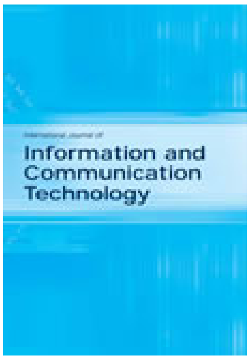


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# Optimisation of visual communication design methods based on scalable machine learning

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# Optimisation of visual communication design methods based on scalable machine learning

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**Abstract:** As artificial intelligence and machine learning technologies advance, design process optimisation – especially in visual communication – is growingly vital. This work presents scalable machine learning for optimisation of visual communication design. The proposed approach enhances design efficiency and creativity by means of flexible and adaptable learning models and machine learning – mostly photo recognition technologies. We construct a scalable machine learning system using photo recognition to find design elements and use extensive assessment criteria to analyse produced designs. By means of thorough testing, the proposed solution surpasses conventional design optimisation strategies in accuracy, efficiency, and flexibility. The model gains over time and fits really nicely to design challenges. This work presents a scalable, flexible approach to visual communication design that can revolutionise practical applications inside artificial intelligence-driven design as well as creative sectors.

**Keywords:** visual communication design; scalable machine learning; image recognition; design optimisation.

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## 1 Introduction

Visual communication design has evolved from hand to intelligent and automated with the explosive development of computer technology (Aceto et al., 2019; Lu, 2019). Design of visual communications transmits knowledge and expresses art. Design presents a great difficulty in terms of producing creative works within time and money that satisfy design objectives. Despite designers' talent and inventiveness, traditional visual design looks inadequate considering complex design requirements and increasing task volume (Chandrasegaran et al., 2013; Grudin, 1991; Wang et al., 2002). Thus, a prominent issue in the design sector is smart ways to maximise the design process and raise quality and efficiency (Chen et al., 2017).

Thanks in great part to artificial intelligence (AI), most especially machine learning and deep learning (Verganti et al., 2020) computer vision and design have lately given fresh ideas for visual communication design. Deep learning in particular allows machine learning to automatically identify trends in data and offer forecasts and optimisation (Sengupta et al., 2020), hence automating design processes. Part of machine learning, image recognition technology has shown remarkable performance in image categorisation and target identification, so offering a technical basis for intelligent design transformation. Image feature extraction and classification make use of convolutional neural networks (CNNs), therefore facilitating automatic recognition and study of intricate design aspects (Chen et al., 2016). Computers help designers match, classify, and maximise images thereby enhancing design efficiency.

Although image recognition techniques and deep learning perform remarkably in some design tasks, current research mostly optimises a single design task, such image classification, image style migration, or automatic image generation, so neglecting the whole and scalable nature of complicated design requirements. For evolving and diversified design projects, conventional design approaches and models could not be scalable or flexible enough. Design intelligence evolution depends on therefore developing a scalable and flexible design optimisation framework (Zhang et al., 2013).

This work suggests an extended machine learning-based visual communication design optimisation technique to get beyond current limitations. Combining scalable machine learning technology with picture recognition technology generates a flexible and adaptive framework that can dynamically change the learning model to match design activity needs, so improving design efficiency, accuracy, and innovativeness. Several important inventions:

1 A visual communication design method based on extensible machine learning is proposed: Here we provide the first visual communication design approach leveraging scalable machine learning. Designed to surpass conventional design constraints, a dynamic optimisation framework makes the model flexible enough to meet several design requirements and obstacles. This system is unique in its adaptability and flexibility to oversee all kinds of design projects with different complexity.

2 Introducing image recognition technology to optimise the automatic identification and matching of design elements: Photo design element recognition and classification is automatically accomplished using CNN image recognition technology. This approach creates the foundation for next design and helps to recognise image elements. Recognising design elements automatically helps the system create design schemes and match styles.

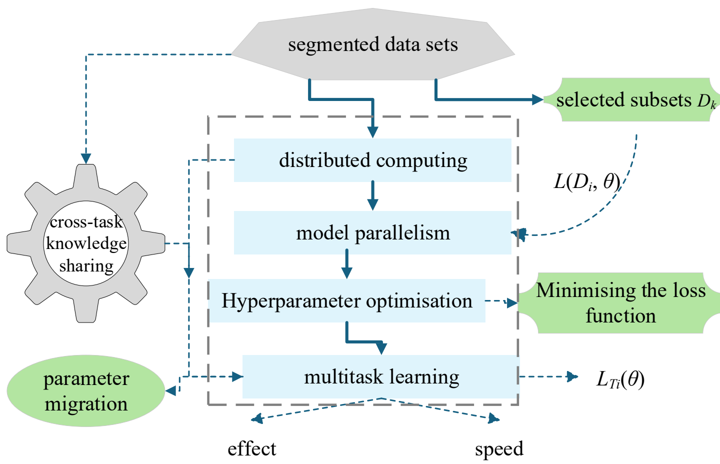
3 A complete system of assessment indicators is constructed to quantify the design effect: This work develops a number of assessment indicators including Intersection over Union (IoU) and Pixel Classification Accuracy in an aim to completely evaluate the quality and accuracy of visual communication design. These numerical evaluations provide an objective basis for the evaluation of the design results, therefore supporting additional optimisation.

# 2 Relevant technologies

## 2.1 *Scalable machine learning*

As picture data increases and design needs vary, scalable machine learning is indispensable to enhance visual design systems in visual communication design (Dudley and Kristensson, 2018). Figure 1 shows how distributed computing, model parallelism, hyper-parameter optimisation, multi-task learning, and other technologies could raise computational efficiency and work demands in the design system.

**Figure 1** Scalable machine learning architecture diagram (see online version for colours)




First of all, distributed computing turns into the foundation for maximising efficiency in handling big datasets. Usually split into numerous subsets $D = \{D_1, D_2, \ldots, D_k\}$, each of which computes the objective function $L(D_i, \theta)$ in parallel on distinct nodes to reduce the global loss, the dataset $D$ is processed. The aim of optimisation is:

$$\theta = \arg\min_{\theta} \sum_{i=1}^{k} L\left(D_i, \theta\right) \tag{1}$$

where $L$ is the loss function; $\theta$ represents the worldwide model parameters. By means of distributed computing, the system can concurrently process several subsets of data, hence lowering the calculation time. The gradient descent approach realisation the gradient update of this process:

$$\theta^{(t+1)} = \theta^{(t)} - \eta \nabla L\left(\theta^{(t)}\right) \tag{2}$$

where $\nabla L(\theta^{(t)})$ marks the current gradient and $\eta$ is the learning rate. To guarantee the consistency of the global parameters, each node in parallel computes gradients synchronised to the central node, so guiding the step-by-step reaching of the best solution.

Model parallelism approaches help to generate additional performance gains grounded in distributed computing (Diaz et al., 2012). Large models sometimes feature distinct components of the model distributed over several computer units to guarantee load balancing. $\theta = \{\theta_1, \theta_2, \ldots, \theta_n\}$ make up the model parameters; each computing unit updates just the parameters for which it is accountable:

$$\theta_j^{(t+1)} = \theta_j^{(t)} - \eta \nabla L_j \left( \theta_j^{(t)} \right) \tag{3}$$

where the loss function of the $j^{\text{th}}$ cell is $L_j$. This accelerates the massive computing task of the model, therefore enabling real-time reaction in the challenging task of visual communication design.

Hyperparameter adjustment therefore also determines the model's performance. Hyperparameter optimisation approaches help to further increase the adaptability and accuracy of the model in visual communication design activities in scalable machine learning. Finding the best hyperparameter combination to reduce the loss function is the aim assuming the set of hyperparameters is $\lambda = \{\lambda_1, \lambda_2, \ldots, \lambda_n\}$:

$$\lambda^* = \arg\min_{\lambda} \sum_{i=1}^{N} L\left(D_j, \lambda\right) \tag{4}$$

where $N$ is the count of hyperparameter combinations; $D_j$ is the data chunks. The model can automatically choose the suitable hyperparameters to enhance the stability and performance of the visual design system by use of the techniques of grid search and Bayesian optimisation.

Apart from hyper-parameter optimisation and distributed computing, multi-task learning is crucial for handling other design challenges (Iliadis et al., 2024). Visual communication design requires several activities, including the identification and development of various styles, so multi-task optimisation via sharing model parameters is the key to increase productivity. Assuming $n$ tasks $T_1, T_2, \ldots, T_n$ with respective loss functions $L_{Ti}(\theta)$, multi-task learning aims to accomplish:

$$\theta = \arg\min_{\theta} \sum_{i=1}^{n} \alpha_i L_{Ti}(\theta) \tag{5}$$

where $\alpha_i$ represents the task weights and multi-task learning achieves cross-task knowledge sharing, so improving the generalisation capacity of the model in visual communication activities.

Migration learning can help to improve system scalability even more. Techniques of migration can make use of past experience to hasten the acquisition of new responsibilities. Assuming, for instance, that the model parameters of the source job are $\theta_S$, the loss function for optimisation on the target task can be stated as:

$$\theta_T = \arg\min_{\theta} \left( L_T\left(D_T, \theta\right) + \beta \left\| \theta - \theta_S \right\|^2 \right) \tag{6}$$

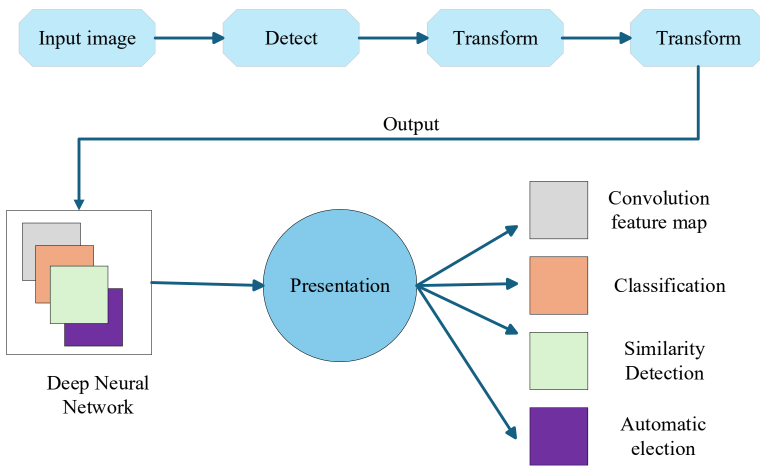
With $\beta$ the regularisation coefficient and $L_T$ the target task loss. By use of parameter migration, this approach satisfies design diversity needs and increases system adaptability in handling various jobs of visual communication.

The expandable machine learning technology provides an efficient technical framework for visual communication design, which enables the design system to take in account the computational speed and effect when dealing with a large amount of image data, and provides scientific and effective support for design optimisation.

## 2.2 Image recognition technology

Strategies include multi-task learning and distributed computing depending on scalable machine learning techniques offer efficient assistance for the efficiency and scalability of the design system in the optimisation of visual communication design. Still, picture recognition technology is indispensible since the foundation of visual communication. The process of image recognition technology is shown in Figure 2.

**Figure 2** Image recognition process (see online version for colours)




Feature extraction is a must for the model to execute classification and analysis in the central goal of picture recognition (Romero et al., 2015). The model first generates the feature representation $F(X)$ from an input image $X$, where $F$ denotes the feature extracting capacity. Usually, feature extracting can be stated as:

$$F(X) = f(W \cdot X + b) \tag{7}$$

where $W$ is the weight parameter matrix; $b$ is the bias term; $f$ is the activation function. Setting the weights and biases helps the feature extraction layer to recognise several image features. Stacking several convolutional layers allows one to obtain higher-order features, therefore supplying richer feature information for next classification or recognition in order to achieve deeper feature extraction.

CNN is a classic deep learning model for handling picture identification issues in visual communication design in the feature extraction phase (Liu et al., 2021). Combining convolutional layers, pooling layers, and fully connected layers, CNN generates hierarchical elements from the input image. Given an input picture $X$ and a convolution kernel $K$, a convolution operation generates an output of the convolution layer that may be stated as:

$$Y = X * K + b \tag{8}$$

where $Y$ is the convolution output; * stands for the convolution procedure. $K$, the convolution kernel, searches several image areas in order to extract local characteristics. Setting several convolution kernels helps the model to identify various visual patterns and textures, therefore enabling various image feature extraction.

A pooling layer helps to further simplify the CNN's feature extracting outcomes (Shin et al., 2016). Retaining the salient features, the pooling layer aims to lower the data dimensions and the computational load. Usually using Max Pooling or Average Pooling, the pooling layer represents the feature values within the pooling window $P$ so that the maximum pooling can be stated as:

$$Y = \max\left(X_P\right) \tag{9}$$

where $X_P$ is the set of pixel values within the pooling window; max is the maximum operation. By means of the pooling layer processing, the size of the feature map is lowered, therefore optimising the model's computational efficiency.

Complex picture contents in visual communication design typically comprise several levels and kinds of visual information, which calls for the model to be able to incorporate various levels of feature information for more accurate classification and analysis. In this type of work, multilevel feature fusion technique performs well since it combines the low-level features (e.g., edges and textures) with the high-level semantic information (e.g., object shape and structure) so increasing the accuracy of image identification. The multilevel feature fusion can be stated assuming the low-level features as designated as $F_l$ and the high-level features as $F_h$ as:

$$F_{\text{fusion}} = \alpha F_l + \beta F_h \tag{10}$$

By changing the weight coefficients, the fused feature representation can be maximised for various kinds of visual communication tasks where $\alpha$ and $\beta$ are the fusion weight coefficients. While preserving computational efficiency, this feature fusion strategy can improve the recognition capacity of the model for intricate design content.

Automatic adjustment of the convolution kernel and feature layers to fit various design criteria is another means of further optimising image recognition methods. Automatic feature selection improves the model's adaptability by letting the most representative feature layer to be automatically chosen from a multi-layer convolutional feature map. For instance, the model can filter the feature layers by best choosing the coefficients $\gamma_i$ to get an optimal output from a set of convolutional feature maps $\{F_1, F_2, \ldots, F_n\}$:

$$F_{\text{selected}} = \sum_{i=1}^{n} \gamma_i F_i \tag{11}$$

where the adjustment coefficient $\gamma_i$ regulates the feature map's significance in the output. Through maximising these coefficients, the model may automatically fit the demands of various visual contents.

Image recognition technology builds a complete solution from image input to recognition outcomes by feature extraction, CNN, pooling, feature fusion and automatic feature selection in visual communication design optimisation.

# 3 Model and architecture of the visual communication design optimisation system

## 3.1 System architecture

Five fundamental modules – data pre-processing, multi-scale feature extraction, distributed feature fusion, automatic model optimisation, and dynamic feedback mechanism – formulate the system to guarantee efficiency, adaptability, and accuracy in the work of visual communication design.

1 Data [reprocessing

Image recognition technology is used in the module of data preparation to carry out noise reduction and enhancement activities (Uchida, 2013), therefore enhancing the quality of the data and increasing its fit for the input of machine learning systems. Its method of data conversion is outlined here:

$$x_i' = h(x_i) + \in, \in \sim N\left(0, \sigma^2\right) \tag{12}$$

The augmentation function is $h(x_i)$, therefore preprocessing the input data, $X = \{x_1, x_2, \ldots, x_n\}$, produces $X' = \{x_1', x_2', \ldots, x_n'\}$ by means of $\epsilon$, the random noise.

Moreover, the data is normalised using a technique to guarantee that the eigenvalues of various samples span the same interval:

$$x_i'' = \frac{x_i' - \mu}{\sigma} \tag{13}$$

where $\mu$ and $\sigma$ are the mean and standard deviation of the data, so that the preprocessed data $X''$ shows consistency and strong fit in the model.

2 Multi-scale feature extraction

Combining the CNN technique in image recognition with the following formula allows the multi-scale feature extraction module to extract several scale aspects of the image:

$$f_{ij} = g(x_i'', s_j), s_j \in S \tag{14}$$

where $g$ is the convolution process and $s_j$ is a varying scale filter. Rich visual information is maintained by the multi-scale characteristics $F = \{f_{ij}\}_{i,j}$ derived by convolution.

Furthermore, a pooling layer is used to lower the data dimensionality while preserving the significance of the characteristics thereby strengthening their stability:

$$f_{ij}' = \text{pool}\left(f_{ij}, p\right) \tag{15}$$

where $p$ is the pooling parameter, maximum or average pooling compresses the features, therefore producing a final generated feature matrix $F'$ more appropriate for later use.

3 Distributed feature fusion

Scalable machine learning for feature aggregation via distributed algorithms is included into the distributed feature fusion module. By means of weight weighting, feature fusion enhances system adaptability:

$$F_m = \sum_j \alpha_j f_{ij} \tag{16}$$

$$\sum_j \alpha_j = 1 \tag{17}$$

where every feature's weight is $\alpha_j$. Training helps to change the weight $\alpha_j$ therefore enhancing the feature fusion impact.

Furthermore, a feature selection technique helps to maximise the fused characteristics by removing duplicated ones:

$$F'_m = \text{select}\left(F_m, k\right) \tag{18}$$

where $k$ is the count of retained elements making the optimal feature $F_m'$ more fit for model training.

4 Automated model optimisation

Through Bayesian optimisation, the automated model optimisation module modulates the hyperparameter $\lambda$ of the model to raise its performance using the following formula:

$$\lambda^* = \arg\max_{\lambda} \mathbb{R}\left[Q\left(F'_m, \lambda\right)\right] \tag{19}$$

where under a given hyperparameter $\lambda$ the model's performance evaluation is expressed $Q(F'_m, \lambda)$. This approach discovers the ideal hyperparameter arrangement.

Furthermore, principal component analysis (PCA) reduces dimensionality by means of which high-dimensional feature redundancy is minimised (Ray et al., 2021), so enabling computational efficiency of the model.

$$Z = F'_m W \tag{20}$$

To streamline the computational cost, $W$ is the dimensionality reduction matrix computed depending on the covariance matrix of the samples and the high-dimensional features $F_m'$ are projected into the low-dimensional space $Z$.

5 Dynamic feedback

Monitoring the model output error in real time and automatically changing the model to increase its adaptability helps the dynamic feedback mechanism to function as Definitions of the error function follows:

$$L\left(y, y_{\text{true}}\right) = \frac{1}{n} \sum_{i=1}^{n} \left(y_i - y_{\text{true},i}\right)^2 \tag{21}$$

Should the error $L$ surpass the threshold, a feedback system activates to retrain the model and maximise the output.

Furthermore, the current optimal model $M_{\text{opt}}$ is chosen from the model set $M$ by use of the model selection technique:

$$M_{\text{opt}} = \arg\min_{M} \mathbb{R}\left[L\left(y_{\text{M}}, y_{\text{true}}\right)\right] \tag{22}$$

Under shifting work conditions, this method guarantees that the system always keeps accuracy and efficiency.

By means of the design of the above five modules and the formulation description, this system significantly integrates data preprocessing, feature extraction, model optimisation and feedback mechanism in the task of visual communication design, so building an intelligent optimisation scheme with great efficiency and adaptability.

### *3.2 Assessment of indicators*

1 Intersection over union (IoU)

An key gauge of the model's segmenting and localising accuracy is IoU (Hasan et al., 2021). By computing the ratio of the intersection and concatenation of the prediction results with the true labelled regions, IoU indicates the prediction accuracy of the model for every category region. The model is more precisely in finding and segmenting the target area the higher the value of this indicator. Its computation formula is:

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} = \frac{|P \cap T|}{|P \cup T|} \tag{23}$$

where $P$ represents the model-predicted area and $T$ the real labelled area. The mean value of IoU for every category region yields the final average intersection and merger ratio:

$$\text{Average IoU}=\frac{1}{n}\sum_{i=1}^{n} \text{IoU}_i \tag{24}$$

where the number of categories is $n$. good average IoU shows that the model is well fit for assessing segmentation impacts in visual communication design and has a good general prediction accuracy for various category areas.

2 Pixel classification accuracy

The accuracy of the model's category prediction at every pixel point—that is, if the model faithfully classifies every pixel in the image—is evaluated using pixel classification accuracy (Pontius and Malanson, 2005). Often employed in image segmentation and classification activities, it computes the proportion of correctly identified pixels among the total number of pixels. Calculated as is the pixel categorisation accuracy:

$$\text{Pixel Classification Accuracy} \frac{\text{Number of Correctly Classified Pixels}}{TotalNumberofPixels} = \frac{\sum_{i=1}^{n} P_i}{N} \quad (25)$$

where $N$ is the total number of pixels in the image; $p_i$ is the count of properly categorised pixels. The prediction accuracy of the model for every pixel category in the image increases with increasing value of this indicator, so better reflecting the correctness of the details in the visual design.

These assessment indicators provide a comprehensive yet appropriate framework for evaluating the performance of the visual communication design optimisation system. While IoU and pixel classification accuracy offer valuable insights into the model's segmentation and classification capabilities, they should be considered as part of a broader set of metrics. This approach ensures a balanced assessment that acknowledges the strengths and limitations of the model, guiding future improvements and applications in visual communication design.

## 4 Experimental results and analyses

### *4.1 Data sets*

We pick Cityscapes and the COCO dataset as the major experimental basis for this work. With 80 object classes overall, the COCO dataset (common objects in context) offers comprehensive multi-class picture annotation information as well as pixel-level segmentation labels for a great number of images. Target identification, image segmentation, scene interpretation, etc., among other visual design tasks, this dataset is appropriate and hence perfect for training and testing the scalable machine learning models in this work.

**Table 1** Dataset statistical information

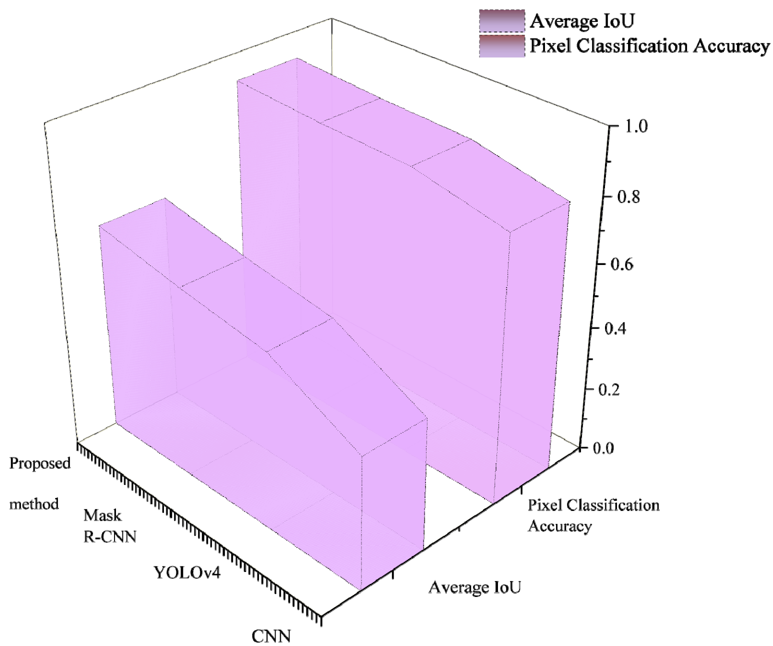
| *Dataset name* | *Number of images* | *Number of categories* | *Annotation type* | *Scene description* |
|---|---|---|---|---|
| COCO | Hundreds of thousands | 80 | Bounding boxes, pixel-level segmentation annotations | Diverse everyday life scenes |
| Cityscapes | 5,000 | 19 | Pixel-level segmentation annotations | Urban street scenes, suitable for scene parsing tasks |
| Dataset name | Number of images | Number of categories | Annotation type | Scene description |

By contrast, the Cityscapes dataset comprises urban street scene images in autonomous driving contexts with comprehensive pixel-level segmentation labels for 19 common categories including pedestrians, autos, buildings, etc., fit for scene parsing. The images in this dataset mostly feature road scenes in several cities with high resolution and clear label annotations to enable the model to understand the semantic links of numerous elements in intricate urban surroundings.

### *4.2 Experimental procedure*

We verified the effectiveness of our work's extensible machine learning-based visual communication design approach by contrasting conventional computer vision models. Multiple standard computer vision techniques are applied in experiments: CNN, YOLOv4 target detection, Mask R-CNN instance segmentation. Using COCO and Cityscapes datasets, the tests track IoU and pixel categorisation accuracy. These measures capture target detection performance and image segmentation of the models. Figure 3 shows COCO dataset trials.

**Figure 3** Experimental results on the COCO dataset (see online version for colours)




The experimental results on the COCO dataset demonstrate the performance of various models using the two evaluation measures: IoU and pixel classification accuracy. The conventional CNN model exhibits a relatively low performance with an average IoU of 0.42 and a pixel classification accuracy of 83.6%. In contrast, the YOLOv4 model shows improved performance in target identification, achieving an IoU of 0.56 and a pixel classification accuracy of 89.3%. The mask R-CNN model further enhances these metrics with an IoU of 0.60 and a pixel classification accuracy of 90.1%, indicating stable and reliable performance.

Notably, the visual communication design method based on extensible machine learning proposed in this research outperforms all other models on the COCO dataset, achieving the highest IoU value of 0.65 and a pixel classification accuracy of 91.7%. This superior performance highlights the effectiveness of the proposed method.

Similar trends are observed in the experimental results on the Cityscapes dataset, as shown in Figure 4, further validating the comparative analysis of the models.

**Figure 4** Experimental results on the cityscapes dataset (see online version for colours)

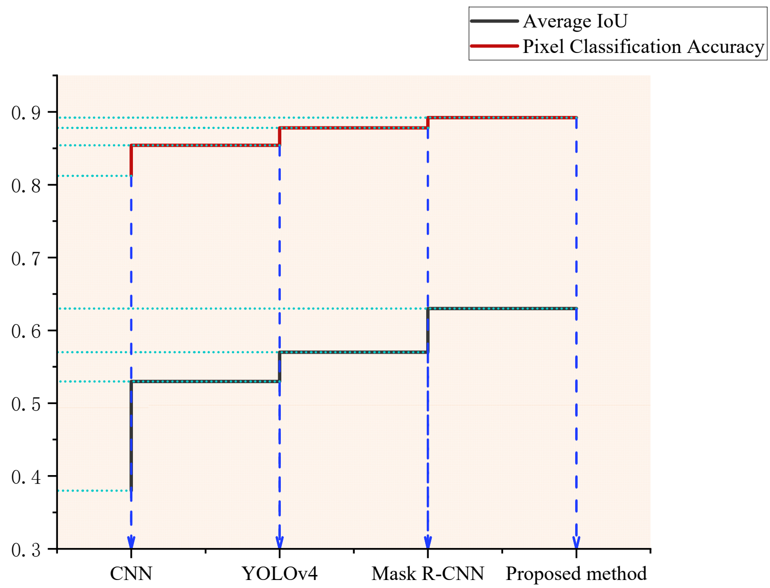
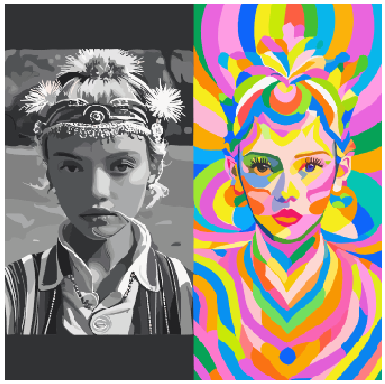



**Figure 5** Comparison of natural scene images before and after optimisation (see online version for colours)

The scalable machine learning technique still prevails even if every model performs worse than the COCO dataset. With IoUs of 0.38 and pixel classification accuracy of 81.2%, traditional CNN models are slow.YOLOv4 does better with an IoU of 0.53 and 85.4% pixel categorisation accuracy. Mask R-CNN boasts 0.57 IoU and 87.8% pixel accuracy. With an IoU value of 0.63 and pixel classification accuracy of 89.2%, the extensible machine learning-based visual communication design method does well on the Cityscapes dataset.

Two examples of comparison between the photographs optimised by this method and the original images help to more naturally demonstrate the influence of the method in real-world visual design optimisation.

**Figure 6** Comparison of abstract graphic images before and after optimisation (see online version for colours)



Through optimisation, the details and general visual impact of the image are enhanced; the optimised image highlights the theme more in terms of colour and composition, so integrating the originally scattered visual focus, so enabling the information contained in the graphic, such as emotions and concepts, to be more clearly conveyed to the viewer, which is applicable to the fields of artistic creation and creative design, and helps to express unique creative ideas and concepts.

In terms of visual effect enhancement, information conveyance, and synergy with experimental methods, the visual communication design method based on scalable machine learning shows excellent performance in the optimisation of natural scene images and abstract graphic images, and brings innovation and value to the field of visual communication design in terms of visual impact enhancement, technical support and theoretical basis for future image optimisation and design work.

## 5 Conclusions

We provide in this work a visual communication design optimisation strategy grounded on scalable machine learning approaches. We effectively improve the efficiency and inventiveness of the design process by combining machine learning – especially image recognition methods – with a flexible and adaptable learning model. This work mostly proposes an extensible machine learning framework to automatically identify design aspects using picture recognition methods and develops thorough assessment criteria to assess the success of the produced designs.

Experimental results reveal that in terms of accuracy, efficiency, and adaptability the suggested approach greatly beats conventional design optimisation techniques. Using an extensible machine learning model allows us to constantly improve the performance based on the demands of various design projects by means of flexible adaptation. Not only speeds up the element recognition process, but image recognition technology also cleverly matches design elements to produce more exact and imaginative design outcomes.

This study has certain restrictions even if its experimental results show greater quality. First of all, our study model is mostly based on current datasets, which might not be able to fully cover all pragmatic design possibilities. Second, while scalable machine learning excels in many design chores, it could still be constrained in some challenging and varied creative design projects. Thus, the following elements for development and extension will be the main emphasis of next efforts:

1 Image data, user interaction data, etc., to enhance the generalisation ability of the model: This helps the model to perform better in several design activities and increase its field of application thereby encompassing a greater spectrum of design situations. This helps the model to perform better in several design activities and increase its field of application thereby encompassing a greater spectrum of design situations.

2 Exploration of advanced machine learning algorithms: Apart from expandable machine learning approaches, more sophisticated machine learning techniques like deep reinforcement learning or generative adversarial networks (GANs) could be tried in the future to improve the accuracy and inventiveness of design automation even. While generative models as GAN can improve the creativity and diversity of produced designs, deep reinforcement learning can give greater freedom for design models to learn and optimise themselves.

3 Cross-domain application and innovation: Although our approach is mostly aimed at visual communication design, future application of it can reach other design disciplines including product design and UI/UX design. The universality of the approach may be confirmed by verifying the resilience and adaptability of the model in actual applications in several sectors. Cross-domain innovation will, meantime, support the widespread implementation of machine learning methods in the design field.

Finally, the scalable machine learning approach suggested in this work shows the vast possibilities of machine learning in the creative domain and offers a fresh optimisation notion for visual communication design. Future research is predicted to realise more intelligent and efficient design systems that will transform design work in many sectors with the progress of technology.

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