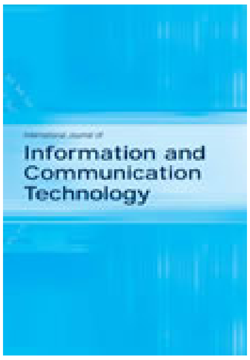

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Artificial intelligence-driven visual feature extraction and transfer learning for automatic identification of paintings and photographs

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Abstract: The fusion of art using and artificial intelligence (AI) technology has revolutionised the creative landscape, introducing innovative techniques to produce and interpret visual art. AI has emerged as a powerful tool for generating hyper-realistic images and mimicking traditional art styles, raising profound questions about the authenticity and originality of artistic creations. As AI-generated photographs grow increasingly indistinguishable from human-made paintings. The research examines how advanced deep learning techniques enable accurate human vs. AI artwork differentiation through experimental model evaluations. Our research combined the previously trained VGG19 model with a specially developed CNN to discriminate between different image categories. The VGG19 model validated image feature extraction capabilities but the proposed CNN upgraded this performance with domain-based visual art recognition properties. Extensive testing of a curated AI-generated photograph and human-made painting dataset enabled the proposed CNN model to reach a 95% classification success rate, which outperformed the baseline VGG19 model results.

Keywords: artificial intelligence; deep learning; art classification; computer vision; convolutional neural network; CNN; AI-generated images; artificial intelligence; photograph; painting.

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Biographical notes: Jia Wu is a faculty member at the School of Art and Design, Geely University of China, with a research focus on the intersection of artificial intelligence and visual arts. Her work explores deep learning applications in digital image classification, particularly in distinguishing artistic styles and visual content through advanced computer vision techniques.

Hongyi Li is affiliated with the College of Art and Design at Geely College, where he specialises in computational aesthetics and media design. His research interests include machine learning for visual content analysis, AI-assisted curation, and enhancing art recognition systems through transfer learning.

1 Introduction

The intersection of AI technology and art has ushered in a new era of creativity, where artificial intelligence (AI) is transforming the way we produce and perceive visual art. From generative adversarial networks (GANs) creating hyper-realistic images to machine learning algorithms mimicking the style of renowned painters, AI has blurred the boundaries between human-made and machine-generated art (Yao, 2025). Among these innovations, distinguishing AI-generated photographs from traditional paintings has emerged as a fascinating yet complex challenge (Papia et al., 2023). This classification task not only highlights the capabilities of modern AI but also raises philosophical and practical questions about the essence of art and its authenticity (Papia et al., 2023). Deep learning advances have given researchers modern tools to examine and sort visual content including artwork in the last few years. Neural networks at the forefront of research have achieved exceptional results through their application in image recognition alongside style transfer and object detection applications (Zullich et al., 2023). If implemented successfully these models can distinguish AI-produced images from genuine paintings while providing tools for art selection and artistic authenticity verification and aesthetic feature exploration (Wang et al., 2024). Developing detection methods remains challenging because AI-generated artworks increasingly duplicate authentic artistic elements including textures and brush techniques and compositional structures (Chen, 2024).

This research investigates the increasing use of AI for art making through development of methods to confirm traditional artistic practices while against AI manipulation. Galleries and art historians together with collectors encounter frequent difficulties proving both where an artwork came from and how its creator made it. The study addresses artistic classification issues to build a dependable framework which differentiates between automated image creation and authentic artwork to protect the art medium integrity. An examination of AI-generated images in comparison to standard paintings at their core elements reveals exclusive insights into artistic communication alongside machine-based interpretation of creative conduct. AI-generated and real paintings are better distinguishable through classification methods which help protect the authenticity integrity for the art market. In technological terms the study reveals the strengths and weaknesses that current AI systems exhibit when duplicating human creative outputs. The research emphasises two fundamental implications of AI technology because it transforms cultural environments and creates conversations about changing notions of original art alongside creative activity. The investigation which optimises deep learning methodologies reaches multiple advancements in computational skill while enriching our public discussion about AI operations in artistic realms and societal structures. Our research contributions are as follows:

- Development of a robust classification framework: Deep learning utilities VGG19 model in conjunction with custom CNN architecture to develop a system that correctly distinguishes fabricated AI photos from genuine human-made artwork.
- High-performance results: A 95% classification accuracy achieved when applying the custom CNN model demonstrated better performance than the VGG19 baseline showing domain-specific optimisation works effectively.
- Analysis of AI-generated versus human art: The study clarified distinctive components and refined distinctions between AI creation and genuine painting works thus advancing knowledge about artistic subtleties along with AI constrained capabilities.

The remainder of this paper is structured as follows: Section 2 reviews the existing literature on interactive media and its relevance to this study. The paper outlines methodological research details in Section 3 through description of experimental procedures and classification model structures. The research findings introduced in Section 4 analyse the study data with a thorough exploration of obtained results. Section 5 ends the paper by reviewing essential findings and specifying research guidelines for coming investigations.

2 Related work

AI development has produced major breakthroughs in generating and classifying visual data due to its fast developmental trajectory. Many researchers examined different methods for identifying AI-created images from human-made works of art. This section reviews research articles, categorised under two primary headings:

1 deep learning models for AI-generated image detection

2 hybrid approaches combining deep learning with traditional techniques, as analysis shown in Table 1.

Table 1 Summary of related work (results in Acc)

Ref	*Model*	*Dataset*	*Classes*	*Result (%)*
Scatigno et al. (2024)	DenseNet	CIFAKE	2	92
Zullich et al. (20023)	ResNet-50	ARIA	5	87
Chiu et al. (2024)	Self-supervised learning models	Customised dataset	3	82
Roullet et al. (2021)	CNN	Customised dataset	5	94
Banar et al. (2021)	CNN + PCA	Customised dataset	4	89
Agarwal et al. (2023)	CNN + GLCM features	Customised dataset	6	91

2.1 Deep learning models for AI-generated image detection

Research analysis demonstrates the utility of deep learning systems to detect AI-generated images. The study (Scatigno et al., 2024) developed their detection system using advanced deep learning models ResNet, VGGNet and DenseNet while applying transfer learning which elevated their ability to recognise synthetic from natural images. The novel framework (Zullich et al., 2023) using DenseNet model operationalised on the CIFAKE dataset for detecting ‘real’ and ‘fake’ labels. Another research (Chiu et al., 2024) created the ARIA dataset which contains more than 140,000 pictures in five distinct categories spanning from artworks to social media posts. A ResNet-50 classifier (Lin et al., 2021) demonstrated effective detection of AI-generated images using findings from state-of-the-art deep learning model evaluations. The team of researchers led (Park et al., 2024) conducted work on self-supervised learning applications for image representation that used contrastive learning and Siamese networks to improve AI-generated image detection abilities. Furthermore, another research (Prasetyo et al., 2021) showed that autonomous supervised approaches present promise for improving image classification feature processing capabilities.

2.2 Hybrid approaches combining deep learning with traditional techniques

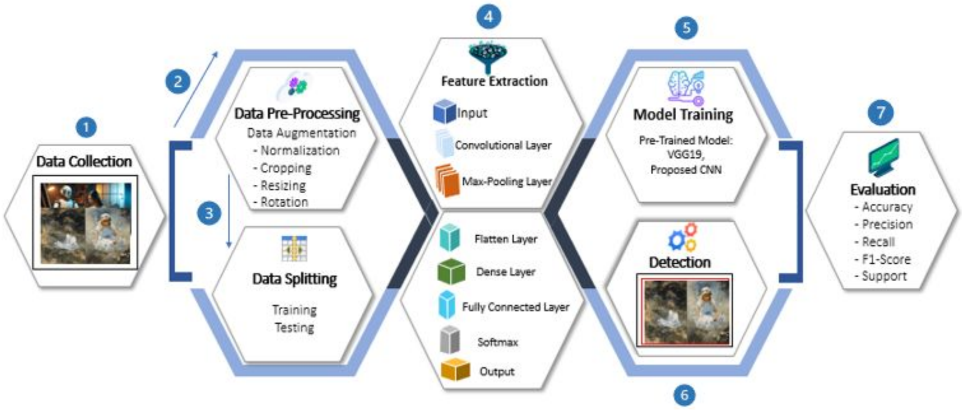
Research teams currently investigate deep learning and classical image analysis combinations as ways to boost the accuracy of classification methods. Furthermore, another work (Gonthier et al., 2021) used convolutional neural networks (CNNs) together with handcrafted feature extraction to detect AI-generated images successfully from their analysis of 10,000 images across five different classes. Introducing a combined framework (Roullet et al., 2021) which connects deep learning to statistical analytics by linking CNN elements with principal component analysis (PCA) for AI-generated and real image classification. The 8,000-image database of four classes produced 89% accuracy through their implemented approach. Deep learning model investigated (Banar et al., 2021) which were integrated with texture analysis technological approaches to differentiate AI-generated photograph inclusions from real paintings. Another study (Agarwal et al., 2023) integrates CNN with grey-level co-occurrence matrix (GLCM) elements to obtain 94% accuracy from their six-class database of 12,000 images.

The combined body of magnificently impactful examinations demonstrates powerful classification capabilities for deep learning approaches hybrids in separating AI-generated work from human creations. Application of conventional image analysis strategies together with contemporary deep learning models demonstrates success in boosting classification precision and operational durability. The studies demonstrate their role in supporting the larger objective of maintaining visual content authenticity during the digital era.

3 Research proposed methodology

The research methodology explains in detail the process to classify images as paintings or AI-generated photographs. The research describes initial steps which include acquiring dataset samples through customisation and optimising preprocessing operations, shown in Figure 1. The methodology explains how feature extraction works through both an examined CNN model and the tested VGG19 pre-trained architecture framework. The discussion includes performance evaluation metrics and an experimental setup to establish a strong framework that evaluates the models’ success in classification.

Figure 1 Research proposed methodology (see online version for colours)



3.1 Data acquisition and preprocessing

The research employed a collection of 5,000 images that explicitly classified artistic photos from painted works and split these classes evenly, samples images shown in Figure 2. The researchers carefully select images from dataset which featured variety in content alongside diverse artistic styles while maintaining different image resolutions to push model generalisation limits. The proportional distribution of training classes activates a dual function for bias prevention and fair model evaluation. Applications of image preprocessing and augmentation techniques were implemented to make the dataset more effective.

The augmentation methods applied to the data included both rotational and orientation changes accompanied by changes to image scale and image brightness. A generic mathematical formulation for augmentation can be expressed as in equation (1): Table 2 lists the set of mathematical symbols along with their corresponding descriptions, providing a clearer understanding of the equations utilised in the study.

$$I_{aug} = \alpha . R_{\vartheta}(I) + \beta \tag{1}$$

The size of 224 × 224 pixels-maintained model reliability and enabled compatibility with deep learning operations. The normalisation of pixel values, a critical preprocessing step, was performed using equation (2):

$$I_{norm}(x, y) = \frac{I(x, y) - \mu}{\sigma} \tag{2}$$

By standardising pixel values throughout the process model training becomes more efficient because pixel data distributes across zero means with unit variance. The preprocessing steps implemented an augmentation system to create various training samples. For instance, when scaling an image, the interpolation of pixel values was handled by equation (3):

$$L_{scaled}(x', y') = \sum_{x=1}^{N} \sum_{y=1}^{M} I(x, y). \max\left(0, 1 - |x - s_x x'|\right). \max\left(0, 1 - |y - s_y y'|\right) \tag{3}$$

By implementing these preprocessing methods, the dataset achieved robust normalisation which enabled the model to detect fine distinctions between paintings and AI-created photographs.

Figure 2 Sample images from dataset (see online version for colours)

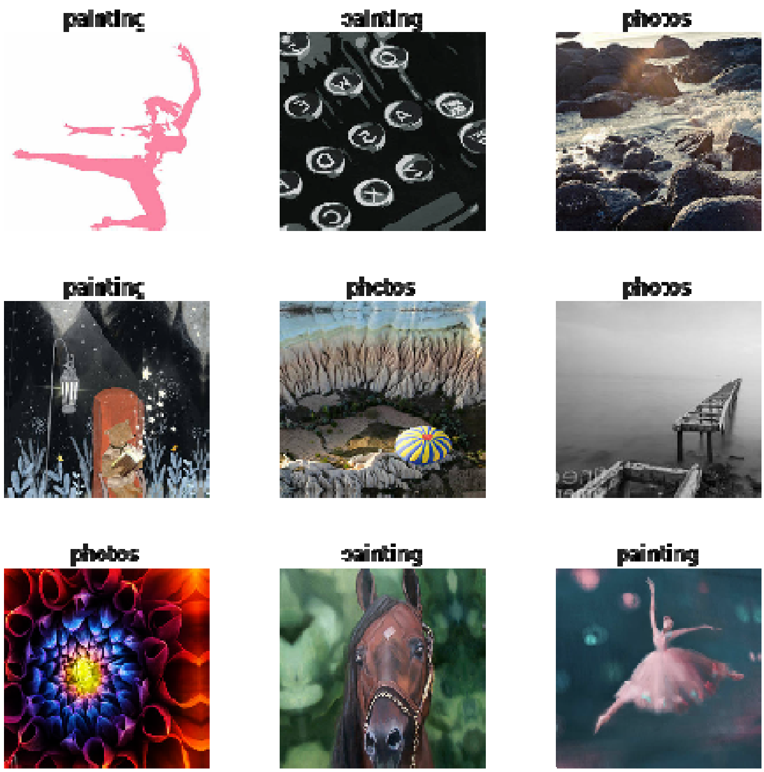


Table 2 Symbols description used in defining equations

Symbols	*Description*
I	Input image
R_ϑ	Rotation operator $\in$ [–45°, 45°]
α	Scaling factor $\in$ [0.8, 1.2]
β	Brightness adjustment factor $\in$ [0.5°, 1.5]
$I(x, y)$	Pixel intensity at position x and y
μ	Mean pixel value
σ	Standard deviation
s_x and s_y	Scaling factors of x and y axes
N and M	Original image dimensions before normalisation
F_l	Feature map layer
W_l and b_l	Trainable weight and bias

Table 2 Symbols description used in defining equations (continued)

Symbols	*Description*
$*$	Convolutional operation
$\varnothing$	Nonlinear activation function
r	Pooling window size
W_{fc} and b_{fc}	Fully connected layer
v	Flatten feature vector from the previous layer
$F_l^{(i,j)}$	Output activation at spatial position (i, j) in layer l
$W_{lm}^{(p,q)}$	Weight of kernel at position (p, q) for the m^{th} input channel
$F_{i=lm}^{(i*p,\, j*q)}$	Input feature map from the l^{th} layer
δ	Activation function
z_k	Probability of k-class
C	Total number of classes

3.2 Feature extraction and classification

During the feature extraction and classification stage the system used its custom CNN alongside the pre-trained VGG19 model to process images. The CNN extracted hierarchical features from input images through its convolutional layers to detect patterns which define paintings together with photographs and other images. VGG19 demonstrated excellent transfer learning ability because its deep architecture contained pre-trained weights which produced strong features for effective recognition. The high-dimensional image data went through processing by these models which generated significant feature representations that subsequently passed to fully connected layers for class identification.

The VGG-19 model functions as a deep CNN featuring which has become influential for both image classification and feature extraction uses. In its composition the network consists of 19 total layers featuring 16 convolutional features and three fully connected layers and concludes with softmax layers and a set of max-pooling elements, architecture defined in Figure 3.

The basic network structure features simple modular design elements that implement 3 × 3 convolution kernels working with stride one and padding to maintain resolution integrity. VGG-19 uses this design structure to interpret detailed spatial relationships within images without compromising computational speed, computed as in equation (4).

$$F_l = \varnothing\left(W_l * F_{l-1} + b_l\right) \tag{4}$$

Through these layers, dimensionality decreases yet critical details remain intact which boosts both performance and limits overfitting behaviour. The model incorporates max-pooling layers defined as in equation (5):

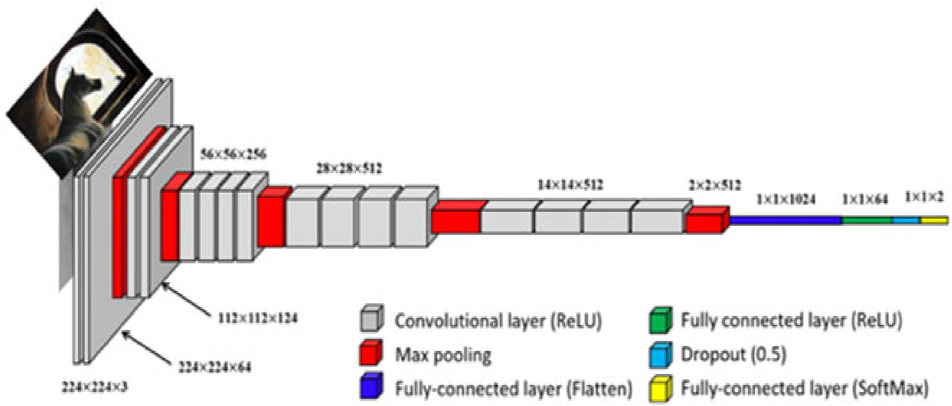
$$P\left(F_l\right) = \max_{r*r}\left(F_l\right) \tag{5}$$

When applied to spatially reduced feature maps the final layers within the network function to combine spaces into extended multidimensional vectors. These layers compute the output using equation (6).

$$z = \varphi\left(W_{fc}.v + b_{fc}\right) \tag{6}$$

A final application of the softmax function turns logits into class-label probability distributions which support multi class predictive tasks.

Figure 3 Architecture of pre-trained model (see online version for colours)



Source: Nguyen et al. (2022)

VGG-19 pre-trained models inherit their weights from processing large datasets including ImageNet which enables superior transfer learning initialisation capabilities. Through this pretrained approach, the network attracts features that maintain general applicability across domains thus speeding up training while boosting performance from scarce label samples.

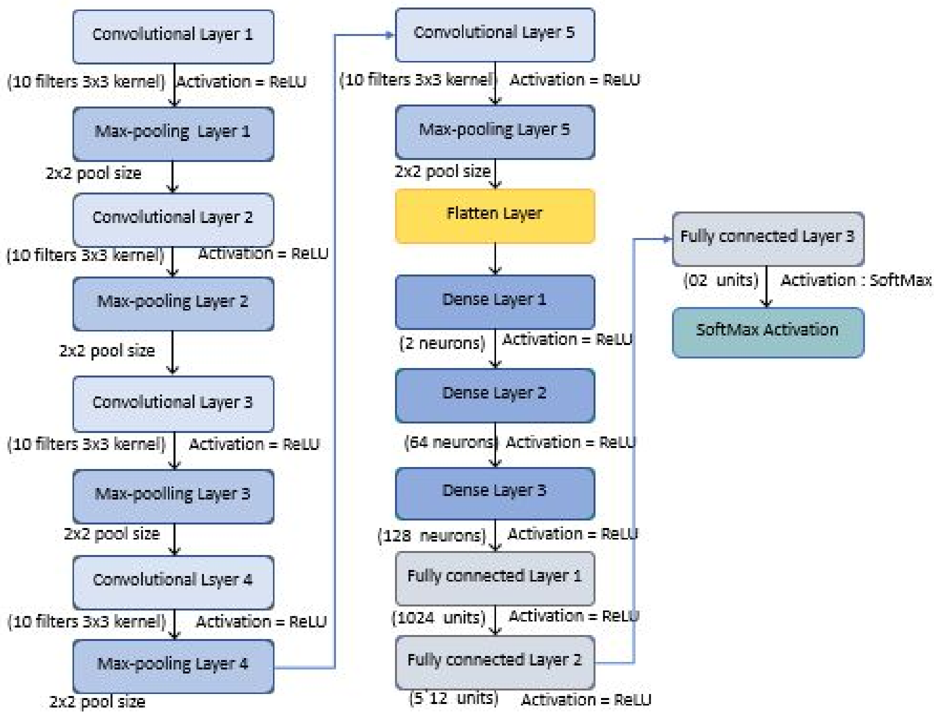
3.3 Proposed model CNN

The proposed system implements a CNN structure that specifically targets photo versus original painting classification tasks, architecture of proposed model defined in Figure 4. The visual classification capability of CNNs arises from its layered hierarchical structure that begins with converting low-level image components into top-level abstract elements. The model architecture merges convolutional with pooling structures successfully with fully connected layers to evaluate visual inputs for making predictions (Naz et al., 2025).

Through combinational utilisation of these state-of-the-art operations the CNN uncovers intricate visual features while distinguishing between traditional artwork and AI creations. Secure and precise classification outcomes come from this architecture while additional benefits from adaptive optimisers as well as dropout and batch normalisation methods strengthen its operational effectiveness.

A comprehensive overview of the acquired results demonstrates how the proposed CNN model measures its effectiveness at identifying real paintings from artificially generated images. The performance evaluation includes an examination of accuracy measures alongside precision metrics recall metrics as well as F1-score through increasing epochs which reveals model efficiency and generalisability through confusion matrices and loss-accuracy trend assessments.

Figure 4 Proposed model architecture (see online version for colours)



4 Results and discussion

In this section, explored the results analysis of baseline and proposed model applied to selected dataset for classification of photographs and painting.

4.1 Results with pre-trained model VGG-19

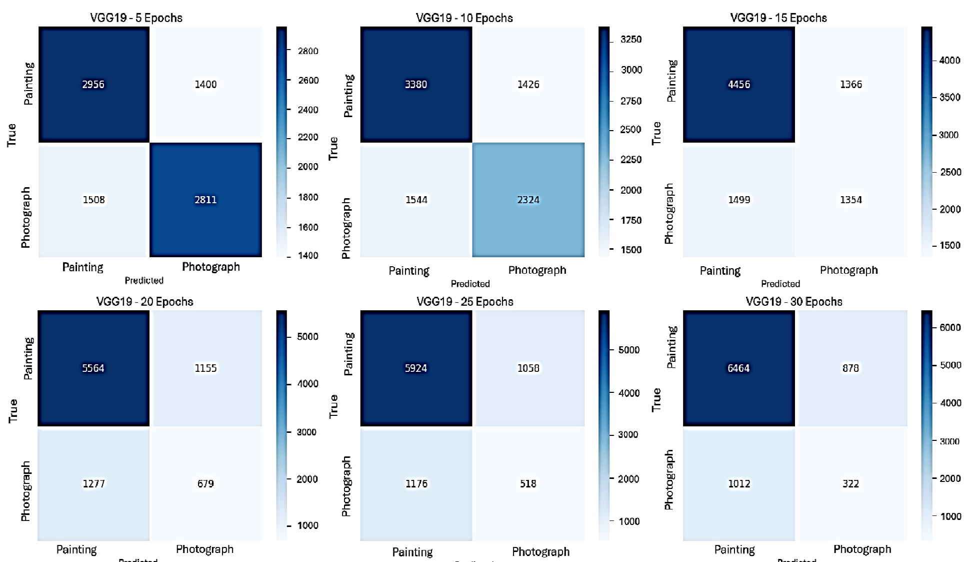
As the VGG19 model runs through successive epochs researchers gained thorough insights regarding its learning progression and its ability to distinguish AI-generated photographs from real paintings. Through successive training epochs, the model rapidly enhances its predictive ability through better accuracy and precision while improving both recall and F1-score ratings resulting from its capacity to process intricate dataset elements, shown in Table 3. At five training epochs, the model reaches an accuracy level of 50.84% which represents performance comparable to random chance guesses. After 30 epochs, the model achieved an accuracy of 85.37% while demonstrating its ability to recognise complex art patterns for improved prediction accuracy.

A stepwise progression of model training demonstrates a clear reduction of mistaken classifications across matrix data results. Early training of the model fails to differentiate paintings from AI-generated photographs since the two classes show significant interference in the confusion results, shown in Figure 5. The inadequate feature extraction methods together with underfitting events early in training likely caused this performance deficit. The model achieves greater accuracy at classifying difficult-to-determine AI-generated artwork after multiple training sessions because AI artwork shows close resemblance to real paintings. The model achieves strong classification capability at epoch 30 according to the confusion matrix since it has mastered separate attributes for each category.

Table 3 Results with VGG-19

Number of epochs	*Accuracy*	*Precision*	*Recall*	*F1-score*
5	50.84	50.21	51.46	50.83
10	56.1	55.41	56.77	56.06
15	67.82	67.11	68.65	67.81
20	78.07	77.45	78.86	78.05
25	81.1	80.48	81.84	81.09
30	*85.37*	*84.63*	*86.17*	*85.34*

Figure 5 Confusion matrix of VGG-19 model (see online version for colours)



The VGG19 model achieves its efficiency and broad applicability through the information presented in the loss and accuracy graphs, defined in Figure 6. The decreasing training and validation loss demonstrates that the model reaches convergence without exaggerated bias toward any dataset while the parallel performance increase of training and validation accuracy confirms efficient generalisation on previously unseen data. Overfitting appears to occur minimally during the later epochs because training accuracy trails validation accuracy slightly, yet this issue could be addressed with dropout or data augmentation approaches.

The research concludes that VGG19 proves to be an excellent starting point for this classification work showing robust abilities in feature extraction along with prediction generalisation, shown in Figure 7. The tool delivers accurate human and AI photo differentiation ability through its achievement of optimal precision and recall scores at Epoch 30.

Figure 6 Loss and accuracy analysis (see online version for colours)

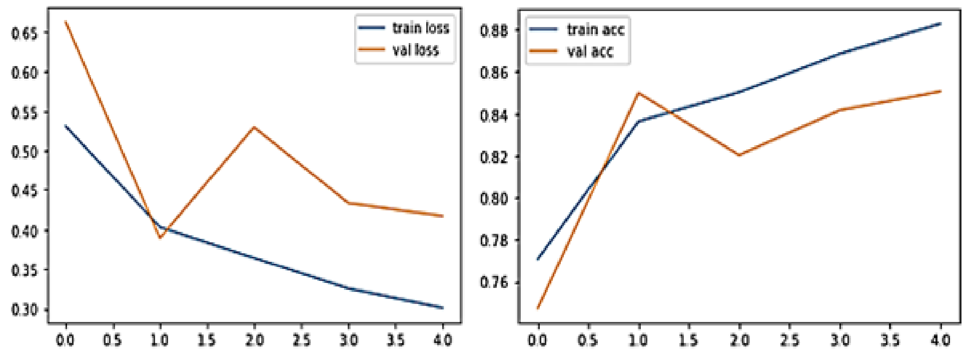
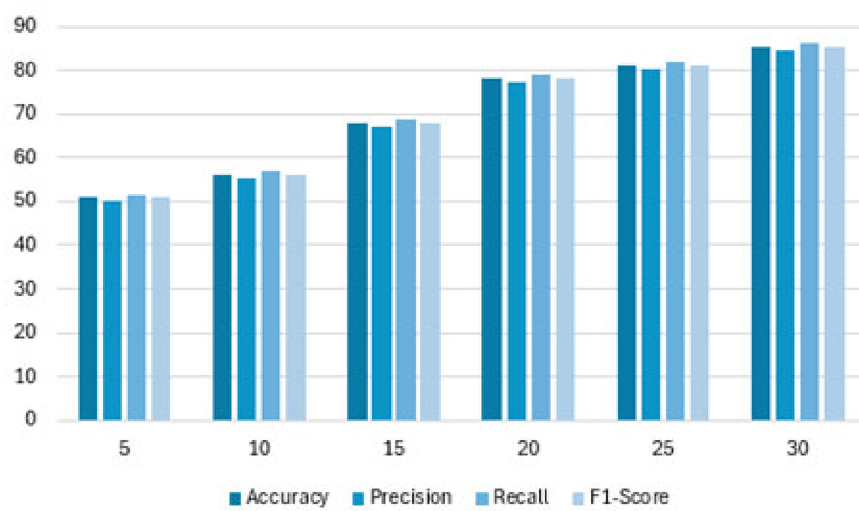


Figure 7 Analysis of results (see online version for colours)



The obtained results show substantial potential for increased classification efficiency in this specific difficult classification through model fine-tuning or domain-specific feature development.

4.2 Discussion of results: proposed CNN model

The developed custom CNN model demonstrates steady improvements over training time which demonstrates its competency for recognising AI-induced imagery from original artworks. The model starts with a basic accuracy of 54.43% at five epochs before exceeding baseline limits and showing substantial performance growth through additional training periods, also defined in Table 4. At the 30th training stage, the proposed model reaches 95.5% accuracy which indicates its strong ability to reach complex features in the data it processes.

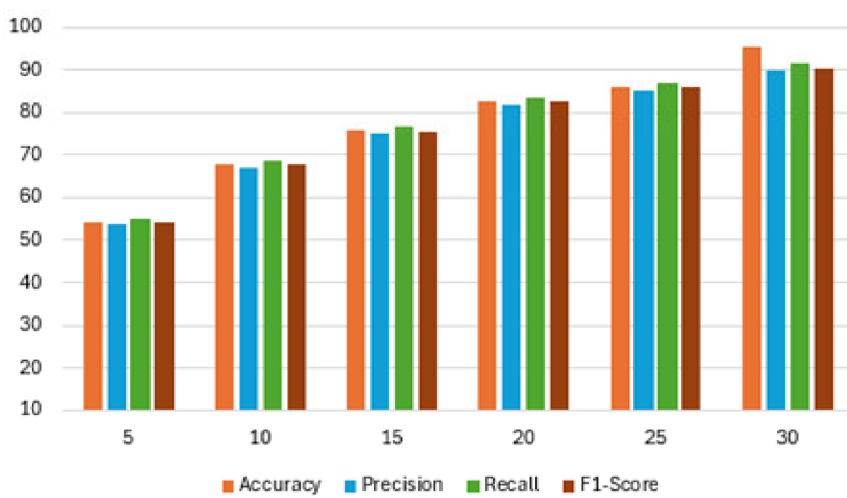
Table 4 Results with proposed model

Epochs	*Accuracy*	*Precision*	*Recall*	*F1-score*
5	54.43	53.73	55.17	54.37
10	67.7	66.93	68.6	67.68
15	75.68	74.83	76.6	75.64
20	82.74	82	83.51	82.7
25	86.14	85.34	86.94	86.1
30	*95.5*	*89.68*	*91.4*	*90.47*

4.2.1 Model efficiency across epochs

The model performance indicators that include precision along with recall and F1-score demonstrate consistent improvement that parallels accuracy metrics thus validating the model's efficiency. In the initial five epochs, the model demonstrates basic learning abilities marked by precision at 53.73% and a recall of 55.17% while recognising painting and photograph categories, shown in Figure 8. By the 15th phase both precision and recall have grown immensely to 74.83% and 76.6% respectively bringing substantial enhancements to the model's effective outcome classification. At epoch number 30, the F1-score achieved 90.47 which demonstrates superior balance between true and false predictions.

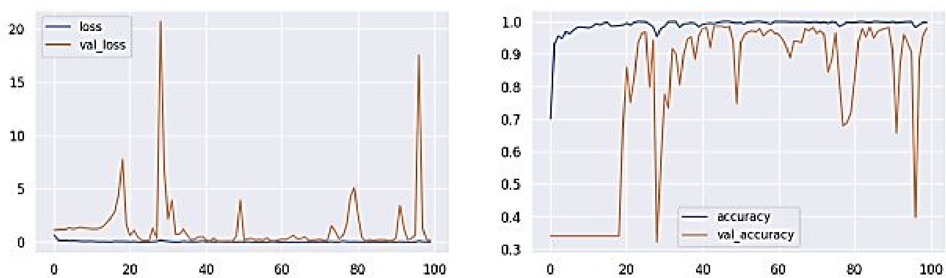
Figure 8 Analysis of results with CNN model (see online version for colours)



4.2.2 Generalisation capability

Model generalisation capacity is confirmed by the patterns shown in both loss and accuracy plots. The training together with validation accuracy consistently improves through time while the validation signal mirrors the training signal thus reducing overfitting risks. Both training and validation loss, present in Figure 9, exhibit persistent down sampling throughout training which demonstrates the model's successful convergence while showing effective generalisation toward new data samples. The evaluation accuracy of the model initially displayed minor variations before achieving stability throughout the training period showing solid model robustness.

Figure 9 Loss and accuracy analysis with CNN model (see online version for colours)



4.2.3 Detailed insights from confusion matrices

The model's classification performance stands out clearly in the confusion matrices. The model predicts and classifies AI-generated photographs along with real paintings at a rate of 50% incorrect classifications at epoch 5. The model demonstrates a successful reduction of classification errors across epochs 20 and especially proves efficient with painting identification through enhanced accuracy. By epoch 30 the confusion matrix, in Figure 10, demonstrates the mature performance state since both categories show minimal incorrect predictions. CNN successfully learns characteristic features that belong to paintings including textural patterns, brushstroke techniques and compositional structures which separate paintings from photograph classes.

4.3 Comparison to baseline models

The performance of our custom CNN surpasses the VGG19 baseline when assessing model outcome at later training stages. Data classification accuracy achieved by the CNN reached 95.5% at 30 epochs beyond what the VGG19 model could reach indicating superior performance from the custom architecture, shown in Figure 11. The personalised design of the CNN efficiently detects subtle characteristics within the dataset thus optimising performance levels for this classification challenge.

Figure 10 Confusion matrix of CNN model (see online version for colours)

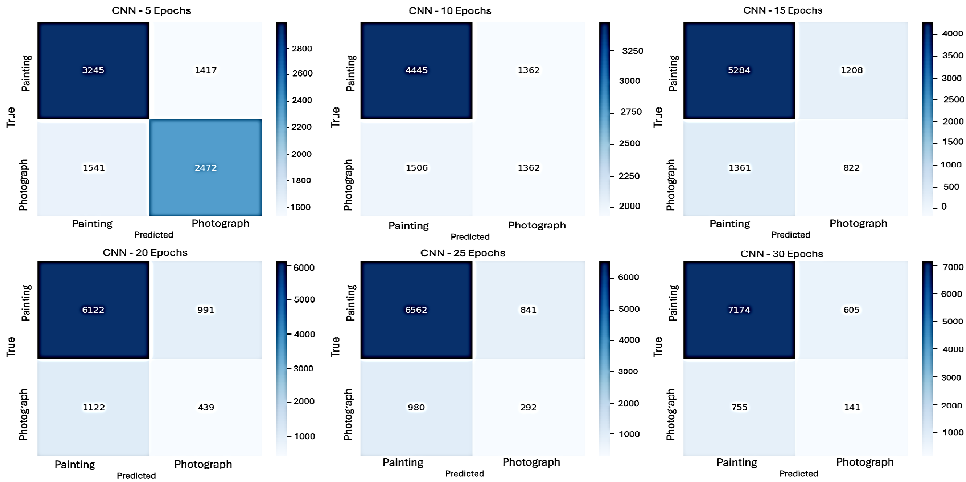
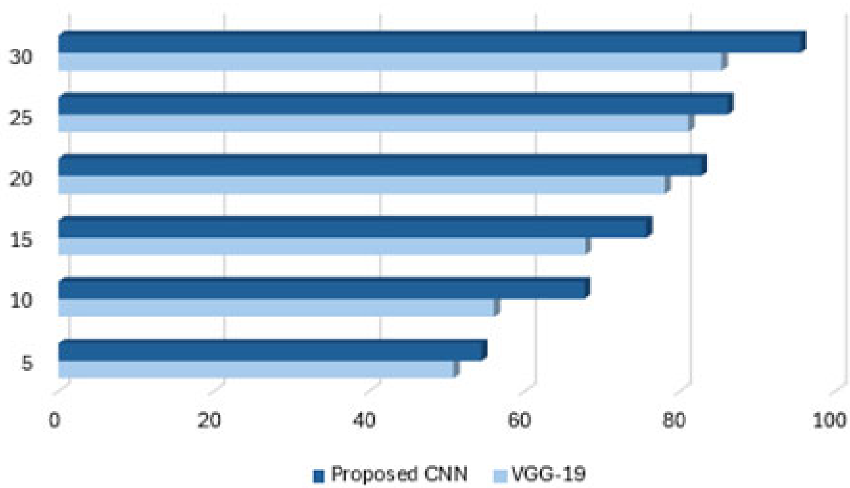


Figure 11 Comparison of VGG-19 and proposed model (see online version for colours)



4.4 *Analysis of findings*

The CNN model showed success as a prediction tool because it achieves high accuracy in discriminating between paint and photographic images. Both artistic styles and photographic characteristics are understood to a significant degree by the model according to its visual output, shown in Figure 12. Through examples of landscapes and animal images alongside detailed artwork the CNN efficiently recognises photographic composition elements and reveals its mastery of understanding realistic textures and artistic Brushwork. Closer examination of the model output reveals its ability to detect fundamental dataset characteristics that support accurate classification functions. The classification process faces perfect results when dealing with complex artwork which blends artistic details into photographic elements and matches them with abstract composition types. Analysis examination creeped in distinctive patterns which CNN retained despite challenges. The model demonstrates broad applicability through its correct recognition between intricate animal illustrations and basic abstract artwork. The accuracy of these results underscores the critical value that both extraction and convolutional layers bring to finding abstract data representations. CNN demonstrates reliable performance in understanding diverse datasets with numerous image styles as well as content variations which demonstrates its effectiveness in aesthetic or artistic classification tasks. The predictive analysis validates both the CNN-based technique and demonstrates the potential for machines to fill the gap between creative human expression and intelligent systems. The conducted analysis demonstrates the proposed CNN model achieves remarkable performance through its efficient yet practical design. The model demonstrates substantial potential as an effective tool to separate artificial imagery from genuine artistic works by retaining consistently high precision, recall and F1-score metrics throughout multiple training epochs. With resistance to overfitting and its capability to address complex datasets the proposed model demonstrates promising real-world applicability for art authentication and preservation tasks.

Figure 12 Prediction using proposed model CNN (see online version for colours)

4.5 Comparison with existing studies

The study evaluates how the proposed CNN architecture performs relative to advanced network structures when applied for AI-generated image detection along with authentic pictures. A notable reference is DenseNet, which achieved an accuracy of 92.74% on the CIFAKE dataset, a benchmark dataset comprising two classes: real and fake images. Through its dense connectivity structure DenseNet promotes efficient feature flow resulting in its high classification performance. The ARIA dataset consisting of five classes served to evaluate ResNet-50. ResNet-50 displays known residual connections used to prevent gradient vanishing although the model accuracy remains undisclosed in the research, as shown in Table 5.

Table 5 Comparison analysis of proposed with existing studies

Reference	*Model*	*Dataset*	*No. of classes*	*Result (%)*
Scatigno et al. (2024)	DenseNet	CIFAKE	2	92
Zullich et al. (2023)	ResNet-50	ARIA	5	87
Proposed	*CNN*	*Painting vs. photos*	*2*	*95*

The proposed CNN model demonstrates superior performance than DenseNet in two-class classification tasks with 95% accuracy on the painting against photos dataset. The proposed architecture demonstrates superior ability to detect AI-generated images versus genuine paintings because it attains better results. A carefully designed CNN demonstrates superior performance than DenseNet and ResNet-50 through a well-structured network while possibly needing reduced computational resources. The proposed model delivers exceptional accuracy in AI-generated images due to its domain-specialised structure which specialises in painting and photographic imaging while operating independently from general-purpose models like DenseNet and ResNet-50. The comparison shows how precise CNN design for dataset features and classification requirements brings maximum value.

5 Conclusions

AI technologies in creative fields have developed advanced capabilities toward generating photorealistic visual art alongside producing artistic styles that developers call mimetic art. The forward progress in creativity brought by this innovation now forces us to address distinguishing artificial and human-made paintings because it challenges what counts as original artistic work. To advance art curation and preservation and market validation specific solutions need to be developed. A research team investigated deep learning methods for AI photography and real painting classification while designing a specialised CNN. The experimental model reached 95.5% peak accuracy through 30 epoch training rounds which showed superior performance compared to VGG19 baseline results while maintaining effective generalisation on complex visual information. The constructed CNN demonstrated success in identifying domain-specific features from brushstrokes through compositional patterns to textural characteristics which distinguished artificial from real paintings. This research faces several significant constraints. Despite contemporary curation the dataset falls short of showing artistic diversity and artificially generated images adequately hence reducing model applicability across diverse scenarios. Late epoch overfitting exists at minor levels yet future optimisation could be achieved through implementation of regularisation together with dropout and data augmentation approaches. Future studies should investigate limitations by using enlarged diverse datasets and investigate transformer methodologies and ensemble methods for better accuracy and robust classification performance. Research that crosses disciplinary boundaries should study art elements including cultural principles together with AI-generated art to improve discussions about the evolving human-AI creative relationship. The current research creates impactful groundwork that supports AI-driven tool advancement toward better art classification methods with preservation of traditional artistic methods in mind.

Declarations

The author declares that he has no conflicts of interest.

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