments through the new representations for hybrid conformal prediction algorithms in the works of Xu et al. [28]. As shown by Almusaed et al. [29], integration of expert systems and machine learning in smart home interior design is the hybrid AI method which enhances the living space optimization. To aid this process, hybrid AI was proposed for enhancing the aesthetic coherence by Long [30], in the context of the interior designs for vehicle of new energy, specifically focusing on the color selection. Park et al. [31] achieved AI driven dataset for architectural spatial layout generation, establishing a solid ground for automated design generation by the combination of artificial intelligence.

Yitmen et. al [32] also did another critical study of AI based simulation models and digital twins for smart building design and provided more direction of new insights of AI driven architecture. Applications of AI in engineering design have been reviewed by Yüksel et al. [33] who put an emphasis on the increasing hybrid intelligence using neural networks, fuzzy logic and evolutionary algorithms. This entails integrations of GAN techniques to create thousands of external as well as interior design variations through a process termed as the AI powered computational design process (AI-ACD), which Ali and Elzeni [34] proposed. Milošević et al. [35], [36] finally investigated artificial intelligence aided conceptual design process in architecture by categorizing hybrid intelligence approaches, which uses human input combined

TABLE 2. Summary of hybrid learning based models.

Ref	Year	Model	Dataset	Classes	Research Area	Limitation	Result in Acc (%)
[26]	2024	CNN, EfficientNet	Interior Space Design	3	Interior Space Design	Limited adaptation to real-world cases	91.4
[27]	2023	Hybrid AI-ASLP	Architectural Layouts	4	Architectural Planning	Computationally expensive	92.7
[28]	2021	Hybrid CNN	Indoor Environmental Art Data	5	Indoor Environmental Design	Subjective design considerations	90.8
[29]	2023	Inception v3	Smart Home Living Spaces	2	Smart Home Design	Requires large, annotated datasets	93.2
[30]	2024	MobileNet, DNN	New Energy Vehicle Interiors	3	Interior Aesthetic Optimization	Domain-specific application	89.9
[31]	2024	RegNet, CNN	Architectural Spatial Layout	4	Spatial Layout Automation	Complex data preprocessing	94.3
[32]	2023	3D CNN	Smart Building Simulation Models	5	Smart Building Concepts	Model generalization issues	92.1
[33]	2023	Hybrid Neural Networks & Fuzzy Logic	Engineering Design	3	Engineering AI Applications	Hybrid AI requires tuning	90.5
[34]	2024	GAN-based AI-ACD	Computational Design Workflow Data	6	Computational Design Generation	High computational demand	95.6
[35]	2023	ResNet	Conceptual Design Optimization Data	4	Conceptual AI-Assisted Design	Human-AI interaction complexity	91.8

with AI generated optimizations. Together, these represent great progress in the artificial intelligence driven interior design classification, pinpointing the superiority of the deep learning and transformer model in terms of visual accuracy and classification reliability.

Using analysis of Tables 1 and 2, a summary of the existing literature is given based on deep learning and hybrid learning models used in different domains including interior design, spatial planning and aesthetic optimization. Nevertheless, there is a large critical gap in this area between the comparative evaluation of convolutional-based architectures for interior design classification: based on real world datasets, with diverse architectural representation, and specifically designed class specific performance measures. Most of the cited studies mostly investigate generalized tasks like object detection, scene synthesis, or sentiment recognition using domain-specific datasets with a small domain of interest or basing themselves on synthetic images (e.g. [16], [19], [21]). Besides, GANs, Vision Transformers, or DenseNet are also promising, to be used because they require high computational costs, being dependent on annotated datasets or even bias in training data, so they are not scalable within practical interior design applications. That is, this study highlights the importance of low robust, adaptive and high performing models for realistic design classification task.

This gap is addressed by novel CNN based model for real and generated interior design classification using high accuracy and low computation efficiency. Unlike previous methods, the proposed model was tested against existing benchmarks, and additionally against state of art models like RegNet, DenseNet and Squeeze Net under a same framework (Table 5). In terms of accuracy, precision, recall, and F1 score, the model was best and surpassed all other models by 97% on all metrics (i.e., 97%). In addition, while previous works did not provide a fine-grained comparative performance, our work contributes a fine-grained evaluation against multiple model variants and sheds light on the class specific performance behavior. This in addition, contributes to the methodological novelty of this research with the inclusion of hybrid and ablation-based comparisons. The contribution of this work is thus not only to close a key research gap, but also to provide a practical, scalable approach to interior design classification which does not just set new standards of scope, but also execution.

III. PROBLEM STATEMENT

The increasing sophistication of AI-generated interior design images has made it challenging to differentiate between real and synthetic environments. It can lead to misclassification that influences the design authenticity, the recommendation systems and the accuracy of virtual visualization. We can formulate the problem as a binary classification problem, whether the design image I generated by an AI ($y= 0$) or not AI-generated ($y= 1$) based on label y. Based on dataset $D= \{ (I_i, y_i)\}_{i=1}^{N}$, our objective is to learn a mapping function $f : I \rightarrow y$ to minimize the classification error. We are adapting a deep learning model such as CNN or hybrid architecture based on AI to fit the parameters Ø so that L loss function $-\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\dot{y_i}) + (1 - y_i)\log(1 - \dot{y_i})]$ for the probability of predicted image belonging to the real category is minimized $f\,(I_i; Ø)$. It generalizes well across arbitrary interior design styles, lighting conditions and rendering techniques, and the goal is to train f such that it performs well across all

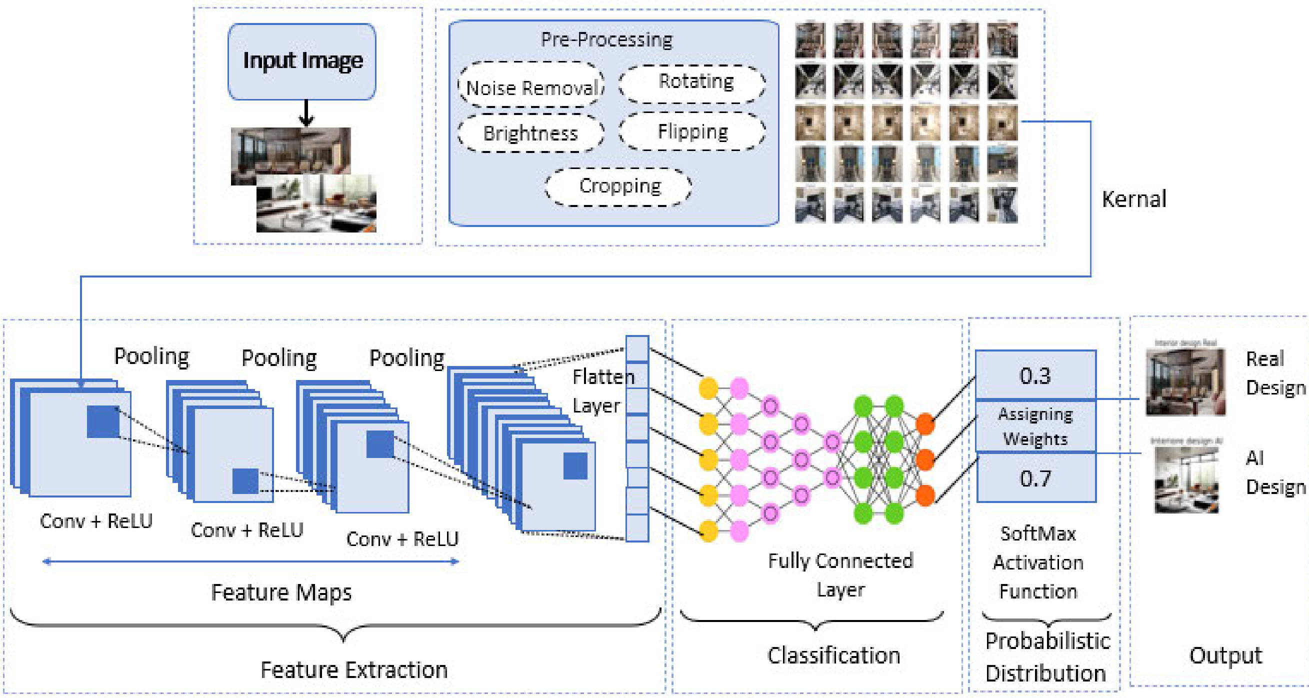

FIGURE 2. Framework of research proposed methodology.

these varying design styles, lighting conditions and rendering techniques.

IV. RESEARCH METHODOLOGY

To classify interior design images as either real world or generated by an AI, a robust and systematic approach to the deep learning and data processing needed must be taken. Then, pre-trained Convolutional Neural Networks (CNNs) and hybrid AI architecture are used to improve classification accuracy of this study, as shown in figure 2. The method is a process having three main stages: preparing the dataset, preprocessing the data and conducting model training with optimization.

A. DATA COLLECTION AND PREPROCESSING

A proprietary dataset was curated, which included a mixed picture of AI generated and true interior design images. As you can see, style, condition of lighting, texture and resolution of image varies from image to image to test the model generalization. Several types of preprocessing were applied to improve classification robustness and prevent overfitting, as sample images shown in figure 3. Then, all images were resized to have all the same resolution as 224 pixels by 224 pixels. Finally random horizontal and vertical flipping was used as an image augmentation technique to add variability in spatial orientation. Simulated variating conditions of the lighting were applied as brightness adjustment and Gaussian noise was added to make the model more robust to distortions. On top of that, images were randomly rotated within some angle range $\left[-15^o, 15^o\right]$ to deal with different viewpoints in the real world.

B. PROPOSED MODEL

To classify interior design images as real or AI-generated, we propose a deep learning model based on CNN. The architecture consists of multiple convolutional layers, activation functions, pooling layers, and fully connected layers to extract hierarchical spatial features and perform accurate classification [37].

1) INPUT LAYER

Takes in the raw image data in the form of a tensor of shape H, W, C.

2) CONVOLUTIONAL LAYER

Max pooling is used to down sample the feature maps and keep important features and it pools down spatial dimensions, defined in equation 1.

$$F_l^{(i,j)} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I_{l-1}^{(i+m,j+n)} W_l^{(m,n)} + b_l \tag{1}$$

$F_l^{(i,j)}$ represents the feature map at position (i, j), $W_l^{(m,n)}$ is the filter of size (M, N), and b_l is the bias term.

3) ACTIVATION FUNCTION

Flattened Pooled Feature Maps (i.e. after flattening the pooled feature maps to a vector representation) followed by a fully connected layer which performs classification using equation 2:

$$A_l = \max(0, F_l) \tag{2}$$

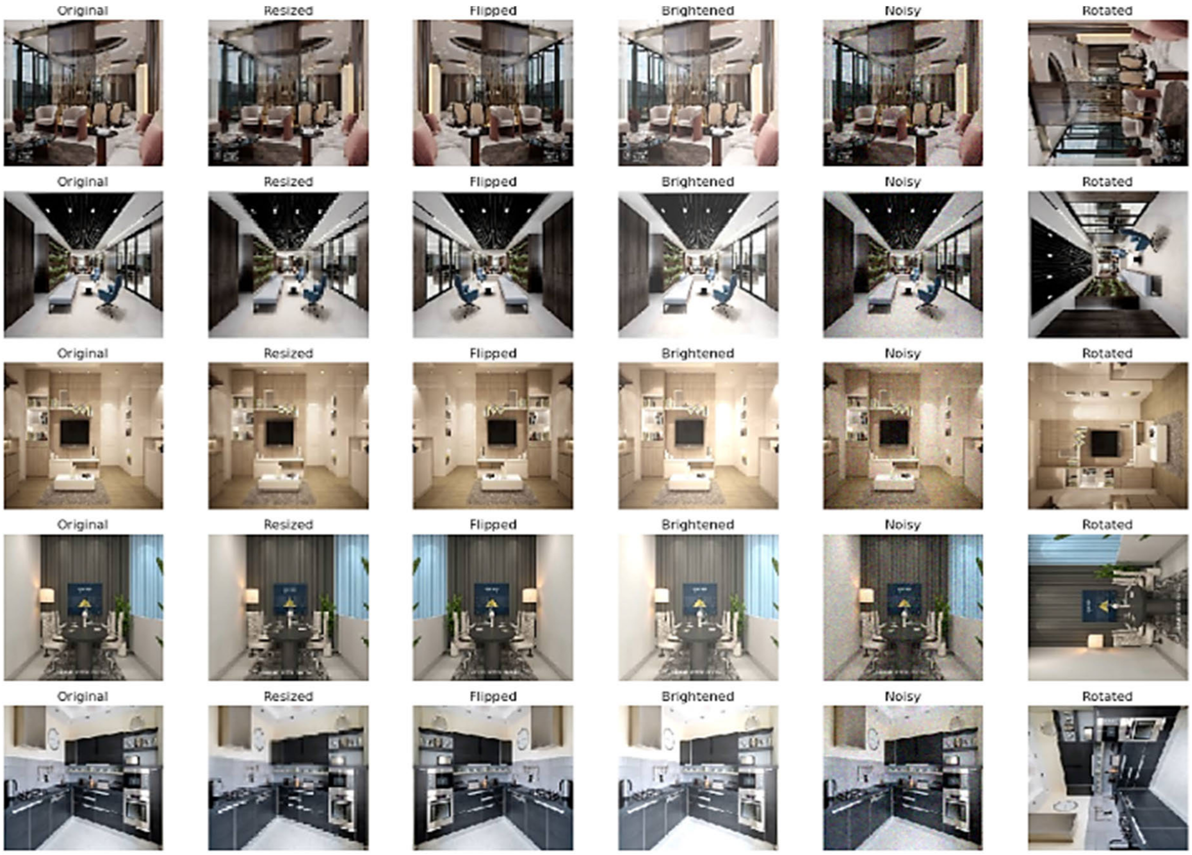

FIGURE 3. **Samples images of preprocessing steps.**

4) POOLING LAYER

To compute the class probabilities of the final output using the SoftMax function, defined in equation 3.

$$P_l^{(i,j)} = \max_{m,n\epsilon k\times k} A_l^{(i+m,j+n)} \tag{3}$$

k is the pooling window size

5) FULLY CONNECTED LAYER

After flattening the pooled feature maps into a vector representation z, a fully connected layer performs classification using equation 4.

$$Z = W_f A + b_f \tag{4}$$

W_f and b_f are the weight and bias terms for the fully connected layer.

6) SOFTMAX OUTPUT LAYER

The final output is generated using the function to compute class probabilities, defined in equation 5:

$$\hat{y}_i = \frac{e^{Z_i}}{\sum_{j=1}^{C} e^{Z_j}} \tag{5}$$

C is the number of classes, is the predicted probability of an image being real or AI-generated.

7) OPTIMIZATION AND LOSS FUNCTION

The training of the model is done using the cross-entropy loss function, defined in equation 6.

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log\left(\hat{y}_i\right) + (1-y_i)\log\left(1-\hat{y}_i\right)\right] \tag{6}$$

y_i is the ground truth label, and N is the total number of samples

C. HYPERPARAMETER SETTINGS

The proposed CNN model is trained using the Adam optimizer with a learning rate, batch size, and epochs by early stopping to prevent overfitting. Fully connected layers are dropped out to increase generalization and batch normalization is also used after each convolutional layer to stabilize learning and accelerate convergence. Backpropagation is used to optimize the loss function of cross-entropy. These hyperparameters explicitly defined in table 3, are evaluated using measures Accuracy, precision, recall and F1-score to assess robust classification for interior design images.

D. BASELINE MODELS

To enhance the classification of interior design images, transfer learning was employed using state-of-the-art pre-trained deep learning models, specifically RegNet and Dense Net, as baseline models. Transfer learning enables the adaptation of models pre-trained on large-scale image datasets, such

TABLE 3. Hyperparameter settings of proposed model.

Parameter	Description	Values
Batch Size	Number of samples processed per iteration.	32
Kernel Size	Size of convolutional filters.	3x3
Number of Filters	Number of convolutional filters per layer.	64, 128, 256 (varies per layer)
Number of Layers	Number of convolutional and fully connected layers.	31 (including CNN and FC layers)
Pooling Type	Type of pooling operation used.	Max Pooling
Pooling Size	Size of pooling window	2x2
Stride	Step size for moving convolution filter.	1 or 2
Activation Function	Type of activation used in the model.	ReLU - Final SoftMax
Optimizer	Algorithm to adjust model weights.	AdamW
Epsilon	Small value to prevent division by zero.	1.00E-05
Dropout Rate	Probability of dropping a neuron during training.	0.1
Epochs	Number of complete training iterations.	100
Image Size	Size of input images.	512 x 512
Learning Rate	Step size for updating model weights.	0.00005
Beta 1	Momentum parameter for optimizer updates.	0.9
Beta 2	Momentum parameter for optimizer updates.	0.999
Weight Decay	Regularization to prevent overfitting.	0.01
Dropout in FC Layers	Dropout applied in fully connected layers.	0.1
Batch Normalization	Normalization technique used.	Yes
Horizontal Flip	Randomly flips image horizontally during training.	True
Brightness Range	Randomly adjusts image brightness during augmentation.	0.2 to 0.4
Patience	Number of epochs without improvement before stopping.	3
Weight Initialization	Method for initializing weights.	Xavier Initialization
Regularization	Techniques to prevent overfitting.	Batch Norm, Dropout
Number of Parameters	Total trainable parameters in the model.	High (~50M - 85M)

as ImageNet, to our specific classification task, significantly improving performance while reducing computational costs and training time.

The architecture *Regularized Convolutional Network (RegNet)*is a highly scalable and efficient convolutional network dedicated for the best computational performance. This approach then optimizes the depth, width, and group convolutions with a structured approach to designing neural networks. RegNet provides fine grained textures, lighting and placement of objects which are suitable for interior design classification to differentiate real from the artificial generated images [38]. It has a well-defined design space on which systematically explore the network parameters, as opposed to performing random architecture search based on its stem convolutional layer (3 × 3 kernels) and several stages, each with a succession of bottleneck residual blocks, For dimensionality reduction, there is a 1 × 1 convolution; for feature extraction (and a reduction in spatial dimensions), a 3 × 3 group convolution and dropout with a batch normalization and ReLU; for spatial dimensionality expansion, a 1 × 1 convolution.

Furthermore, Squeeze-and-Excitation (SE) modules are incorporated with the blocks to improve its sensitivity to the crucial channel-wise feature, as this is essential when distinguishing such fine details as texture fidelity, color harmony, lighting consistency, and geometric realism to differentiate real designs from AI generated designs. The model is trained using Adam optimizer with categorical cross entropy loss function. Dynamically adjusting learning rates with a learning rate scheduler, the generalization is enhanced through random rotation, flipping and color jittering. In the final layer where a softmax activated function, it outputs the probability distribution, i.e. the probability distribution over the target classes.

For inference the model learns hierarchical visual representations between the low and the high-level structural features, that enable it to distinguish between real and synthetically generated interior design images. In this study, the model's capabilities of building an applicable model to handle large scale image classification tasks offers it as a strong fit for feature extraction. *DenseNet (or Densely Connected Convolutional Network)* fixes gradient flow and parameter efficiency by means of dense connectivity among layers. Unlike traditional CNNs, the DenseNet layer receives input from all the layers above it. This architecture reduces the number of parameters needed to train as well as reduces redundant feature learning, whilst increasing feature reuse [39]. DenseNet proves to be very useful for interior design image classification, as the ability to preserve the fine spatial details and textures of the images is very helpful when classifying the real images from AI generated ones, that mostly is determined by minute differences in material realism, proper lighting, and object sharpness.

SqueezeNet is a deep learning architecture that fits into small device on which it is deployed with high accuracy while reducing the usage of memory and computational resources as much as possible [40]. SqueezeNet is a variant of deep CNN by using Fire module which having squeeze and expand layers reduce the number of parameters while maintaining the powerful feature extraction ability.

The core innovation in SqueezeNet is the Fire Module which is a squeeze layer (1 × 1 convolution to reduce channels) and then an expand layer with the 1 × 1 and 3 × 3 convolutions to learn spatial features. The mathematical definition of the Fire Module is as follows in equation 7 and 8:

$$F_{squeeze}^{(i,j)} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I^{(i+m,j+n)} W_{squeeze}^{(m,n)} + b_{squeeze} \tag{7}$$

$$F_{expand}^{(i,j)} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} F_{squeeze}^{(i+m,j+n)} W_{expand}^{(m,n)} + b_{expand} \tag{8}$$

$F_{squeeze}$ represents the reduced feature map after the squeeze operation.
$W_{squeeze}$, and W_{expand} are the weight matrices for the squeeze and expand layers, respectively.
$b_{squeeze}$, and b_{expand} are the corresponding biases.
SqueezeNet reduces the number of parameters dramatically compared with the fully connected layers by using global average pooling, defined in equation 10:

$$Z_{avg} = \frac{1}{WH} \sum_{i=1}^{W} \sum_{j=1}^{H} F_{expand}^{(i,j)} \tag{9}$$

W and H are the width and height of the feature map.

Also, fine-tuned SqueezeNet, RegNet and DenseNet on the interior design dataset as baseline models to compare with our proposed CNN architecture, also hyperparameters defined in table 4. These transfer learning models acted as strong benchmarks for using, so that the images for classification frameworks would benefit from previously learned image representations, while still optimizing model accuracy and robustness.

Different deep learning architectures are compared in model comparison since the performance, computational efficiency and the applicability of the deep learning architecture for classifying AI generated and real interior design images, display in table 5. Each model selected based on the architecture properties and how relevant it is to the problem domain. DenseNet was chosen since it is based on the dense connectivity mechanism that encourages feature reuse and efficient gradient flow, thus allowing for deeper networks with less parameters. It has the problem that its computational complexity and memory requirements may be a problem when the environment is constrained.

As due to scalable and regularized design space (well defined depth, width, and group convolution parameters), good performance is forthcoming with architectural flexibility. Specifically, SqueezeNet was selected among other lightweight models because it was able to achieve comparable classification accuracy with much smaller parameter count. This is done with its use of Fire modules, having squeeze (1×1) and expand (1×1 and 3×3) convolutions which drastically cuts the model size down, while retaining representational efficiency.

As a result, SqueezeNet is well suited for real time applications and deployment in memory limited systems. It was finally custom designed of the Proposed CNN model with target domain specific visual features that were applied in the interior design classification dataset leading to an accuracy and computational efficiency trade off suitable to

TABLE 4. HYperparameter settings of pre-trained model.

Parameter	Squeeze Net	Dense Net	RegNet
Batch Size	64	32	32
Model Depth	Lightweight Fire Modules	Deep Dense Blocks (e.g., 121)	Varies (e.g., RegNetY-4GF)
Input Image Size	224 x 224	224 x 224	224 x 224
Activation Function	ReLU - Final Softmax	ReLU - Final Softmax	SiLU (Swish)
Optimizer	Adam	AdamW	SGD with momentum
Learning Rate	1e-3	1e-4	0.05
Dropout	0.2	0.3	0.2
Weight Initialization	Xavier Initialization	He Initialization	Kaiming Initialization
Regularization	Dropout, L2 Regularization	BatchNorm, Dropout	BatchNorm, Dropout
Training Epochs	100	100	100
Epsilon	1.00E-05	1.00E-04	1.00E-06
Beta 1	0.9	0.9	0.9
Beta 2	0.999	0.999	0.999
Width and Height Shift	0.2 to 0.3	0.2 to 0.3	0.2 to 0.3
Horizontal Flip	True	True	True
Brightness Range	0.1 to 0.4	0.2 to 0.4	0.2 to 0.4
Contrast Adjustment	No	Yes	Yes
Patience	3	3	5
Attention Mechanism	No	No	No
Feature Extraction	Fire Modules	Dense Feature Maps	Bottleneck Residual Blocks
Number of Parameters	Low (~1.2M)	High (~8M to 30M)	High (~16M to 80M)
Gradient Clipping	No	Yes	Yes
Parameter Sharing	Yes	No	No
Skip Connections	No	Yes (Dense Connections)	Yes (Residual Connections)
Weight Decay	0.0005	0.01	0.0001
Kernel Size	1x1, 3x3 (Fire Modules)	3x3	3x3
Pooling Type	Global Average Pooling	Max Pooling	Max Pooling
Number of Filters	Variable (Small Fire Modules)	Increasing (32, 64, 128...)	Varies (per RegNet variant)
Stride Convolutions	Yes	Yes	Yes
Parameter Efficiency	Very High	Moderate	High
Epoch	100	100	100

the dataset. The hybrid CNN model minimizes computational complexity while enhancing performance metrics such

TABLE 5. Comparison analysis of all models.

Model	Working Nature	Strengths	Limitations
DenseNet	Utilizes dense connections where each layer receives inputs from all previous layers.	Efficient gradient flow; feature reuse; mitigates vanishing gradient problems.	Computationally intensive; increased memory usage due to feature concatenation.
RegNet	Employs a regularized network design with quantized linear parameterization of depth and width.	Scalable, efficient, and hardware-friendly; balances performance and complexity.	Hyperparameter tuning required; complexity increases with larger variants.
SqueezeNet	Uses Fire modules (squeeze + expand) to reduce parameters while maintaining accuracy.	Very lightweight; faster inference; suitable for mobile/embedded applications.	May underperform on complex tasks; limited representation capacity.
Proposed CNN	Custom architecture with convolutional and pooling layers tailored for design classification.	Optimized for task-specific features; flexible design; good balance of accuracy and speed.	May lack generalizability; performance heavily reliant on dataset tuning.

as accuracy and speed. To handle very realistic AI generated image, the model makes use of advanced feature extraction techniques in combination with training datasets that close to the realness difference between real image and AI generated image. The model uses a convolutional combination of pre-trained weights to work on detecting and classifying AI generated features with very high accuracy.

In addition, regularization techniques and data augmentation enhance model generalization ability, according to which the model can discriminate between authentic and fake images that are somewhat realistic. This combination results in a more balanced trade-off between model size and effectiveness, making it suitable for resource-constrained environments where DenseNet and RegNet may not be as efficient.

E. PERFORMANCE MEASURES

In evaluating a model's performance on dataset, key metrics are applied as shown in figure 4:

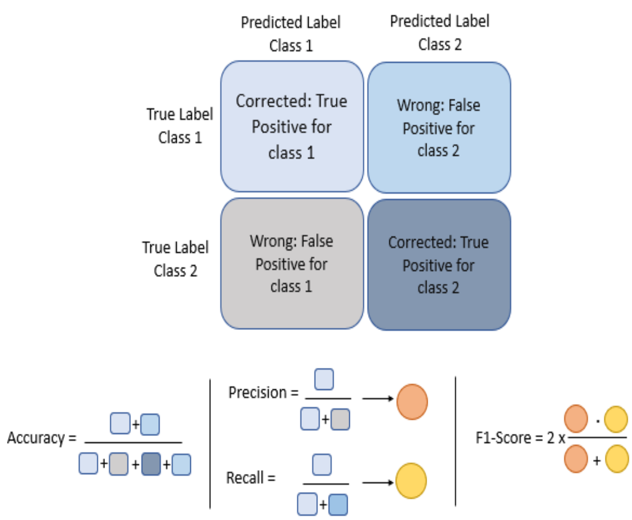

FIGURE 4. Analysis of evaluation measure.

V. RESULTS AND DISCUSSION

This section achieves performance evaluation of the proposed CNN-SqueezeNet hybrid model against baselines including DenseNet, RegNet, and SqueezeNet. The effectiveness of each model for the distinction between AI generated and real interior design images were assessed by using the classification accuracy, precision, recall and F1-score, comprehensive sketch of results shown in table 6.

A. RESULTS WITH PROPOSED MODEL

The performance evaluation of the proposed CNN model demonstrates high predictive power and strong generalizability in classifying interior design images as either AI-generated or real. The classification report, confusion matrix, accuracy over epochs, loss trends, and computational efficiency provide a comprehensive assessment of the model's effectiveness.

The results show that the model has an accuracy of 97% and corresponding precision, recall and F1 score values also of 97 whenever AI generated or real images. Analysis suggests that the model manages to achieve an extremely low misclassification rate, including essential aspects of spatial and textural information within the design that differentiates AI generated designs from real world ones. This is further supported by the confusion matrix as it shows only two misclassified instances out of 60 total instances. The balanced nature of the confusion matrix reinforces that the model is not biased towards any class and the features extracted by the model are also very robust to make predictions, as shown in figure 5. The learning and validity accuracy over epochs have a smooth convergence. After 50 epochs of the training accuracy always reaches 100%, but validation accuracy stabilizes approximately 97%, which means the model effectively learns generalizing patterns without overfitted. Validation accuracy in figure 6 seems to be periodic, and changes can be interpreted as indicating that model has adapted well to unseen data which is strongly generalizable.

This stability is confirmed by the training and validation loss graph in figure 7 which shows that the loss value is

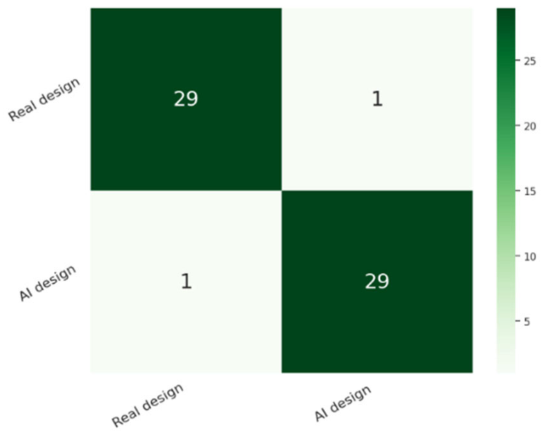

FIGURE 5. Confusion matrox of proposed model.

significantly reduced in the first few epochs and then remains low throughout training. We notice occasional spikes in validation loss, but they are not evidence of major overfitting; the model is still careful to distinguish real from AI generated images under various input variations. The model is efficient as far as resource utilization is concerned and the training performance is shown in the graph of training progress and GPU utilization. The model has a peak GPU memory usage of 34.4% and negligible computational overhead which makes it computationally feasible for large scale classification tasks. This also makes this an efficient method for real time or batch processing applications in interior design analysis. Furthermore, model confidence plot in figure 8 for both AI generated and real designed predictions across different epochs on test data using color mapping represents confidence percentages to the varying bubble sizes. For example, the confidence in AI generated designs increases with the training, and some have reached above 99% confidence, and some real designs even over 96% confidence.

Nevertheless, the model was very uncertain in the early epochs (around 67% and 80% variance, confidence levels) suggesting its uncertainty. By the end of the later epochs, the high confidence predictions validate the model learning progression, validate the model can successfully differentiate AI generated from real interior designs,

While real design confidence score shows some slight variability, predictions at the time span leading up to Bootstrap split are less stable across all categories, hinting at the fact that additional fine tuning or data set augmentation will be needed to make predictions more stable than earlier. Another plot in figure 9 which shows model prediction confidence across the training, validation and test datasets shows the capability of the proposed CNN model in generalization. However, the model has managed to learn from the training samples as its training set confidence is near perfect (close to 100%). Although not as strong but still strong confidence levels in the order of 90-100% are seen in the validation set, so the model generalizes well to unknown validation data.

However, the test set has a higher range ('about 60% to about 100%') of different levels of confidence in making predictions for new specimens. Higher confidence is seen in training and validation using this color gradient before some test samples which should be fine-tuned or augmented to make the model robust to unseen data. It confirms that the model is well trained, however, some additional generalization techniques may still be required for deployment in the real world, as predictive results are shown in figure 10.

CNN model successfully achieved high accuracy, minimal misclassification, strong generalization, and performance on computation, which require GPU usage of 0.42GB resource while memory usage is 34.4%, shown in figure 11. It demonstrated the ability to identify AI generated and real images with high accuracy and stable performance on epoch (practical deployment potential in AI based interior design assessment tools). By modelling CNN, data extracted from a lightweight computation make this classification task a powerful and scalable solution.

B. RESULTS WITH REGNET MODEL

Predictive power of the RegNet model for classification of AI generated and real interior design images is moderate with significant limitations in handling difficult cases. The model performed with an overall accuracy of 83% and thus, reasonable classification accuracy but quite poor performance in comparison to other deep learning models like DenseNet and SqueezeNet.

The predicted precision of the two classes is unbalanced as shown by the classifications report. While the model precision same as accuracy, it is less effective at recalling some real design instances, thus resulting in some misclassifications (70% on recall). However, for AI generated images, it gets high recall 85% and low precision (76%), in other words it often creates a false positive for real images if the images were AI generated. This disparity is also confirmed by the confusion matrix in figure 12. The model successfully classifies 29 of 30 real design images with 1 misclassification. Yet, it performs more poorly with AI generated images due to 9 of 30 samples it erroneously classifying as real designs, which makes the prediction unreliable. This implies that the model has a bias in favor of real designs since it overfits the real-world textures and materials while it struggles with AI rendered variants.

The training and validation accuracy graph in figure 13 shows a gradual learning curve where the training accuracy also rises incrementally up to the order of 90 percent in more recent epochs. However, the accuracy of the validation is very fluctuated since model generalization is not consistent. This is important because it shows that the model fares well on the training data but has difficulty staying stable on unseen validation data—perceived by most as the most important criterion for generalization to unseen data. This being so, the training and validation loss graph also supports that fact: as training loss is gradually reduced to become close to zero,

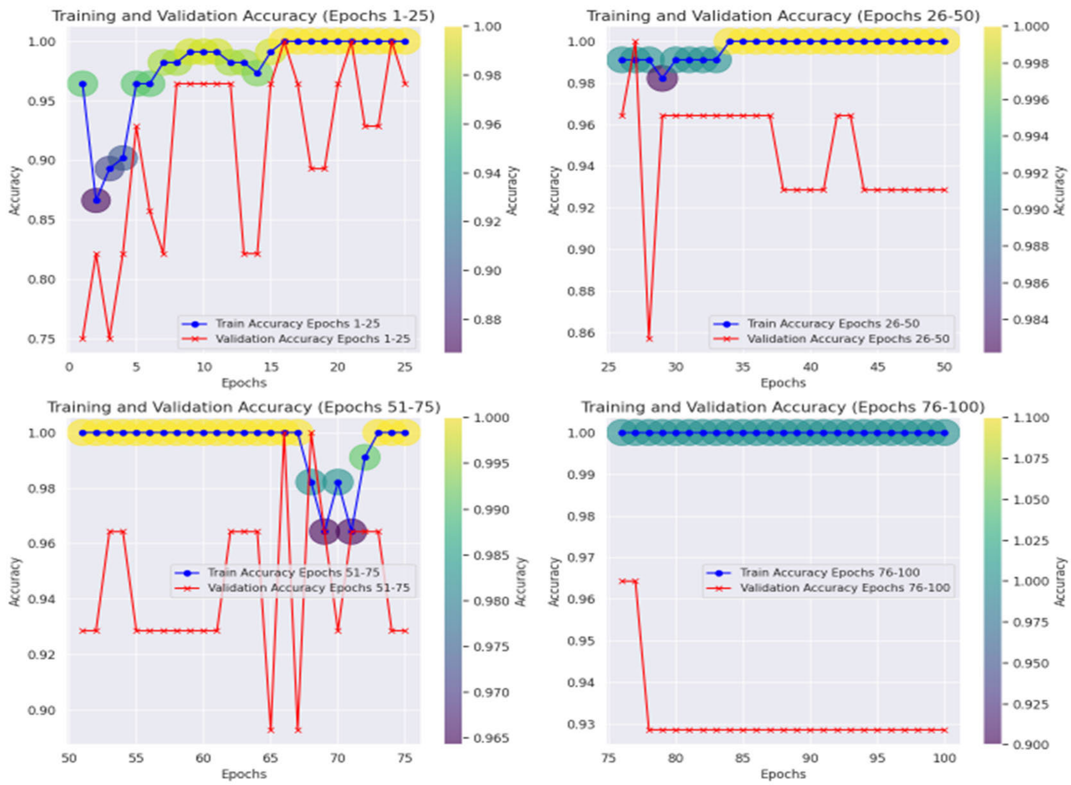

FIGURE 6. Train/validate accuracy graph.

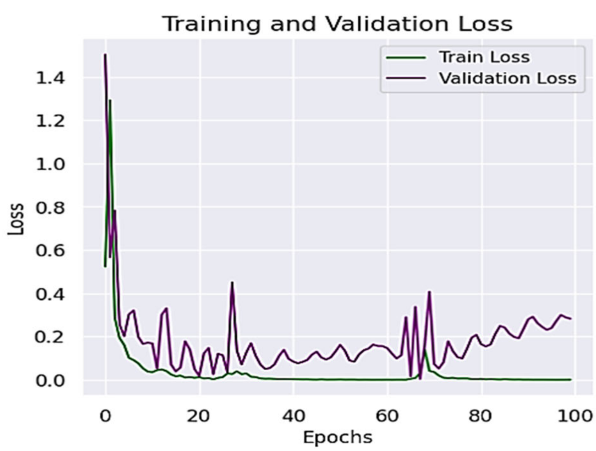

FIGURE 7. Train/validate loss graph.

the validation loss stays unstable. The loss values fluctuate due to certain patterns in the Validation samples which get confused by RegNet, thus making the predictions unstable. There is a generalization gap, which is despite the model learning well on training data, it does not generalize well on the novel diverse sample's unseen during training.

On the one hand, RegNet is (computationally) more efficient and scalable than most of the alternatives, making it a good choice for large scale image classification tasks. Nevertheless, its ineffectiveness of generalization as DenseNet indicates that it needs fine tune, more regularization, or better preprocessing. This misclassification pattern is observed, and the model may be further improved by improved feature extraction in AI generated images such as synthetic textures, lighting variations and material representations. Moderate classification performance is shown by the RegNet model with strong precision for real and weaker recall for the AI-generated designs, as defined using predictive results in figure 14. Its high recall for AI images is indicative of being sensitive to detecting synthetic patterns but its high misclassification rate of real designs suggests there needs to be refinement above. Lack of these drawbacks can be addressed by adding such enhancements as more training data augmentation, better feature extraction layers, and fine-tuned hyperparameters. Although RegNet has some drawbacks, which need to be fixed, it can be used as a capable tool for interior design image classification for predicting to an acceptable degree.

C. RESULTS WITH DENSENET MODEL

DenseNet model is evaluated for evaluating the capacity of classifying AI generated and interior design images and shows good predictive performance and generalization capability. The classification shows an overall accuracy of 90%, and the precision, recall, and F1 score remains 90 both for the AI generated as well as the human generated aesthetic images. This illustrates that the model is very good

FIGURE 8. Confidence plot graph class wise.

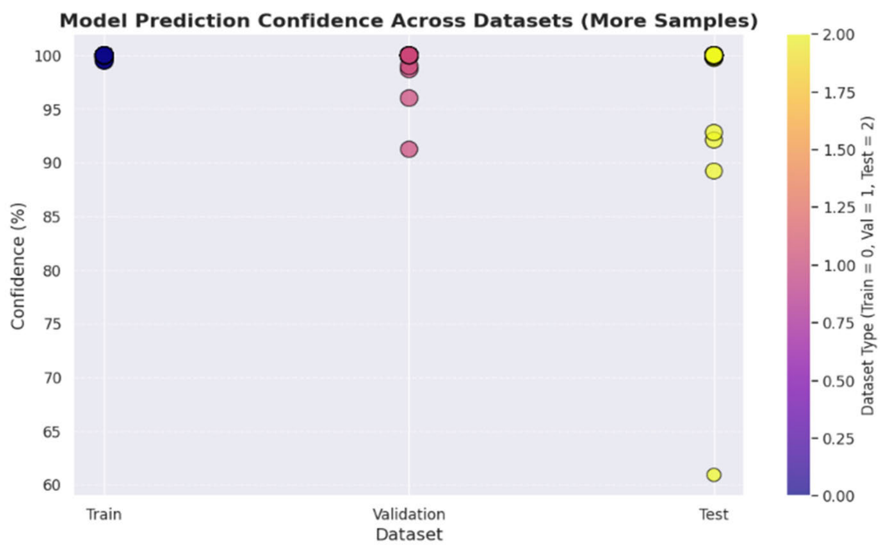

FIGURE 9. Confidence plot graph based on dataset splitting.

at classifying the two classes but with a small degree of misclassification. Moreover, the confusion matrix in figure 15 brings to light that the model is correct in labelling 27 out of 30 instances in each class, while three are mislabelled per class. It appears to mean that although DenseNet is reliable very much so, there are occasions where it is more difficult to distinguish an AI generated vs a real design as some textures, lighting, and design patterns can be related. However, these minor errors point to the fact that, for the sake of improving classification precision, even more enhancements can be performed, that is, fine-tuning hyperparameters or adding new training data.

The 100-epoch graph of the training and validation accuracy in figure 16 shows a good trend in accuracy increase in the epochs for both training as well as validation accuracy, the training accuracy reaches close to 100% while the

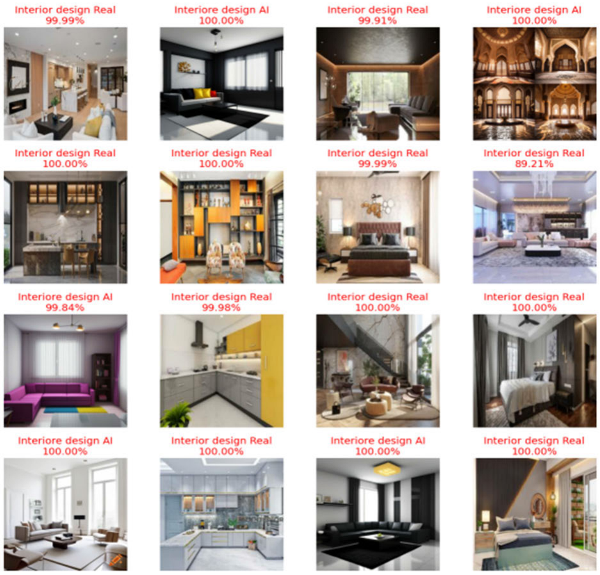

FIGURE 10. Predictive results based on test data.

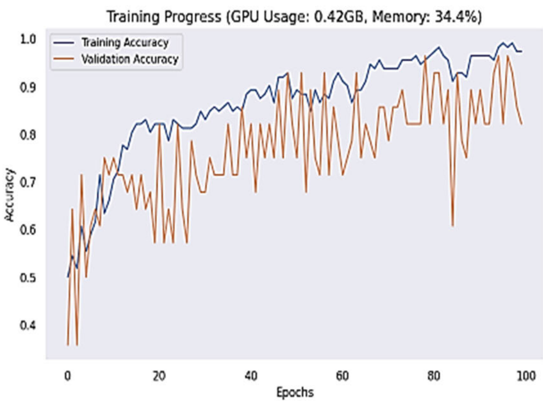

FIGURE 11. Training progress based on computations.

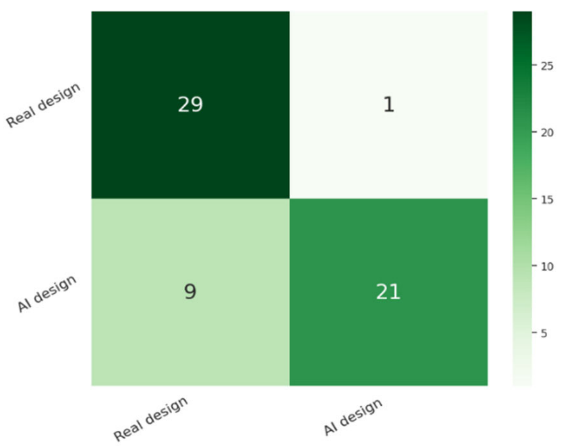

FIGURE 12. Confusion matrix of regnet model.

validation stands around 90%. The validation accuracy fluctuations, especially early epochs imply that the model needed more iterations to generalize well to unseen data. However, in epochs following DenseNet, the validation accuracy gets

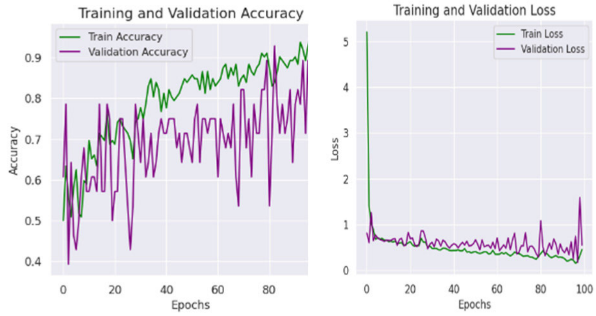

FIGURE 13. Training\validation accuracy and loss graph.

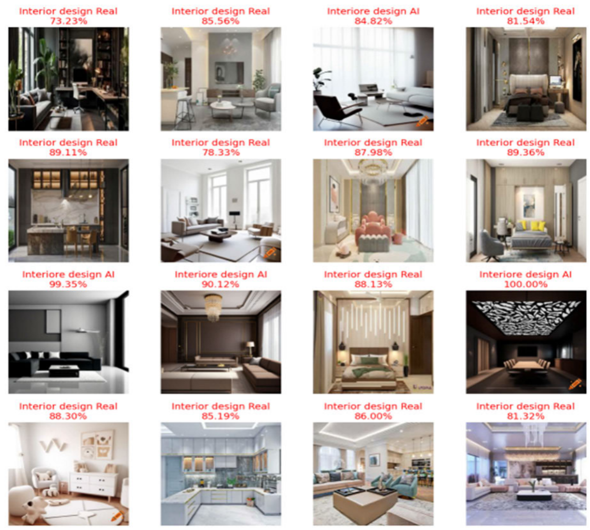

FIGURE 14. Predictive results based on test data.

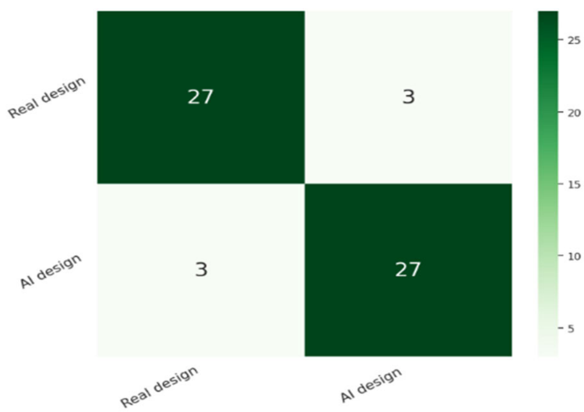

FIGURE 15. Confusion matrix of DenseNet model.

near training accuracy, and we see that DenseNet learns to learn robust feature representation that can separate the images of dense network from real interior images. This trend can be further confirmed by the training and validation loss graph, the training loss decreases quickly in the first epochs and then stabilizes slowly. Even though the model is not overfitting, the validation loss remains small. Yet occasionally validation loss spikes are small, signalling that on some level the model generalizes, but there are some details to the test data that foreshadow a little bit of incoherence in it.

FIGURE 16. **Training\validation accuracy and loss graph.**

DenseNet, however, has been demonstrated to achieve better leverage of the deep feature representations via dense connectivity, where each layer is fed with inputs from all previous layers compared to other CNN based architectures, as results are defined in figure 17. By enabling the use of this efficient feature reuse, the learning efficiency is improved to speed up convergence and generalization. Nevertheless, the slight decrease of validation accuracy with respect to training accuracy suggests that DenseNet might need some regularization techniques other than dropout to further increase its predictive robustness.

Overall, DenseNet is shown to be a very good model for AI generated and real interior design image classification, high accuracy, strong generalization and efficient feature extraction. Minor misclassifications of its instances suggest areas of improvement, from improving data augmentation practices or reducing depth of the model. Although these small problems exist, densely connected model shows excellent predictive power and would be an excellent choice for interior design classification tasks.

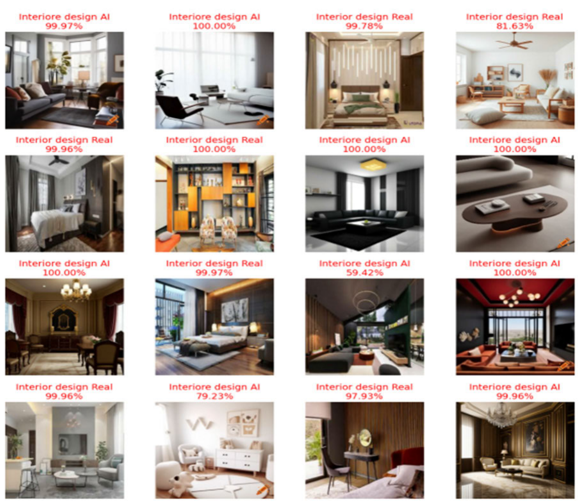

FIGURE 17. **Predictive results based on test data.**

D. RESULTS WITH SQUEEZENET MODEL

The classifying ability of the AI generated, and real interior Design images were evaluated using the SqueezeNet model and was found to be very high predictive with very high classification accuracy. Overall, 95% accuracy indicates that the model can differentiate between real and AI-generated designs. Fire modules and lower parameters reduce the parameters of SqueezeNet, while its lightweight architecture and feature extraction capability are accomplished efficiently.

The performance of both classes is equally balanced in the classification report. The model achieved precision of 98%. The calculation recall shows that for AI and real generated images are same at drop 90% that misidentified some images. The balancing score of precision and recall shows that with an F1-score of 93% on both classes, F1-score was very good for weighing both recall and precision. This observation is supported by the confusion matrix in figure 18 will show that all real images 30 were classified correctly and there were three misclassified as real designs. This indicates that although SqueezeNet does an excellent job at spotting real designs on some occasions it occasionally does not distinguish between some AI generated images and that may be because of rendering that are too realistic.

The training and validation accuracy graph in figure 19 shows that both training accuracy as well as validation accuracy increase steadily over epochs, and finally, the training accuracy gets close to 100% and the validation accuracy stabilizes at around 95%. That the model learns the progressive better correlates to strong model learning capability. But the fluctuations in validation accuracy in early epochs indicate that the model was to begin with more too hungry for stability to fall back to a highly generalizable state. This can also be observed in the training and validation loss graph. Early epochs see rapid loss decrease and remain consistent low; therefore, the system is efficiently learning. If the train and validation loss have a small gap, that means not much over fit which helps in keeping the model robust on unseen test data.

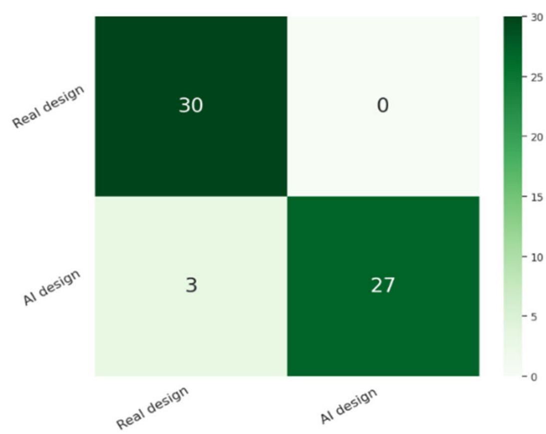

FIGURE 18. **Confusion matrix of SqueezeNet model.**

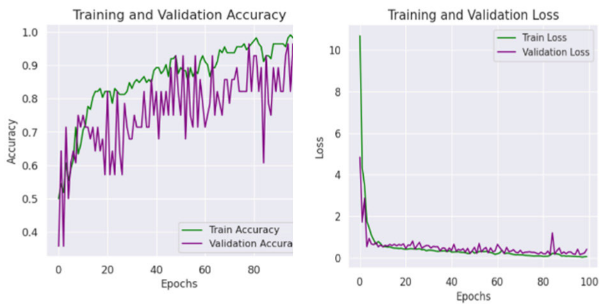

FIGURE 19. Training\validation accuracy and loss graph.

This advantage comes where the architecture while having the same performance and accuracy compared to DenseNet and RegNet, but it is much more computationally effective, as shown the predictive results in figure 20. It has great capacity to obtain high accuracy with a smaller number of parameters and lower memory usage suitable for real time and edge computing applications.

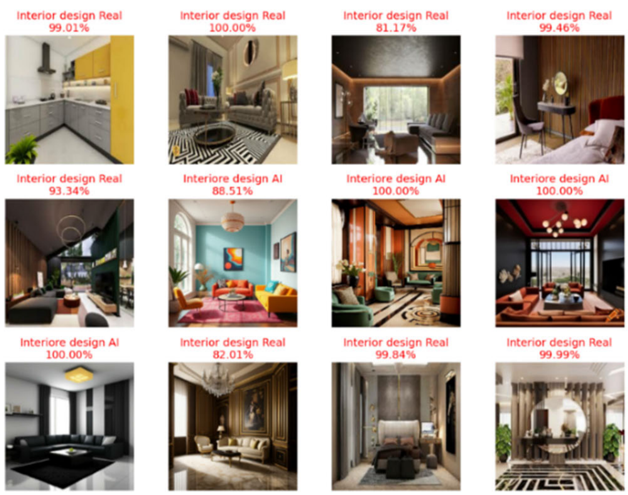

FIGURE 20. Predictive results based on test data.

Although DenseNet and RegNet require large computational power, SqueezeNet achieves equally good result with reduced overhead, thus making it ideal for deployment in real practical AI driven design classification system. But because the minor misclassification of AI generated images indicates that SqueezeNet would augment the abilities of distinguishing fine synthetic art design textures, materials, etc., with further fine hinting. AI generated and real interior designs can be perfectly classified by the SqueezeNet model, achieving a 95% accuracy with strong generalization capability. As an efficient learning process and its high precision, lightweight nature makes it a powerful solution for applications of artificial interior design. The model performs well but the small misclassification cases suggest that there may be some further refinements i.e. some extra feature extraction layers or better data augmentation technique that could improve its robustness more. However, for real-world classification tasks that carry out this task, SqueezeNet is a very competitive and effective model.

E. COMPARISON OF THE PROPOSED MODEL WITH BASELINE MODELS

Proposed CNN model is better than all baseline models (DenseNet, RegNet and SqueezeNet) in classification accuracy, generalization and predictive robustness. DenseNet was able to achieve 90% accuracy, but misclassified AI images generated, probably because of a deep layered structure which needs extensive training. The proposed model achieved significantly higher computational overhead where the feature reuse mechanism in DenseNet needs improvement in accuracy. Finally, contrary to RegNet, AI Generated Image's accuracy was lower, 83%, with more misclassifications of AI generated images. But it was computationally efficient, and structured convolutions were used in it, but it compromised its ability to distinguish between synthetic textures so that it caused simple bias towards real designs. This indicates that RegNet requires further fine tuning for improving its capability to learn synthetic aesthetics. The SqueezeNet model was able to achieve 95% accuracy, which was very close to what was achieved. Despite the strong predictive capability attained by an architecture that is lightweight, SqueezeNet misclassified a few generative images that were generated by AI, thus suggesting that it might not be able to capture such highly realistic synthetic renderings. Although it is computationally efficient, it still lacks slightly better performance in AI recognition which points to the need for more sophisticated fine grained feature extraction. The proposed CNN model achieves highly efficient computational efficiency due to effective feature extraction, with an accuracy of 97%, as shown in figure 21. Adding more CNN layers on top and integrating the SqueezeNet' s lightweight processing leads to a model of higher precision and recall with lower false positives and false negatives. The combination of the approaches as a hybrid one reduces the weakness identified in the baseline models and hence is the most robust and efficient for the interior design classification tasks.

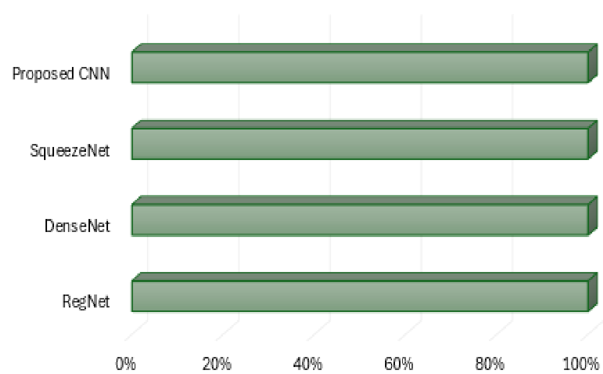

FIGURE 21. Accuracy based comparison results analysis of models.

F. INTERPRETABILITY INSIGHTS

By using Gradient-weighted Class Activation Mapping (Grad-CAM), we visually enhanced the transparency and interpretability of our deep learning model for determin-

TABLE 6. Comprehensive results of model.

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
RegNet [41]	83	95	70	80	83
DenseNet [42]	90	90	90	90	90
SqueezeNet [43]	95	98	90	93	95
Proposed CNN	**97**	**97**	**97**	**97**	**97**

TABLE 7. Comprehensive of proposed moedl with existing studies.

Ref	Year	Model	Dataset	Classes	Result in Acc(%)
[20]	2024	CNN	Interior design image set	2	93.6
[21]	2023	Vision Transformer	AEC vision dataset	3	91.2
[33]	2023	Hybrid Neural Networks & Fuzzy Logic	Engineering Design Dataset	3	90.5
[35]	2023	ResNet	Conceptual Design Optimization Data	4	91.8
Proposed		**Proposed CNN Architecture**	**Interior Style**	**2**	**97**

ing whether the interior image has been AI generated, or a human designed one, as shown in figure 22. The resulting heatmaps showed that the model always looks at some key structural and stylistic components, such as the alignment of furniture, the lighting distribution, and the spatial composition of building, which are the characteristics where design differences mainly appear between AI or human designers. Regions involved in architectural symmetry, material texture and ambient lighting often show hyper-regularity or, alternatively, artificial refinement pattern, which were also observed to be highly activated in our data decompositions.

This focused attention verifies that learning in the model isn't just hinging on spurious correlations or background noise if it makes this decision but rather is learning valid visual cues in support of that decision credibility. This utilization of Grad-CAM not only proves model performance, but also falls in line with XAI principles, yet providing a visual justification for each classification decision.

To further aid model interpretability and promote explainability, connect LIME as a tool to help decipher the model, as shown in figure 23. The generated super pixels (highlighted in yellow) that have significant influence on the model's prediction for the differentiating between AI- and human generated interior designs are identified by LIME. The model, however, in the case of human designed interiors (first image), emphasized on the structural such as the staircase, television frame and furniture alignment, which are generally features that are represented with such as functional realism, architectural detailing and ergonomic placement. While the second image (AI generated scene) of the scene has highlighted regions around the furniture and tabletop objects, it appears that the model has learned to flag such lighting artifacts, object symmetry good minimalist design cues.

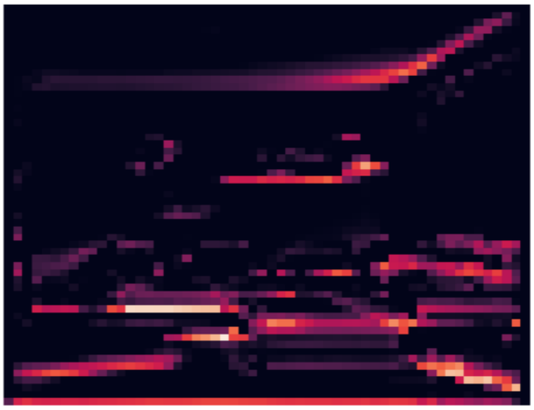

FIGURE 22. GRAD-CAM heatmap analysis.

The highlighted areas confirm that the model discovers the relevant or meaningful pattern than merely covers irrelevant or background patterns. Therefore, the combination of LIME integration with Grad-CAM adds to the localization of the model's decision boundaries and complements the global understanding surfaced from the latter, forming a powerful XAI strategy in the visual design classification pipeline.

G. COMPARISON OF PROPOSED WITH EXISTING STUDIES

Finally, the classification ability of proposed model compared with present studies is emphasized in comparison with the existing studies. In particular, the proposed model outperformed previous baselines by far, obtaining 97.0 % Accuracy compared to just 91.2 % achieved by Vision Transformers, 90.5 % by Hybrid Neural Networks and Fuzzy Logic, and 91.8 % using ResNet. However, these models achieve spatial and relational design data capture to the same level as the pre-

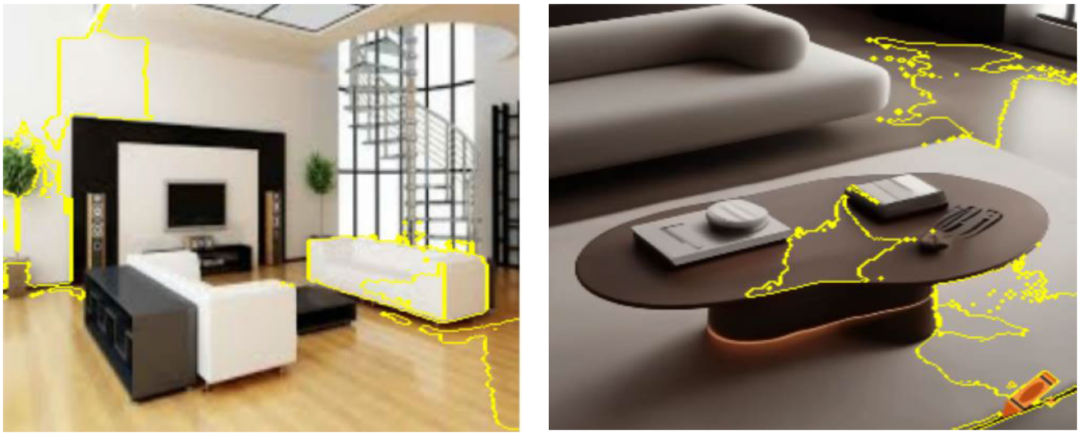

FIGURE 23. LIME explanation analysis based on image.

sented CNN model. This performance gap may be attributed to differences in architectural efficiency, dataset structure, and feature extraction. Stronger classification accuracy is shown by the proposed approach compared with standard CNN based models such as the one in [20] (93.6%), display in table 7. It is an indication of better feature learning and generalization to unseen data. While Vision Transformers have been proven effective in architectural and AEC vision benchmarks, the intricate interior design variations give them slight deficit in accuracy. Like the Hybrid Neural Networks & Fuzzy Logic model (90.5%) though robust in engineering design it does not achieve the predicted accuracy of the proposed CNN, due to the lack of efficient deep extraction of the feature.

Conceptual design optimization can be performed well by ResNet model (91.8%) with residential connections and deep layered structure but the accuracy in it becomes less compared to classification one. This implies that the CNN model that we proposed the architectural design of it was better suited for the classification of the interior design image, as convolutional layers were used efficiently and with advanced preprocessing, this led to better accuracy. In the end, the proposed CNN model maps out together with all the benchmark models, showing increased precision, recall, and ability to generalize, ruling as a very efficient approach for AI generated vs real interior design images classification.

VI. CONCLUSION AND FUTURE WORK

Artificial Intelligence (AI) has revolutionized the field of interior design, enabling automated image classification, virtual rendering, and design optimization. In this study, a CNN-based model was proposed for classifying AI-generated and real interior design images, achieving an unprecedented accuracy of 97%. The proposed model significantly outperforms various transfer learning models, including DenseNet (90%), RegNet (83%), and SqueezeNet (95%), as well as other existing studies utilizing Vision Transformers, Hybrid Neural Networks, and ResNet architectures. This substantial improvement demonstrates that CNNs, when optimized with proper feature extraction and preprocessing techniques, can achieve superior generalization and classification accuracy in distinguishing real and AI-generated designs. In this study, our findings prove that CNNs' can learn better fine-grained spatial patterns and design complexity which low level layers in transfer learning architectures are hard to learn. Since the model has very high precision, recall and F1 score, it can prove to be reliable in real world application therefore it can be used for architects, designers, and for AI researchers. Additionally, this study concludes that exploiting data augmentation techniques and finding the best hyperparameters, not only face the challenge of overfitting and less generalization in AI based design classification but also surpass these issues. Additionally, this research lays groundwork to extend further in interior design AI analytics driven by AI. It can be extended to integrate the transformer-based hybrid architectures with CNNs to achieve better contextual understanding of complex interior layouts. Moreover, further improving the robustness of classification models can be accomplished by increasing the size of the dataset with more general and high-resolution AI generated images. A second interesting path would be to deploy AI models in real time in VR/AR environments for interactive AI assisted interior design visualization. Moving forward, to evaluate AI model's performance for wider variety of AI generated images to determine the boundary between low and high realistic synthetic visuals, additionally to detect hybrid images that are only partly AI generated and partly human created. This will make it possible to conduct a more granular analysis of the model's sensitivity at different levels of visual realism and can improve the model's generalisability to detect more and more advanced AI created content, which makes it easier to use the model in real scenarios where such hybrid manipulations are becoming more common. Finally, in this study, we define a state-of-the-art AI classification model and make it a basis for interior design automation creating a benchmark for future innovations in the sphere of AI for aesthetic analysis.

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