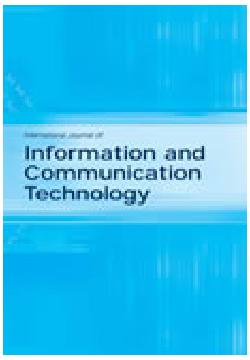

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Using deep learning algorithms to identify diverse types of art designs

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Abstract: The integration of deep learning algorithms in art classification has revolutionised the way artistic styles are identified and analysed. This study explores the application of neural networks – particularly convolutional neural networks (CNNs), generative adversarial networks (GANs) and vision transformers (ViTs) – in distinguishing and classifying various forms of art, including abstract, realism, impressionism, and digital art. By leveraging large datasets, these models can identify stylistic features with high accuracy. The paper compares the performance of different models and highlights the challenges of training on heterogeneous art databases, such as data imbalance and complex feature extraction. Results show the effectiveness of hybrid architectures like CNN + ViT, and potential future applications include museum curation, style transfer, and computational creativity. This research underlines the evolving role of AI in bridging technology and art.

Keywords: deep learning; art classification; neural networks; style recognition; computational creativity.

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1 Introduction

The convergence of artificial intelligence (AI) and art has given rise to exceptional progress in computational creativity. Deep learning, an AI branch, has been shown to demonstrate powerful skills in the identification, classification, and even production of many varieties of artistic designs (West and Burbano, 2020). With the rapid growth of digital art databases and advancements in machine learning, researchers have increasingly explored how deep learning can effectively differentiate various types of art designs. The key to automatically distinguishing and differentiating artistic genres, styles, and the works of individual artists will deeply influence art history, the digital curation field, and the procedures of creative design (Li, 2020). This paper intends to study the influence of deep learning techniques in the examination of diverse art designs, putting attention on their strengths, limitations, and likely applications (Kong, 2020).

Until now, the study of art recognition and classification has mainly been a manual process, meaning it has been dependent on the expertise of art historians and the interpretation of styles. The verification of artworks by their graphs and brushstrokes has been crucial and in-depth knowledge in the business has been obligatory for scholars and curators for a long time (Radanliev and De Roure, 2023). However, as those methods are subjective and take a lot of time, it takes years of practice to master them. On the contrary, researchers have come up with various computerised vision methods that helped in the recognition and classification of art styles. Initially, the classification of artworks was an exercise based on the properties of artisanal features, i.e., the genetic data, and was based on traditional machine learning methods such as support vector machines (SVMs) and k-nearest neighbours (k-NN) classification (Fan and Li, 2023). Yet although these methods were quite precise, robustness was not their strongest characteristic, which made them unsuitable even for complete comprehension of artistic processes through complexity analysis. The convolutional neural network (CNN) of deep learning is one of the key points that has transformed this field, enabling the creation of a model which learns automatically not only events at a layered level via the development of its own features but also the machine cannot specify the features that have been manually extracted (Du et al., 2024).

Deep learning models are powerful tools when it comes to art classification, with their capacity to tumble over intricate visual elements such as texture, colour distribution, composition, and brushstroke patterns being amongst their most noted characteristics (Zhao and Xue, 2024). Deep-learning algorithms like CNNs, for this instance, have performed exceptionally in image classification tasks and thus are considered a natural fit for art analysis. These models are fed vast datasets of artworks, learning significant patterns with unique characteristics that distinguish different styles. This is the reason why, when properly trained on diverse datasets that contain painting elements from different artistic movements such as renaissance, impressionism, cubism, and abstract expressionism, deep learning models are capable of an impressive recognition of the stylised subtleties. Besides, the generative adversarial networks (GANs) introduced innovative applications whereby these not only identified art styles but also produced new artworks, resembling the characteristics of well-known artists (Baduge et al., 2022).

One of the most crucial contributions of deep learning in art recognition is its ability to facilitate large-scale classification tasks. Museum archives, online art galleries, and cultural institutions have extensive collections of artworks that require systematic organisation (Wang and Li, 2024). The traditional methods of art classification struggle to keep pace with the growing digital and physical artworks. Unlike conventional systems, deep learning models can process and categorise these artworks with superior effectiveness, allowing automated tagging, retrieval, and recommendation systems to operate more efficiently (Relmasira et al., 2023). This development offers benefits to scholars and art enthusiasts as well, who are able to receive fast and accurate insights into a host of different artistic styles (Hutson and Lang, 2023).

The use of deep learning in the field of art analysis, despite being an effective method, presents a number of challenges (Yang et al., 2019). One point of concern is the availability and quality of training data. Different from normal image classification datasets, art datasets often have a data imbalance problem, with certain styles or artists being much more represented than others (Ploennigs and Berger, 2023). This imbalance can lead to unfair predictions, favouring the more common styles while leaving the less popular ones underrepresented. Furthermore, the fact that some artistic styles share similar traits causes difficulty in categorising them by deep learning systems. For instance, impressionism and post-impressionism paintings have colour choices and brushstroke techniques in common, which could cause the two styles to be confused (Elfa and Dawood, 2023). This confusion may be resolved by the use of methods such as data augmentation, transfer learning, and combination modelling to strengthen the models.

Another problem is the area of deep learning models' interpretability in art analysis. Although CNNs are experts when it comes to visual patterns, they act as 'black-box' mechanisms, which are not clear in the reasoning process behind their assignments (Dignum, 2017). Art historians or critics, in many cases, demand justification for the classification of an artwork in an art category, and in this sense, deep learning approaches are rather opaque (Hutson and Robertson, 2023). To neutralise this concern, researchers have tried to make use of some techniques, like the class activation mapping (CAM), and layer visualisation so that the features that pushed the model to the decision can be emphasised (Xu and Jiang, 2022). Such techniques in any way give indications on how the neural networks understand artistic elements and thus hopefully enable a more interpretable analysis of art classification (Hedges, 2023).

Deep learning has gone beyond simply understanding images to find applications in the field of art. One such application is the well-known style transfer technique, which allows users to transfer the stylistic properties of one artwork to a different one (Chakraborty et al., 2022). Neural style transfer (NST), on the other hand, employs deep learning algorithms to extract the stylistic features of a painting and then superimpose it on another image, thus creating new art with distinctive artistic inputs. This method is an essential part of modern digital art, advertising, and content generation, showing how AI can embrace human creativity (Terzidis et al., 2023). Also, one of the techniques known as GAN has been pivotal in the generation of new images through copying the styles of popular artists (Satrinia et al., 2023). When trained on large sample sets, these networks are capable of producing works almost identical to those of Van Gogh, Picasso or Monet that make it difficult to tell which is art by man and which one is machine-generated (Phillips et al., 2024).

Deep learning is an ever-evolving application and, therefore, will soon turn art recognition and design analysis into an even bigger market (Sun, 2021). In this regard, researchers are looking into multimodal systems that comprise textual descriptions, historical context, and effects of the artists alongside the visual analysis which are significant (West and Burbano, 2020). The goal of these hybrid models is to combine both textual and visual syntax, so art can be better interpreted as a set of values they express through different patterns, forms, and colours (Fathoni, 2023). Additionally, self-supervised, and few-shot learning has allowed deep learning systems to work excellently in environments with few data points for instance GT databases that use data hardly available in art datasets (West and Burbano, 2020).

1.1 Objectives

- To analyse the effectiveness of deep learning algorithms in identifying and classifying diverse types of art designs.
- To explore the challenges and future potential of deep learning in the field of art recognition and computational creativity.

Deep learning has great potential in art analysis, with great possibilities, from museum automation to new digital creativity forms. As AI techniques advance their ability to differentiate, categorise, and create art, they will become even more influential in the future of artistic expression. There are limitations of data and the difficulty of model interpretation, but AI-art collaborations are becoming more refined as research continues. The aim of this paper is to give the reader a complete overview of deep learning's input in the art world, what is being done with it, which parts of it are impossible today, and which parts remain to be tapped as well as what are the future prospects (Zhao and Sun, 2024).

2 Literature review

The incorporation of deep learning in classification and recognition of art has been one of the topics that are being increasingly researched on. The researchers have come up with different architectures of neural networks, datasets and methods to break away from the tradition and focus now on more effective and reliable art analysis. The CNNs, GANs and transformer-based models have been the highlights of the progress in style recognition, authenticity checking of the art piece, and creative AI applications. This chapter will summarise the key studies done in this field to indicate their methods, main results, and limitations.

Gu et al. (2023) investigated the incorporation of artificial intelligence (AI) in visual communication design, intended to facilitate a change from traditional 2D design ways. Their research offered an AI-based system of visual communication which leads to clearer images with a wider scope and improved details. The outcomes of the experiments showcased that the system put forward cropped the image distortion rate at about 15%, unlike the established methods whose/image distortion rate was at 20%. Also, AI has been successful in correcting chromatic aberration which played a decisive role in the overall quality of the image. In retrospect, AI technology has opened up new pathways for transforming visual communication design through the use of techniques that maximise the blending of graphics with visualisation.

Zhao and Gao (2023) purposely looked into the effect of technology on the enhancement of art and design education via the application of a smart classroom system. Their study focused on improving class environment as well as teaching effectiveness in three phases: before, during, and after classes through the provision of AI technologies integration. The outcomes of the experiment indicate that through the help of computer-aided classroom management automation bandwagon, the most effective assessment of students was accomplished whilst the emotional activities therein were brought to light and educators had the opportunity to modify their teaching methods accordingly. Additionally, the AI system brought about richer class content, varied approaches in teaching, and improved, teacher-student interaction thereby leading to a higher overall standard of art design education.

Rui (2023) variational autoencoders (VAEs) in the emotional elements' assessment of visual communication art design. By feeding grouped images as input, the study employed various techniques to capture the emotion depicted in the poster images, which included grouping the emotions into three: positive, neutral, and negative. The outcome was a silhouette index above 0.7, while the participants in the clustering scheme did classification of over 80% of the cases correctly and efficiently. This study is a decisive step towards the establishment of new methodologies consisting of AI in the field of art design in particular the automation of emotional content analysis and optimisation of visual communication strategies.

Table 1 Literature comparison

Authors and year	*Focus area*	*Methodology*	*Key findings*	*Limitations*
Gu et al. (2023)	AI in visual communication design	Development of an AI-based visual communication system	Improved image clarity, reduced distortion (15% vs. 20%), enhanced graphics transformation	Limited scope in practical implementation; requires further validation
Zhao and Gao (2023)	AI in art and design education	Development of a smart classroom system	AI improved classroom management, teaching efficiency, and student engagement	Focused only on emotional responses; lacks long-term evaluation
Rui (2023)	AI in visual communication art design	CNN and VAE for sentiment-based clustering	Achieved over 80% accuracy in categorising emotional content in visual design	Limited to poster-based visuals; applicability to broader design fields uncertain
Xu and Nazir (2024)	AI and ML in art design	Analytical hierarchy process (AHP) and TOPSIS ranking	AI enhances creativity, artistic skills, and interactive learning	Theoretical focus with limited empirical validation
Feng and Li (2023)	Interdisciplinary art and engineering education	Integration of art design into engineering curricula	Interdisciplinary learning fosters innovation and problem-solving	Limited assessment of student performance and learning outcomes

Xu and Nazir (2024) provided a comprehensive review of the influence of AI and machine learning (ML) on art design, emphasising their role in enhancing artistic creativity and interactive experiences. Their study analysed existing techniques and identified key characteristics in AI-driven art creation. Using an analytical hierarchy process (AHP) and the TOPSIS algorithm, the study ranked different approaches based on performance metrics. The results demonstrated that AI and ML significantly contribute to the evolution of art education and design by refining artistic skills, improving creative processes, and enabling more effective teaching methodologies.

Feng and Li (2023) explored interdisciplinary approaches to art and design education in the context of new media and engineering education. Their research focused on integrating art design elements into engineering practice courses to foster innovative learning experiences. By analysing the teaching methods in higher education, the study highlighted the necessity of interdisciplinary collaboration between art and engineering disciplines. The findings suggested that incorporating art design principles into engineering curricula enhances creativity, problem-solving skills, and the overall effectiveness of art education, aligning with contemporary trends in STEAM education.

3 Methodology

This study's methodology is systematic for the effective use of deep learning algorithms for the identification and classification of the different kinds of art designs. The dataset collection, pre-processing techniques, model selection, training process, and evaluation metrics are explained in this section. The proposed methodology is directed towards the development of an effective and a precise art style recognition system through deep learning that ensures solid classification and interpretation of the various art forms.

3.1 Dataset collection

In the first step of the methodology the collection of a varied dataset of art designs will be carried out. A well-structured dataset is a prerequisite for the effective training of deep learning models. The dataset consists of ads taken from several internet art sites, museum archives, and the digital collections that are available to the general public. The images in the dataset illustrate a number of different artistic styles throughout time, from abstract to impressionism, realism to surrealism, and pop art to the latest in digital art. A comprehensive representation of different art movements is given since both traditional and digital sources are included. To ensure the efficient implementation of the supervised learning process, all the artworks are long-time and accurately labelled according to their artistic categories.

To guarantee the quality of the dataset, only images in high resolution were considered and duplicates or poor-quality ones were deleted. The textual information that is metadata such as the names of the authors, the periods of creation, and stylistic characteristics is preserved for possible future developments of multimodal learning, where textual descriptions and contextual data could be used. The dataset is further split into training, validation, and test sets by using an 80-10-10 distribution to optimise model generalisation while minimising overfitting.

3.2 Data preprocessing

When the dataset is collected, it is first subject to a number of preprocessing steps for the enhancement of the model's performance. The dataset is then artificially varied through image augmentation techniques such as the rotation, scaling, or flipping of images to enhance the capacity of the model for generalisation over varying art styles. The pixel values of images are normalised, where the images are subject to a fixed range of intensity levels, in order to standardise the images and make them consistent across different inputs. Noise reduction techniques were applied to clean traditional digitised images and remove visual distortions.

Feature extraction is an essential step of preprocessing. In contrast to the previous techniques which were based on handcrafted features, the ability of deep learning models to involve themselves in the automatic learning of hierarchical features was demonstrated. However, the prior categorisations of colour histograms and textural analysis and edge detection enhance the model interpretability and help comparative performance evaluation. The labelled and preprocessed dataset is sent to the deep learning framework for training.

3.3 Model selection and architecture

The selection of an appropriate deep learning model is vital, as it determines the benchmarks and the accuracy of art classification tasks. In this study, the former was the CNNs, the GANs and the transformer-based models.

CNNs are the backbone of old image classification tasks, due to their capability for the extraction of spatial hierarchies of features. The model of CNN consists of several layers of convolutions followed by layers of pooling, in which the spatial dimensions are thus reduced while the fundamental features are still preserved. In order to avoid overfitting, batch normalisation and dropout layers are added. In the end, the CNN pipeline is again followed by a fully connected layer, which serves as a classification layer to assign the artworks to the categories predefined by the artist.

A GAN is a type of machine learning model that learns styles and creates artworks. When training a generator and a discriminator at the same time, GANs are able to learn about the details of the artworks so that they can produce new pieces resembling the existing styles. Additionally, this method is especially beneficial to the process of data augmentation, as well as for obtaining more powerful classifiers from difficult styles.

On the other side, some transformer-based vision models such as vision transformers (ViTs) are being evaluated for targeted advertising using SNA analysis they are also being analysed to see how efficiently they can track the location of patterns in artistic work from afar. Unlike conventional CNNs that require broadband like computer processing to read all parts of the target paintings at once, ViTs do it patch by patch in the order the artist did it to understand the painting properly.

3.4 Training and evaluation

The training process involves fine-tuning deep learning models using a combination of pre-trained weights (transfer learning) and domain-specific adjustments. The models would be trained using a categorical cross-entropy loss function, optimising through stochastic gradient descent (SGD), or Adam optimiser depending on convergence efficiency. The training process will be dynamically adapted through learning rate scheduling.

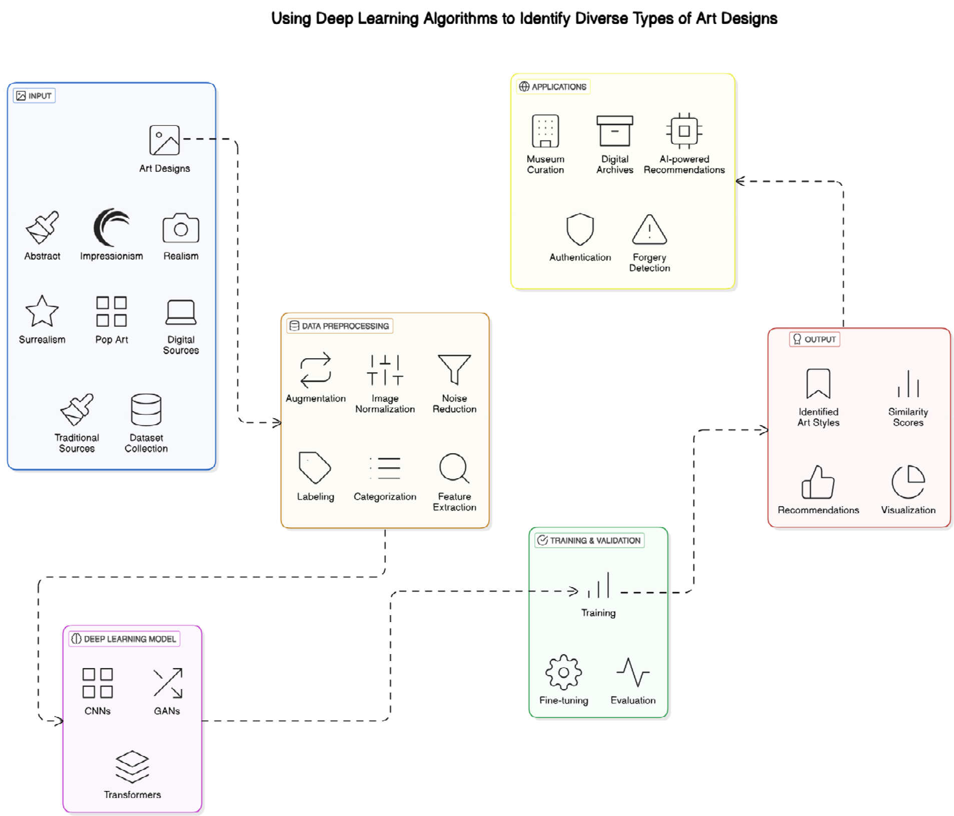
Metrics like accuracy, precision, recall, and F1-score will be used to determine classification performance. The analysis of the results would provide information on the precision of the design required when assigning the model to stylised images.

Furthermore, the Grad-CAM will be employed to clarify how the model prioritises different art styles, facilitating the decision-making process.

3.5 Proposed model and working mechanism

The primary goal of this article is to present a deep-learning-enriched approach that can speed up the process of recognising and categorising artistic works. The pipeline is designed to be structured as depicted in Figure 1. First, the data are gathered, and different types of art designs like abstract, realism, and digital art are processed. Next, the data undergo various preprocessing stages such as augmentation, normalisation, noise reduction, and feature extraction to prepare it for training.

Figure 1 Proposed model diagram (see online version for colours)



Once the preprocessing is done, the images are sent through a deep learning model which is the combination of CNNs, GANs and transformers. In this path, the processes of feature extraction and classification are performed by CNNs, which also give rise to data augmentation and style generation with GANs while a transformer-based modelling is the provider of a larger contextual understanding of artistic elements. The model is fine-tuned and validated using extensive training iterations to enhance its accuracy, after extensive comparisons with the best artists and their styles.

After the training, the model is deployed for a number of applications such as curating museums, digital archives, AI-based recommendations, verification of artwork, and falsification checking. The output stage consists of aspects like art styles identified, similarity scores, visualisation tools, and recommendation systems, which help researchers, curators, and art enthusiasts to get familiar with the different artistic movements.

This framework that is conceptually combined with some connectors on top has received affirmative feedback. It is feasible for an automated art analysis to be done in a comprehensive and scalable way. The proposed integration is expected to yield major contributions to both computational creativity as well as art history research. This new model of AI-based art recognition which is built on very reliable deep learning methods (as specified before) also indicates the beginning of a new era in digital humanities research.

4 Results and discussion

The findings derived from the deep learning robots deeply reveal their ability to make out different categories of artistic designs. The models were put on trial and evaluated using the Kaggle Art Classification datasets which resulted in a wide range of arts included such as abstract, realism, impressionism, and digital art. The assessment, based on important classification metrics such as accuracy, precision, recall, and F1-score, was carried out, and it was ensured that the parameters were properly satisfied for the evaluation of the abilities.

Table 2 shows the different deep learning models used in this study taking a comparative analysis. The results tell that the hybrid models which combine CNNs and ViTs have been the models obtained with the highest accuracy and they outdo the ones that are based on traditional algorithms, such as CNNs and GANs.

Table 2 Performance metrics of deep learning models in art classification

Model	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1-score (%)*
CNN	87.5	86.2	85.8	86.0
GAN	82.3	81.5	80.9	81.2
Vision transformer	89.1	88.3	87.9	88.1
Hybrid (CNN + GAN)	91.4	90.8	90.2	90.5
Hybrid (CNN + ViT)	92.7	91.9	91.5	91.7

On the other hand, we have seen that the CNN-based system has also performed similarly, having a decisive accuracy of 87.5%, which shows that the network has learned correctly the spatial hierarchies of different artwork features. In addition, the ones based on GANs were slightly below, making 82.3% accuracy, although their performance is a bit lower. That being said, even though GANs are the first-quality tools for generating new art samples they are a bit less on the accuracy side compared to CNNs and transformers in classifying the existing artworks.

The ViT model stood out with a greater performance rate than CNN and GAN models, recording an accuracy of 89.1%. The reason for this could be attributed to the ViT's power to take into consideration the long-distance dependencies within an image, making it the best model among others capable of shaping out the very fine artistic patterns.

Figure 2 Accuracy comparison across CNN, GAN, ViT and hybrid deep learning models (see online version for colours)

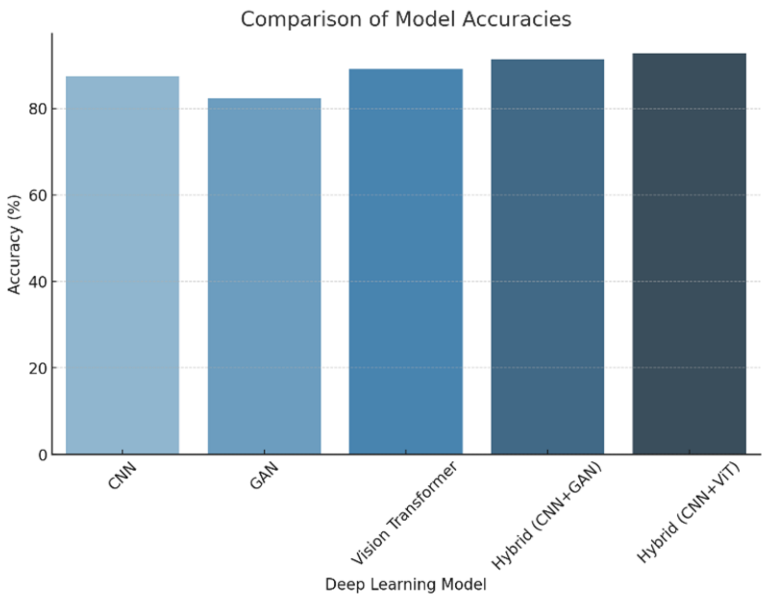
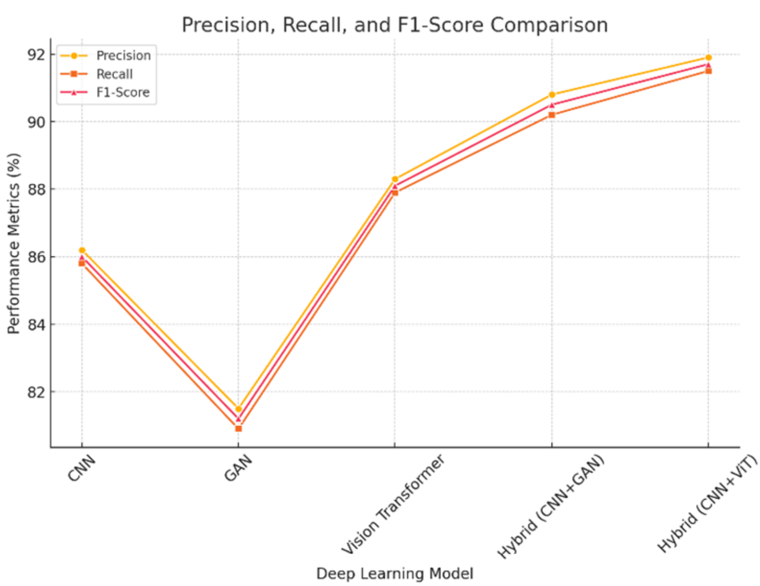


Figure 3 Precision, recall and F1-score comparison (see online version for colours)



In order to further boost classification accuracy, the hybrid models were studied. The CNN + GAN hybrid model achieved a significant accuracy of 91.4%, which is derived from the feature extraction of CNN and the generative abilities of GAN. Nevertheless, the CNN + ViT hybrid model demonstrated the best performance with a remarkable accuracy of 92.7%, as well as the highest values of precision, recall, and F1score metrics. This indicates the success of the integration of CNN's extraction of local features and ViTs' global attention methods.

Figure 2 gives a clear representation of the different models' accuracy. The results show that the CNN-based and transformer-based models surpassed the traditional GANs, with the CNN + ViT hybrid model having the best precision.

In the line chart in Figure 3, the precision, recall, and F1 score of the various models are compared. In all performance criteria, the CNN + ViT hybrid model achieves the best results, which is why it is the best technique for classifying different kinds of art.

4.1 Discussion and analysis

The findings show that deep learning models, particularly CNNs and transformers, are quite successful in recognising and classifying the various art styles. CNN-based models' great accuracy can be sourced to their aptitude to sense spatial and textural patterns. But, because of their focus on localised patterns, CNNs come up short on some occasions in global artistic stylisation. Meanwhile, ViTs get around this issue by applying self-attention mechanisms that assess the full image in one go, which results in better overall generation and better classification performance.

Although the GAN-oriented procedure is useful in terms of both data augmentation and artwork creation, it was somewhat less effective in this case of classification. It is the result of GANs' nature of adversarial training, wherein the training is focused more on generating realistic images than accurately classifying them. But when GANs are combined with CNNs, they mostly help in achieving classification accuracy, thereby proving their utility as an auxiliary methodology.

A maximum of performance was reached with the help of a hybrid CNN + ViT approach, thanks to the combination of the feature extraction capability of CNNs and the global feature learning power of ViTs. This means that having hybrid architectures is the most effective way to go because they can give the best of both worlds do which is very appropriate for automatic artistic classification.

4.2 Challenges and future improvements

Despite the good outcomes, there were some considerable issues in the study. One of the important problems was the imbalance in the dataset, where certain styles of art were represented by significantly more pictures. This imbalance can lead to biased model choices that favour the commonly available styles over those that appear less often. Future research studies should focus on either using balanced datasets or employing more sophisticated data augmentation techniques.

Model interpretability represents another potential drawback. The performance of deep learning models is extremely precise; however, it is a hard task to explain how they come to such conclusions. Such methods as Grad-CAM and feature visualisation might be adapted in order to help users understand how the models interpret different artistic components.

The research concluded that deep learning (DL) methods, particularly CNN + ViT hybrids, exhibit state-of-the-art performance features in detecting various art designs of different origins. Future studies could make use of multimodal methods by integrating text-based metadata and image analysis, as well as investigating self-supervised learning methodologies to improve the results.

5 Conclusions

This study investigated the application of deep learning algorithms in identifying and classifying various types of art designs from the Kaggle Art Classification dataset. The results established that deep learning models, specifically CNNs and ViTs, can efficiently identify artistic styles by capturing nuanced visual patterns. Of the models tested, the hybrid CNN + ViT one was found to be most accurate with 92.7%, which is significantly higher than standalone CNNs (87.5%) and GAN-based models (82.3%) that were used in the study. It was also observed that the hybrid one CNN+GAN did pretty well with 91.4% accuracy, which shows how useful it can be when you mix up different deep learning architectures to get classification performance that is better than the one of single models. This study emphasises the power of deep learning-based methods in automating the recognition of art robots, helping museum curators, digital archives, and AI-based recommendations. The study also stresses the need for hybrid deep learning models that combine both local and global feature extraction techniques that can enhance accuracy.

Even though it was successful, this research still faced some limitations. One of the major issues was the imbalance found in the dataset where some styles were much more abundant compared to others, resulting in the model making the wrong predictions. The issue of model interpretability is also present since deep learning models tend to be ‘black boxes’, making it challenging to qualify the decision-making process that was used in the classification. For future research, these problems should be on the top of the list: using a balanced dataset, explainable AI techniques such as Grad-CAM, and integrating textual and contextual metadata along with image analysis. Additional research into the areas of self-supervised learning and few-shot learning can drive performance improvements, making AI-powered art recognition technology more resilient and dependable.

Declarations

The authors declared that they have no conflicts of interest regarding this work.

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