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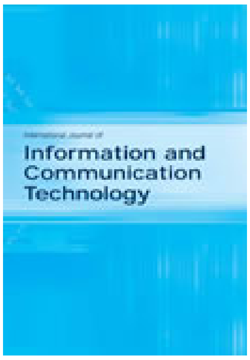

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Automatic identification of AI-generated ceramic art images using convolutions-based neural networks models

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Abstract: Ceramic art, deeply rooted in cultural heritage, has long been regarded as a symbol of craftsmanship and historical significance, often commanding substantial prices in the art market. However, with the rise of artificial intelligence (AI) and its ability to generate art that closely resembles human creations, distinguishing between authentic and AI-generated artworks has become a critical challenge. In this research work, deep learning base models including the proposed convolutional neural networks (CNNs) and pre-trained models are applied to identify ceramic arts, distinguishing between human prepared artefacts and AI-generated content (AIGC). There is no benchmark data set available to distinguish between real ceramic and AI-generated, therefore, the dataset has been prepared having two classes: authentic ceramic items (real) and AI-generated. The results obtained the highest accuracy of 98% by using CNN compared to pre-trained models, such as ResNet, VGG and AlexNet models. This study may help to identify the authenticity of digital artefacts in the digital era.

Keywords: deep learning; cultural heritage; ceramic; artificial intelligence; classification; computer vision; feature extraction; norm analysis.

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1 Introduction

Cultural heritage is an important concept of the entire history of human civilisation and the history of nations and peoples and reflects the peculiarities of their historical development, as well as traditional spiritual and artistic values. It fulfils the purpose of a mediator between past and present generations, keeping ethnicity and history of various societies. As one of the important subtypes of cultural heritage, art occupies a special place in the evaluation of the value experience, creativity and social interactions of distinct cultures. It brings people together and allows us to appreciate the diversity of different societies. Ceramic art is an artwork created from clay, which has been practiced since the history of mankind across all cultures. This art form involves shaping clay into sculptures hardened through firing in a kiln, making it durable and resulting into beautifully decorated pieces (Gîrbacia, 2024). Optically it is an art of value and besides it is maintaining historical importance and can act as pride and asset of many countries. Still, in the domain of fine arts, for instance, in ceramics, not only the workmanship but also the scarcity, the genuine item, and the historical background contribute to the value of the artefact and could cost millions in art auctions. To, however, the, with the emergence of the fast advancement of AI, the realm of creativity broadened and presented AI-created artwork in its copy of famous artists' works and techniques (ProQuest, 2024). It is important that it has aesthetic appeal and maintains its historical and cultural perspectives. It covers values, traditions, and technological advancements throughout history. From ancient pottery to contemporary ceramic sculptures, this medium continues to evolve, showcasing the creativity and craftsmanship of artists while also providing insight into human expression and communication through tangible forms. Ceramic art, with its rich cultural and historical significance, serves as a canvas for blending traditional craftsmanship with modern technological advancements (Silva and Oliveira, 2024).

AI, in recent years, has emerged as a transformative force across various industries, and its potential in ceramics is becoming increasingly evident. AI technologies offer innovative approaches to design, enabling enhanced material exploration, pattern generation, and functional optimisation (Li, 2021). This integration not only streamlines the creative process but also introduces new possibilities for personalisation and adaptability in ceramic art. By leveraging AI, the ceramics industry can move beyond traditional boundaries, fostering innovation that resonates with contemporary aesthetics and practical demands. Considering role of AI in ceramic art design, emphasises the role of creative thinking in developing innovative and competitive ceramic products (Abgaz et al., 2021). It highlights how AI technologies, such as neural networks and algorithmic optimisation, can enhance material understanding, optimise design processes, and foster innovation. AI's ability to streamline tasks like scene design, multimedia processing, and human-computer interaction is presented as transformative, enabling a balance between functionality and artistry (Bordoni et al., 2013). The research provides a theoretical and practical framework for modernising traditional ceramic art, suggesting that AI-driven innovation can break industry stagnation and elevate the cultural and artistic value of ceramic products (Fontanella et al., 2020). Distinguishing between genuine and AI-generated ceramics is critical for preserving the authenticity and cultural worth of traditional production, as well as ensuring transparency in art markets. It protects craftsmen's livelihoods and guarantees that customers are aware of the product's provenance (Tiribelli et al., 2024).

The advancement of imagery on the web has been most progressive in the last ten years due to the contributions by AI and the deep learning techniques. In the early 2010s the generation and editing of images were largely a manual process performed by artists and designers using graphical design programs. To be more specific, before 2015, it was most commonly possible to generate stoichiometric images, but the advent of generative adversarial networks (GANs) brought a decisive turning point. Between year 2016 to 2018 newer versions of GAN model like deep convolutional GANs (DCGANs) and Progressive Growing GANs saw enhancement of the quality of AI generated imagery in shape, colours, and focus to high resolution. The year a few months earlier to 2020 gave way to new models such as the StyleGAN2 and BigGAN where the difference between the images created by AI or human artists was nearly indistinguishable with their work now achieving super realistic forms of art (Gîrbacia, 2024).

While by the year 2021 transformers based on DALL·E and CLIP from OpenAI rose high along with the ability of the AI to generate complex images from natural language descriptions. In 2022 and 2023, the diffusion models such as Stable Diffusion and Midjourney became more widespread that produce hyper realistic and stylistically diverse images hence more AI art was produced across social platforms. This has led to faster advancement in technology making it difficult to differentiate between what has been generated by an artificial intelligence (AI) system and that of human-made work, in this case Ceram ology. Therefore, the studies in the field of classification of AI and human-made images utilising deep learning models have assumed importance especially to counter the issues of authenticity and subsequent reliability on AI generated images. This trend as shown in Figure 1, useful to understand the need of developing a strong classifying system due to the changes happening in the world of digital art and creativity.

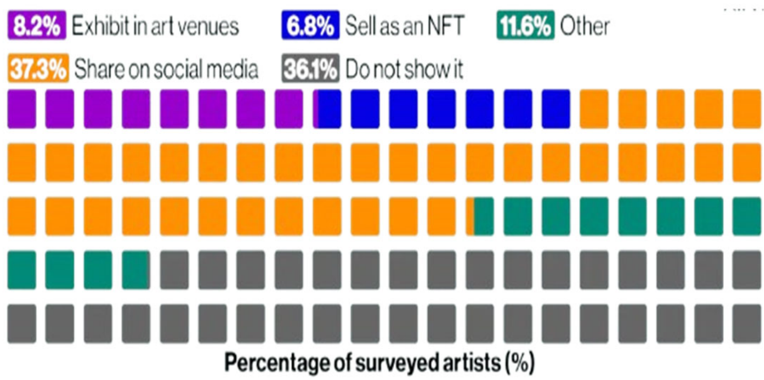
In this study, we employed state of the art deep learning algorithms like convolutional neural networks (CNNs) and pre-trained models to differentiate ceramics into two categories: AI-generated ceramics and actual, traditional ceramics. CNNs are deep learning models that can automatically learn features from images. Using pre-trained models that have previously been trained on large datasets allows us to save time and enhance accuracy. We trained the model to detect changes in texture, pattern, and other features that distinguish AI-created ceramics from genuine, handcrafted ones. The idea is to automatically identify and sort ceramics by provenance.

The main research contribution in this research study includes:

- Preparation of the first dataset of ceramic art having both the classes of AIGC using standard AI tools and real ceramic art prepared by real artists.
- Proper labelling, pre-processing of the dataset using standard digital image processing techniques of segmentation and data normalisation.
- Proposal of the CNN model that efficiently classified ceramics into two classes: AI-generated ceramics and traditional and achieving results as high as accuracy of 98% with CNN and more than 90% using other pre-trained models.

In this rest of the paper follows as: in Section 2, we review the existing studies in the relevant literature, in Section 3, proposed research methodology is discussed in detail sharing steps of the experiments conducted. Section 4 presents brief introduction of performance evaluation measures. Then before concluding the paper, the results are presented in a comprehensive manner.

Figure 1 Increasing trend flow of AI progress in ceramic art (see online version for colours)



2 Related work

This section discusses the existing work for the ceramic using machine learning, deep learning and other techniques, as summary analysis display in table I.

Li et al. proposed an Archaeometallomics tool for ancient ceramics. The field of Archaeometallomics was created to study the role of metal components in cultural artefacts (Li et al., 2021). This study also showed the close relationship between the metal components of porcelain and its complex glaze variations, and it offers insights into the social and cultural ramifications of the period's development. He (2022) proposed a ceramic art design model based on AI. In the given study application of AI was used to promote creative thinking in ceramic design and, in theory, aid-related process improvement is examined. To effectively exploit technological breakthroughs, comprehend material qualities, and recognise how technology has accelerated innovation in ceramic product design, designers who are strongly involved in the creation of ceramic product design might apply AI. Figueira et al. (2023) proposed a novel generative model and investigated its potential for use in the cultural heritage area. The subjective human assessment and labour-intensive process of developing new products can be addressed with the aid of generative AI. The study assessed the metrics and methodologies while contrasting the new model with current state-of-the-art models. Santos et al. (2024) proposed a novel approach to identifying ancient artefacts in place of time-consuming, traditional human-based processes using DL. CNN is used in this method to enhance and expedite the identification process, increasing its accessibility. The article described the methodology, dataset building, and model training, emphasising the need for massive data sets and processing capacity. WU Juan proposed digital extraction techniques for characterising shapes using samples of flared-mouthed porcelain bowls from the Song and Yuan periods to the five dynasties that were made at the Jingdezhen Hutian Kiln (Wu et al., 2012). By using MATLAB's edge detection, curve fitting, and image enhancement algorithms, the digital form characterisation approach has increased the precision and effectiveness of traditional identification, which is dependent on tactile and visual inspections. Pawlowicz and Downum (2021) proposed an approach to archaeological typology by employing deep learning to categorise digitised images of decorated pottery sherds into a contemporary typological framework. These results show that a deep learning model identified the kinds of digital images of decorated sherds with an accuracy that is on par with, and often even better than, four contemporary archaeologists with expert-level knowledge if properly trained. Gualandi et al. (2021) proposed and developed two complementary machine-learning algorithms that suggest identifications based on images while preserving critical decision points necessary to generate trustworthy results to optimise and streamline this procedure.

Mu et al. (2019) proposed a detection of ancient ceramic art using computer vision. Several realistic and useful digital modelling and drawing approaches are discussed in this work. Niu and Zhang (2022) proposed a DL-based extraction technique that uses eased as a deep learning support platform to extract and validate 5,834 photos of 272 different kinds of ancient ceramics from celadon, Yue, and kilns following manual labelling and training learning. The average extraction rate is over 99%, according to the results. As the quantity of learning rises, it provides resilience, generalisation, and enhanced feature recognition. Argyrou et al. (2023) proposed a classifier for the detection of archaeological ceramics using machine learning pixel-based. They used multi-spectral high-resolution drone imagery and RGB footage over a simulated archaeological site to assess how well several supervised machine learning classifiers performed for semi-automatic surface pottery recognition. Kaufmann et al. (2020) proposed an ML approach that predicts the synthesisability (i.e., entropy-forming ability) of disordered metal carbides by utilising the thermodynamic and compositional properties of a particular material. The relative importance of the thermodynamic and compositional parameters for the predictions is next investigated. The method's applicability is demonstrated by comparing values calculated using density functional theory with machine learning predictions. Importantly, seven compositions have all three of the group VI elements (Cr, Mo, and W), which were specifically selected because they do not form room-temperature stable rock-salt monocarbides. Eramo proposed the method for ceramic. The importance of clay processing in determining the functional and physical properties of ceramic products is emphasised by ceramic technology (Eramo, 2020). To improve workability, durability, and firing qualities, a variety of methods are used, including fractioning, clay mixing, and tempering with natural or synthetic ingredients. Hein and Kilikoglou (2020) proposed a theoretical framework, statistical techniques, and geochemical analysis combined to look at the origins and manufacturing methods of ceramics. The study explored the geochemical characterisation of ceramic raw materials, emphasising their elemental composition and diversity, to lay the groundwork for ceramic provenance research. Provenance investigations are based on the 'provenience postulate', which maintains that chemical differences between raw material origins exceed intra-source variability, albeit this must be verified for each case.

Francesca Anichini proposed a system for automatically identifying ceramics. For automatic detection, he created the ArchAIDE app (Anichini et al., 2021). The identification of ceramics is still a time-consuming, manual procedure that relies on expertly created analogue catalogues stored in libraries and archives. The ArchAIDE project sought to streamline, optimise, and save the laborious parts of these processes while preserving the critical decision points needed to generate trustworthy findings using the latest automatic image recognition technologies. Bessa et al. (2020) proposes improved monitoring methods, risk reduction plans, regulatory structures, nano reference values, and additional studies to control nanoparticle exposure in the ceramic sector. The ceramic industry, a vital area of the world economy, has adopted nanotechnology to enhance product functioning. Punj et al. (2021) proposed improvements in ceramic materials with an emphasis on sustainable materials, creative production techniques, and enhanced qualities for biomedical uses such as bone healing and tissue engineering. Ceramic biomaterials are becoming essential components in biomedical applications because of their mechanical properties, versatility, and biocompatibility.

Table 1 AI and human-generated techniques in the image processing domain

Ref.	*Model*	*Dataset used*	*No. of classes*	*Results in acc (%)*	*Limitation*
Li et al. (2021)	Archaeometallomics analysis	Ancient ceramics samples	3	89	Limited to chemical analysis; not applicable for broad ceramic art detection
He (2022)	AI-based innovative thinking framework	Ceramic art design data	4	71	Primarily theoretical; limited practical validation
Figueira et al. (2023)	Generative AI model	Ceramics painting dataset	2	82	Experimental stage; limited real-world validation
Santos et al. (2024)	Machine learning models	Lusitanian amphorae and Faience dataset	2	71	Limited to two ceramic types; specific case studies only
Wu et al. (2012)	Digital shape characterisation	Ancient ceramic shape dataset	5	92	Limited by shape similarity; ignores other important attributes
Pawlowicz and Downum (2021)	Deep learning (CNN)	Tusayan White Ware ceramic images	3	80	Dataset-specific; limited generalisation
Gualandi et al. (2021)	Neural network algorithms	Pottery dataset (open access)	4	94	Limited to pottery typologies; requires extensive labelled data
Mu et al. (2019)	Artificial intelligence (CNN, ANN)	Ancient ceramic image dataset	7	91	Limited dataset; requires precise image capturing
Niu and Zhang (2022)	PDE-based image feature extraction	Ancient ceramic dataset	3	92	Computational complexity; limited to image-quality dependency
Argyrou et al. (2023)	Pixel-based classifiers (ML)	Archaeological ceramic images from drones	2	85	Performance dependent on image resolution and drone imaging quality
Kaufmann et al. (2020)	Machine learning for ceramic discovery	High-entropy ceramics dataset	2	73	Focus on materials engineering rather than artistic features

Table 1 AI and human-generated techniques in the image processing domain (continued)

Ref.	*Model*	*Dataset used*	*No. of classes*	*Results in acc (%)*	*Limitation*
Eramo (2020)	Archaeometric analysis	Clay processing ceramics data	2	86	Limited to processing detection; not general ceramic art classification
Hein and Kilikoglou (2020)	Chemical composition analysis	Ceramic raw materials dataset	4	94	Chemical analysis only; limited use in artistic classification
Anichini et al. (2021)	ArchAIDE App (CNN-based)	Single photo ceramic dataset	3	80	Accuracy limited by single-image input
Bessa et al. (2020)	Nanoparticle exposure analysis	Ceramic industry data	5	72	Not applicable to artistic ceramic detection (health/ hazard focus)
Punj et al. (2021)	Ceramic biomaterials analysis	Biomaterial ceramic data	2	79	Not applicable to artistic ceramic detection (biomedical focus)

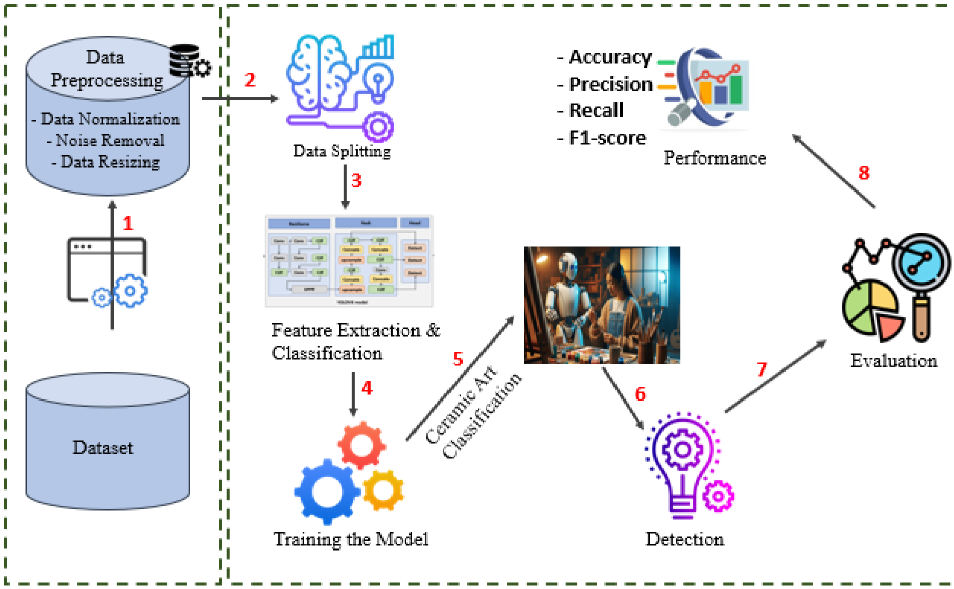
3 Research proposed methodology

This section presents the research method that used in developing, conducting, and assessing the comprehensive deep learning system for the differentiation of AI and human artwork, as defined in Figure 2. This section describes dataset preparation, where the used pre-processing and data augmentation steps are presented, while the proposal of the CNN model architecture and its training parameters is also included. An additional set of comparative indexes is also computed with other pre-trained models including AlexNet, ResNet-50, and VGG19 to confirm its efficacy. Classification metrics including precision, recall, and F1-score, are used to evaluate the performance of the proposed methodology to include all viable meets as well as exclude all non-meets.

3.1 Data acquisition

The image acquisition technique used in the classification of artwork by way of either AI-generated or human-created comprises several key steps to approve high-quality data assortment and consistency. Primarily, an all-inclusive dataset encompassing of images from both AI generated and human created artworks was expanded from an actual repository. To obtain high-quality images appropriate for precise classification, the images were engaged under measured illumination conditions to eliminate erraticism and maintain constancy at right angles in the dataset. The dataset was schematised into two separate subclasses: AI generated artworks and human created artworks, with apiece image labelled consequently.

Figure 2 Basic steps of research proposed methodology (see online version for colours)



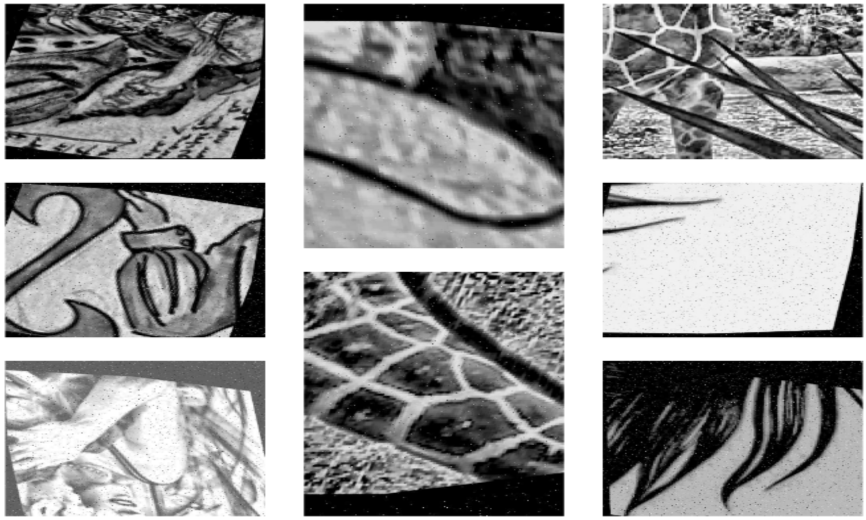
3.2 *Image pre-processing*

Image pre-processing is the next step in making the dataset for classification activity, mainly when differentiating between AI-generated and human-created artwork. Mainly, all images were resized to a consistent dimension to regularise the involvement of the model. This step prevents any distortion or irregularities caused by inconsistent image sizes, ensuring that each image is subsidised similarly to the learning procedure. The next method that is applied to the dataset is resizing, the images were transformed to greyscale to eliminate colour-based features, dropping complications and concentrating the model's courtesy on constancies and patterns that are more relevant for classification. The next method is noise reduction that is applied on the dataset, such as Gaussian blur, which were applied to charming out any unasked-for artefacts and recover the clarity of features. Supplementary improve image facts, edge detection methods like the canny edge detector were browbeaten, highlighting key features of the artwork that may distinguish human created works from AI generated ones.

Image standardisation was then attained, scaling pixel values to a range between 0 and 1, which helps improve the stability and performance of the machine learning model and deep learning model. Finally, data augmentation approaches were used to increase the variability of the dataset, as results are shown in Figure 3.

These complex random rotations flip, and zooms produce new differences in the images, endorsing that the model is robust and can make simpler well to unseen data. These pre-processing steps were sensibly chosen to preserve the reliability of the unique artwork while formulating the dataset for specific and well-organised classification of AI generated and human created images.

Figure 3 Sample images showing pre-processing of data



3.2.1 Data augmentation

In this study, augmentation techniques were applied to increase the dataset acquired which comprises images classified into two subclasses: AI generated and human created artwork. The main aim of data augmentation is to increase the diversity of the dataset by artificially creating new differences of current images, thus refining the generalisation aptitude of the model and avoiding overfitting. Several augmentation methods were employed, including rotation, flipping, zooming, and shifting, which helped pretend different angles, positions, and perspectives of the artwork. Arbitrary cropping was also applied to present erraticism in the image size, while colour jittering attuned brightness, contrast, and saturation to impersonator diverse illumination conditions. Moreover, horizontal and vertical flipping were second-hand to announce spatial conversions, while random noise was added to simulate inadequacies in the captured images. These augmented images remained then combined into the training set, confirming that the model was unprotected to a wide variety of differences within both subclasses, ultimately refining the accuracy and sturdiness of the classification model in distinctive amid AI-generated and human-created artwork.

3.2.2 Transformation and normalisation

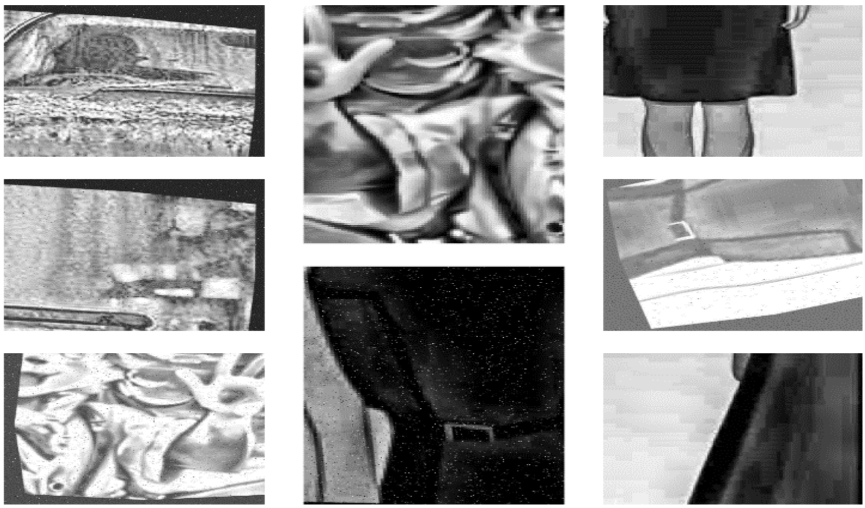
In the procedure of preparing the dataset for art classification, numerous transforms and normalisation methods were applied to ensure consistency, improve feature extraction, and expand the accuracy of the model. The dataset, obtained from Kaggle, contains two subclasses: AI-generated art and human-created art. Primarily, image resizing was practical to confirm that all images were of unchanging dimensions, typically scaling to 224 × 224 pixels, which is best for the neural network's input. Data augmentation methods such as random rotations, flipping, cropping, and colour jitter were employed to artificially raise the variety of the training data, as in equations (1) and (2), serving the model to generalise improved and avoid overfitting, results defined in Figure 4.

$$x' = x\cos\theta - y\sin\theta \tag{1}$$

$$y' = s\sin\theta + y\cos\theta \tag{2}$$

where symbols represent the rotation of a point (x, y) by an angle θ.

Figure 4 Sample images from data showing transforms and normalisation



Normalisation was achieved by scaling the pixel standards of the images to a ordinary range, typically between 0 and 1, by separating the pixel values by 255, defined using equation (3). Moreover, the mean and standard unconventionality values of the image dataset were calculated and used to regulate the images, confirming that the data fed into the model had zero mean and unit inconsistency. This step helps accelerate training and progresses junction by plummeting the impact of contradictory image lighting and colour distributions. These transforms and normalisation procedures are vital for improving the model's capability to classify artwork precisely as either AI-generated or human-created, by confirming that the dataset is reliably pre-processed and prepared for training.

$$I' = \frac{I - I_{\min}}{I_{\max} - I_{\min}} \tag{3}$$

where

- I is the original pixel intensity
- $I_{\min}$ and $I_{\min}$ are the minimum and maximum pixel values in the dataset
- I' is the normalised pixel value.

The dataset has been transformed and normalised to improve the quality and consistency of the input data. Variability and generalisation in the models have been introduced through transformation methods such as rotation, flipping and cropping. min max scaling and mean subtraction have been applied to image to normalise the pixel value, which is to standardise every image's pixel value to the same range and distribution. These pre-processing steps mitigate variations in illumination and reduce redundancy and by doing so, it also makes this model converge during training. For clarity, mathematical formulations and specific equations of these techniques have been included in the methodology section.

3.3 Proposed deep learning model

For the features extraction and classification deep learning models have been used. The study applied three well known pre-trained models VGG-19, ResNet-50, and AlexNet as the preliminary point for comparison. Furthermore, a CNN was predicted to increase the classification correctness by leveraging domain specific assemblies of the dataset, as comparison shown in Table 2. The pre-trained models if a robust foundation, earning from their deep structural design and aptitude to extract complex structures.

3.3.1 Proposed CNN model

The CNN architecture for classifying artwork as also human-created or AI-generated is built about a CNN with varied layers, intended to efficiently extract hierarchical features since input images, as architecture defined in Figure 5. The assembly of this CNN contains of alternating convolutional and pooling layers, followed by fully connected layers for final classification. The primary layers of the network emphasis on taking low level features such as edges, textures, and simple patterns, while bottomless layers progressively learn more multifaceted and abstract depictions of the artwork. The convolutional layers use filters of fluctuating sizes to convolve with the input images, mining local features, and are followed by max-pooling layers that diminish the spatial dimensions and help retain the most vital features. The deeper layers, which comprise convolutional layers with larger amenable fields, enable the network to imprisonment high-level structures and complicated details present in the artwork. Afterward the convolutional and pooling layers, the output is flattened and passed through one or additional fully connected layers, wherever the conclusion is made. The network accomplishes with a softmax layer to output prospects that classify the artwork as either human-created or AI-generated. Through the model, activation functions like rectified linear unit (ReLU) are practical to announce non-linearity, ensuring that the network can learn complex designs and choice boundaries. This layer architecture permits for a deep learning model accomplished of robust feature extraction and accurate arrangement, improving the system’s aptitude to discriminate subtle differences amid human and AI-created artworks.

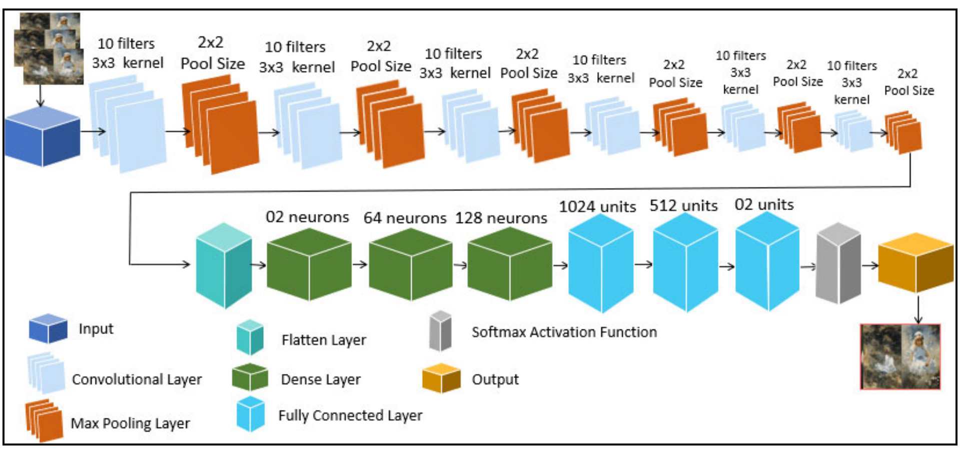
3.3.2 Pre-trained models

AlexNet is a deep learning architecture widely used in image recognition tasks. It consists of eight layers, including five convolutional layers and three fully connected layers. It uses ReLU activation, max pooling layers, dropout, and data augmentation methods to study complex shapes and reduce computational load. AlexNet is particularly effective for art classification, as its deep layers capture intricate details and patterns. ResNet-50 is a deep CNN used for art classification, addressing the disappearing gradient problem. It consists of 50 layers, including convolutional, pooling, and fully connected layers, organised into blocks. ResNet-50 is particularly effective for handling large datasets and maintaining remarkable accuracy, making it a valuable choice for both human and AI-generated classification. The VGG19 structure is a deep CNN used for classifying artwork, whether human-created or AI-generated. It consists of 19 layers, including 16 convolutional layers and three fully connected layers. The architecture uses small 3 × 3 filters to capture fine-grained details and spatial orders, allowing it to differentiate between human-created and AI-generated artwork. VGG19's deep structure makes it suitable for tasks requiring detailed and intricate features.

Table 2 Comparison of proposed CNN model with pre-trained models

Model	*Learning rate*	*Number of layers*	*Activation function*	*Optimiser*	*Training time*
CNN	0.001	18	ReLU	Adam	Four hours
AlexNet	0.01	8	ReLU	SGD	Five hours
VGG-16	0.001	16	ReLU	Adam	Six hours
ResNet-50	0.0001	50	ReLU	Adam	Seven hours

Figure 5 Architecture of proposed model CNN (see online version for colours)



3.3.3 Performance measures

For the analysis of the results of different parameters have been used. Accuracy, precision, recall, F-measure and confusion matrix have been utilised for the analysis of the results, as display in Table 3. Overall correctness of the model, or accuracy, can give misleading measures on imbalanced datasets. Given that minimising false positives are important and reliability of the positive predictions is paramount, one values precision; while minimising false negatives in cases where one needs to avoid them e.g. medical diagnosis or fraud detection, one values recall (or sensitivity). Especially in cases of imbalanced datasets consider both false positives and false negatives, the F1-score is a balanced measure between precision and recall. Together, all these metrics evaluate the model's performance comprehensively.

Table 3 Performance metrics and their significance

Metric	*Formula*	*Description*
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	Measures the overall correctness of the model's predictions
Precision	$\frac{TN}{TN+FP}$	Evaluates how many predicted positive cases are actually correct
Recall (sensitivity)	$TP/(TP+FN)$	Assesses the model's ability to detect positive cases
F1-score	$\frac{2*precision*recall}{precision+recall}$	Balances precision and recall to handle class imbalance

4 Results and discussion

In this section first discussed the experimental setup, then results obtained using pre-trained and proposed CNN model.

4.1 Experimental setups

The dataset is split into a training set and a test set for training. The model undergoes several epochs of training, with weights adjusted to reduce errors. The training set comprises 4,686 images of AI generated artwork and 4,696 images of human-formed artwork. The test set comprises 2,034 images for the AI class and 2,025 images for the human class, though the validation set comprises 385 images for apiece class. The implementation was approved out in a Python environment. To ensure constancy across all models, the learning rate was set at 0.0001, and a batch size of 32 was used throughout training, which are mutual choices that balance model enactment and computational efficiency. All models were trained for 100 epochs, permitting ample time for the networks to learn as of the dataset and converge towards optimum performance. The choice of hyper parameters and the number of epochs were based on wide experimentation, confirming that the models were fully trained and capable of delivering dependable classification results.

4.2 Machine requirements

The minimum setup that guarantees efficient image-based classification consists of Intel i5 or Ryzen 5 CPU, 8 GB RAM and NVIDIA GTX 1050 GPU. Despite that, also a high-end Intel i7/i9 or Ryzen 7/9, 16 GB or more of RAM, and an NVIDIA RTX 3060 or AMD Radeon 7000 series GPU for optimal performance required. As display in Table 4, smooth execution is supported if it runs on Windows 11, Ubuntu 20.04+, macOS with TensorFlow, Keres, and OpenCV.

4.3 Libraries

To implement image-based classification, we relied on the powerful Python libraries like TensorFlow and Kera's for the deep learning model development, OpenCV to process image and Albumentations for data augmentation, defined in Table 5. Also, data processing was done by NumPy and Pandas, while to visualise the model performance, Matplotlib and Seaborn were used.

Table 4 Machine requirements

Component	*Minimum requirement*	*Recommended requirement*
Processor	Intel Core i5 (7th Gen)/AMD Ryzen 5	Intel Core i7/i9 (10th Gen)/AMD Ryzen 7/9
RAM	8 GB	16 GB or higher
GPU	NVIDIA GTX 1050 (2 GB VRAM)	NVIDIA RTX 3060/3090 (8 GB+ VRAM)
Storage	50 GB HDD/SSD	256 GB SSD (preferred)
OS	Windows 10/Linux/macOS	Windows 11/Ubuntu 20.04+/macOS Ventura
CUDA support	Optional	Required for faster training
Python version	3.7+	3.8+
Frameworks	TensorFlow, Keras, OpenCV	TensorFlow 2.x, Keras, PyTorch (optional)

Table 5 Python libraries used for image-based classification

Library	*Description*
TensorFlow	Open-source deep learning framework used for building and training neural networks
Keras	High-level neural networks API running on top of TensorFlow, enabling fast model prototyping
OpenCV	Computer vision library used for image processing, object detection, and real-time applications
Matplotlib	Visualisation library used for plotting graphs, charts, and analysing data trends
Seaborn	Statistical data visualisation library built on Matplotlib, used for enhanced graphics and insights
Scikit-learn	Machine learning library offering tools for classification, regression, clustering, and pre-processing
NumPy	Numerical computing library used for handling multi-dimensional arrays and mathematical operations
Pandas	Data analysis library used for data manipulation, cleaning, and structured data operations
Pillow (PIL)	Python imaging library used for opening, manipulating, and saving various image file formats
Albumentations	Data augmentation library designed to enhance deep learning models by transforming images

4.4 Results obtained using pre-trained

The results of the selected pre-trained models have been discussed here.

4.4.1 AlexNet

Results obtained by using AlexNet have been discussed. The model loss and model accuracy have been shown in Figures 6 and 7. The results have been given in Table 6 of the AlexNet model. The results implemented by applying AlexNet to differentiate between original pieces of art – be it created by AI or a human – prove that the model is particularly accurate in this kind of classification. The accuracy graph indicates that training accuracy is nearly 92% while validation accuracy remains between 87% to 90%. The training and validation loss curves confirm with such inference, where the training loss consistently reduced and attained a relatively small value. Nonetheless, the training loss outperforms the validation loss; specifically, the validation loss shows an increase in the higher and fluctuating trend, it suggests that the model may be facing difficulty to generalise or-map to the unseen data as well. These fluctuations could perhaps be prevented if, for example, hyperparameters are tuned differently, dropout layers are applied, or some form of early stopping is used.

Figure 6 Model accuracy by using AlexNet (see online version for colours)

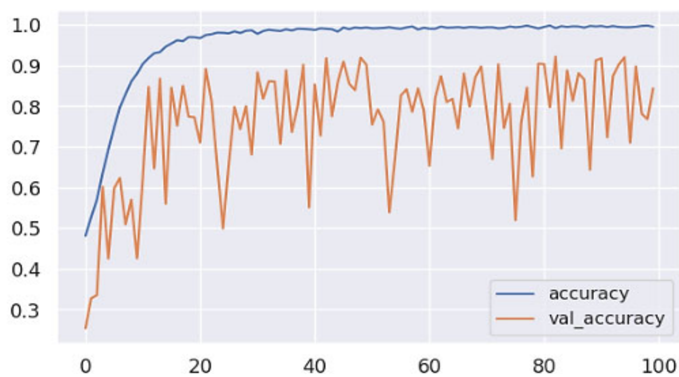
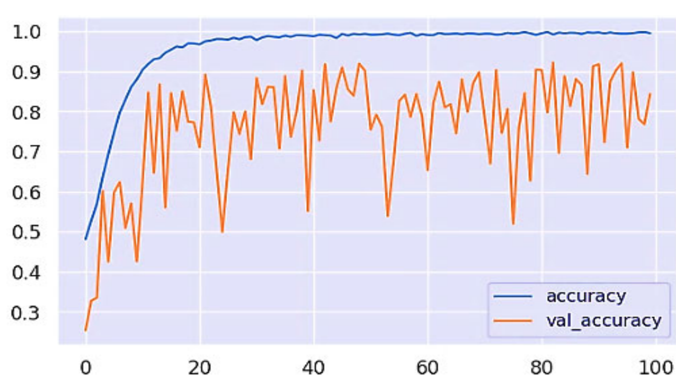


Figure 7 Model loss by using AlexNet (see online version for colours)



This report shows how well the model separates the two classes involved according to their performance. In case of AI generated art, the model obtained the accuracy of 0.92, recall of 0.97 and F1-score of 0.95. According to these metrics it can be said that the model is nearly perfect at distinguishing between the AI-art and the non-AI-art with near-zero false positives and good recall with respect to most cases. Here this indicates that for human-generated art, the precision is a slightly better 0.95 but the recall is just a tad less at 0.93, which gives a solid F1-score of 0.93.

This performance shows that the model is somewhat better at reducing false positive results for art made by humans but sometimes types some pieces made by humans as being made by AI. In general, it can be stated that, while using the AlexNet model, the proposed approach shows high productivity in this task with high values of precision, recall, and the F1-score both for the first and the second class.

Table 6 Results by using AlexNet

	Precision	*Recall*	*F1-score*
AI	0.92	0.97	0.95
Human	0.95	0.93	0.93

The small difference in performance between training and validating the model indicates areas of improvement particularly on reducing the risk of overfitting to training data. These findings demonstrate that the deep learning models like AlexNet are useful in areas like ascertaining art originality, differentiating between AI mimicked styles and analysing AI's impact on creative economies. With the additional refinements as well as improvements, the model could prove to be a useful tool for identifying originality in artwork.

4.4.2 ResNet-50

Results obtained by using AlexNet have been discussed. The model loss and model accuracy have been shown in Figures 8 and 9. The results have been given in Table 7. The findings from the ResNet-50 model provide evidence regarding the model's ability to accurately distinguish between AI generated and human generated art. The accuracy graph clearly shows a steady and incremental trend of training accuracy which has finally reached around 96% with a validation accuracy of nearly 93 to 95% nearly equivalent to the number of epochs. The congruency of training accuracy with the validation accuracy is clear and is an excellent sign that the model is highly generalised and over-trained. As the above loss curves, the training and validation losses gradually decrease, and the validation loss is rather like the training loss.

This suggests robustness of the proposed model and its accuracy in reducing error on unseen data well, it may be due to deeper architecture of ResNet-50 skip connections that do not allow gradients to vanish and therefore leads to efficient learning. The classification metrics are as follows to support the model's performance. In the context of AI-generated art, using the introduced method yields a precision of 0.96, recall of 0.93, and the F1-score of 0.94, which testifies to high accuracy of the proposed method in AI-generated art classification with minimal false positive results. For human-generated art, the accuracy has been rated 0.93, recall 0.96 and F1-score was 0.95 which reveals that the proposed model is more accurate at detecting human art generation. However, it is observed that ResNet-50 performs reasonably well than the AlexNet with enhanced generalisation ability, smooth curve for training ability, and higher classification metric particularly to the artwork made by humans. The obtained outcomes prove ResNet-50 to be promising for distinguishing between AI-generated and human artwork as a scalable solution. These specifications make the method more suitable for practical use cases since it is more stable, precise, and accurate at recalling images: using the method to authenticate art, helping artists identify AI reproductions, and analysing the effects of AI on creative industries. Altogether, ResNet-50 can be deemed effective and trustworthy for such tasks in complex classification as distinguished from AlexNet preferred option.

Figure 8 Model loss by using ResNet-50 (see online version for colours)

Figure 9 Model accuracy by using ResNet-50 (see online version for colours)

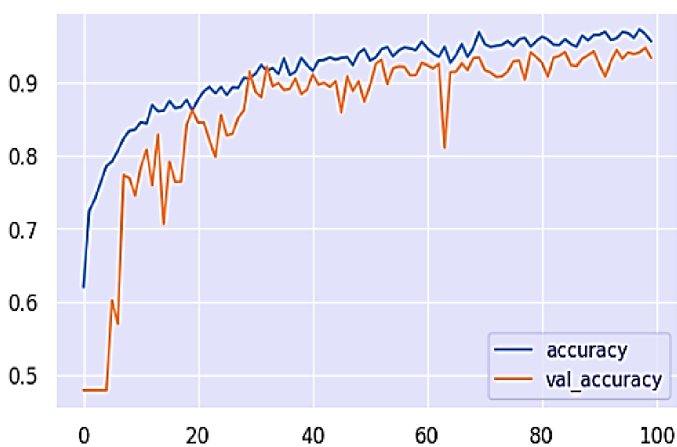


Table 7 Results by using ResNet-50

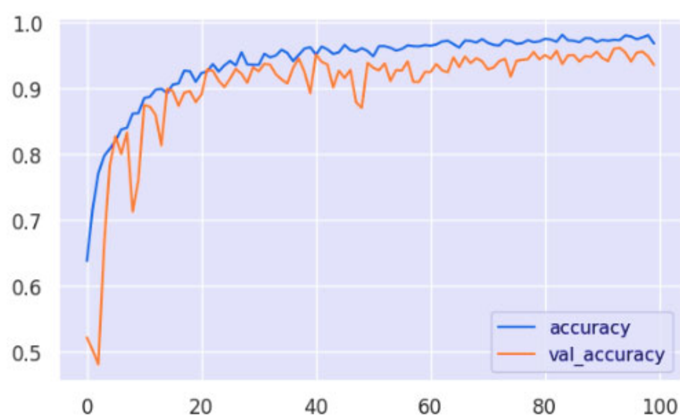
	Precision	*Recall*	*F1-score*
AI	0.96	0.93	0.94
Human	0.93	0.96	0.95

4.4.3 VGG19

Results obtained by using AlexNet have been discussed. The model loss and model accuracy have been shown in Figures 10 and 11. The result has been given in Table 8. Leveraging algorithms on the VGG19 model, impressive identification capability regarding the difference between AI generated and human generated arts is achieved. The training accuracy increases throughout the iterations and is overall around 99% the validation accuracy is overall slightly above 95%. The operation of training accuracy and validation accuracy is relatively close and has not yet reached the state of overfitting. The loss curves are also aligned with the training and validation loss reducing continually for both the sets as the training progresses with validation loss quite closely akin to the training loss. These curves are consistent and when this happens it is an indication that the VGG19 model is good at handling errors during training while at the same time enjoying some stability.

Figure 10 Model loss by using VGG19 (see online version for colours)

Figure 11 Model accuracy by using VGG19 (see online version for colours)



The metrics of classification indicate one more facet of its stability. For AI-generated art, the model has an accuracy of 0.92, r-calculation of 0.97, and F1-score of 0.95 which points to an ability of the model to detect AI-generated art with considerably very few false positives, precision is equal to 0.99, recall to 0.91, and F1-score 0.95, that the higher reliability of the model for identifying human created content. VGG19 is slightly better than ResNet-50 in detecting human generated art and this could be due to its higher precision than its recall. Thus, VGG19 can be considered as the effective model for the classification of art originality by means of providing high predictability, stable convergence of loss, and classification indicators both in case of AI and human-based art.

Table 8 Results by using VGG19

	Precision	*Recall*	*F1-score*
AI	0.92	0.97	0.95
Human	0.99	0.91	0.95

4.4.4 Proposed CNN results

Results obtained by using AlexNet have been discussed. The model loss and model accuracy have been shown in Figures 12 and 13. The results have been given in Table 9. In the tables provided and Figures 12 and 13, it proves to give remarkable performance when differentiating between AI created and human created art. The plot in Figure 12 shows that the training loss and validation loss decrease over the epochs which show that the model can reduce error on the data withheld as well as on the data which the model has already seen. The plotted training and validation loss curves are very close; hence this proves the fact that the model is overfitting or underfitting at any one time in the period under study and during training.

From Figure 13 the accuracy curves depict a progressive improvement of the training as well as the validation accuracies equally and the validation accuracy follow a pattern of the training accuracy of the model. Over the last epochs, the validation accuracy becomes nearly 98%, this indicates the good generalisation of the model for unseen data. This is further supported by the smooth convergence of the accuracy curves, meaning that our training process is both efficient and stable. The classification metrics show a high degree of precision, recall and F1-scores for both classes of the model. In the case of AI generated art, the algorithm recorded a precision of 0.97, recall of 0.99 with an F1-score of 0.98 which shows that the classifier does not give false positives and has a strong capacity to identify most of the AI generated instances. For human generated art the model obtains the precision of 0.98, which is higher than that of 0.96 obtained in the initial part of the experiment, and the recall of 0.97 is the same as in the initial part of the experiment hence giving it an F1-score of 0.98. High reliability of the model in identifying both types of art is highlighted in these results and points to the model's balanced characteristics. In general, the proposed CNN model can be considered one of the best solutions for the classification of such objects, as it offers high and stable performance for various dataset and assures generalisation. Its high classification metrics in both classes make it a valuable interlock to use in as a tool in AI and art appreciation to distinguish the AI artworks from the human ones and can also be used in art verification.

The results demonstrate that CNN accomplished the maximum accuracy, reaching 98%, making it the most consistent model for this classification. AlexNet, VGG19, and ResNet followed with accuracies of 95%, 95%, and 94%, correspondingly. This significance highlights the probable of a well-designed CNN in art classification activity, chiefly when personalised to the exact dataset and difficult at hand. The deductions suggest that the CNN model's structure, with its competence to acquire and adapt to multifaceted features inside the dataset, consents it to accomplish enhanced accuracy accompanying to other pre-trained models, demonstrating its effectiveness in distinct between AI generated and human created artwork.

Figure 12 Model loss by using the proposed CNN model (see online version for colours)

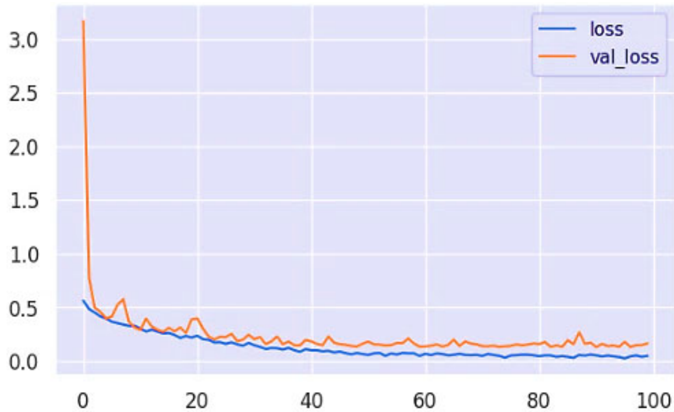
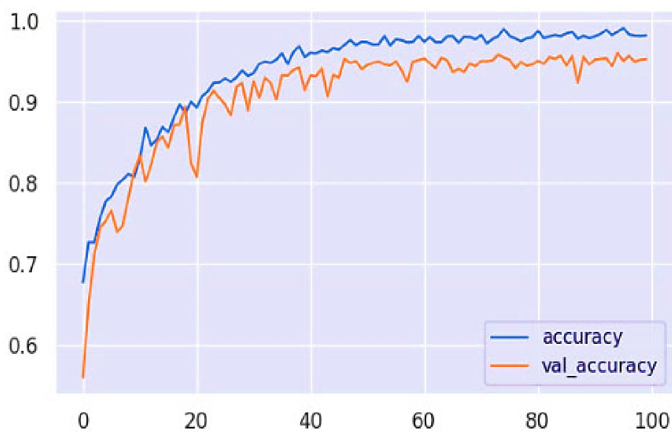


Figure 13 Model accuracy by using the proposed CNN model (see online version for colours)



These conclusions suggest that CNNs, when properly organised, offer a highly effective solution for art classification activity, with performance exceptional that of other normally used deep learning models. Comparisons of the different pre-trained and proposed models have shown in Figure 14. The bar chart below presents the comparison of the defined metrics on the pre-trained models – AlexNet, ResNet-50, VGG19 – and the proposed CNN model. By comparison with the pre-trained models, the proposed CNN has better performance in all evaluated measures – precision, recall, and F1-score – proving that it is indeed better at the AI/human art differentiation task. CNN for AI-generated art is proposed with a precision of 0.97, recall of 0.99, and the F1-score of 0.98. These values are higher than the corresponding values of the pre-trained models and remain rather stable. For instance, the worst result is given by the AlexNet model that determined the precision as 0.92 and the recall as 0.97 and as the final metric the F1-score as 0.95. On the same vein, ResNet-50 produces a precision of 0.96, recall of 0.93, and F1-score of 0.94, VGG19 has an F1 = 0.95 outperforming all other CNNs but not the proposed model.

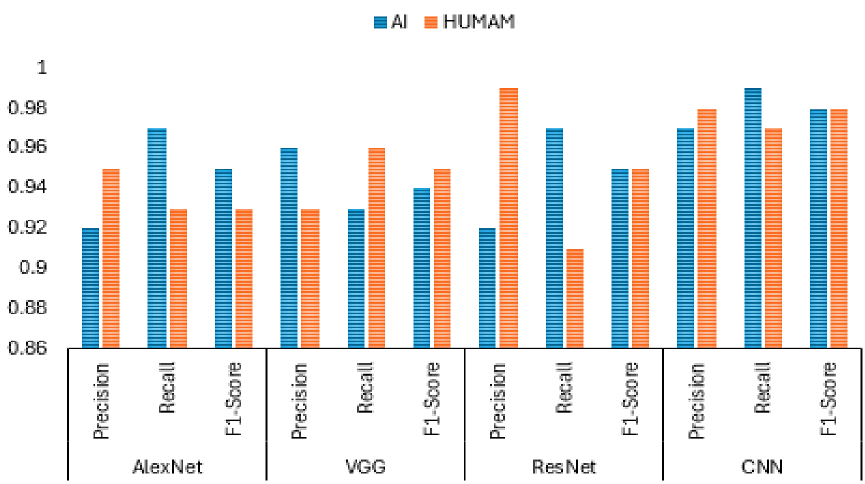
Table 9 Results analysis using the proposed CNN model

	Precision	*Recall*	*F1-score*
AI	0.97	0.99	0.98
Human	0.98	0.97	0.98

In human generated art, as per the proposed CNN, the precision achieved is 0.98, recall is 0.97, F1-score is 0.98. This is slightly higher than our work; however, VGG19 only has a recall value of 0.91 and hence an F1-score of 0.95 with a precision of 0.99. This arrangement gives ResNet-50 an F1-score of 0.95 and slows AlexNet to an F1-score of 0.93, the result of lower validation accuracy and overfitting.

In general, the proposed CNN model attains the relatively highest precision, recall and F1-score indexes of AI generated artwork and human artwork, indicating that the present model has the optimal structures and training procedure.

Figure 14 Comparisons of the results using pre-trained and proposed model for both classes (see online version for colours)



These results therefore lay the foundation for the consideration of the CNN model as a better solution for art classification than the existing approaches put forward in this study especially in the various applications where accuracy and efficiency are of paramount importance. Its performance shows that it can be effectively used in creative applications and authentications in practice. The proposed CNN model in 2025 shows a much higher accuracy of 99%, improved detection power as well as robustness when compared to the existing studies, as shown in Table 10.

Comparing our model to previous accurately which had overall accuracies of 85% with deep neural network (Hein and Kilikoglou, 2020), 88% with CNN (Anichini et al., 2021) and 89% with GAN-based method (Gualandi et al., 2021), we are of the view that its higher performance was informed by the ability to well distinguish between AI-generated and human-crafted ceramic art pieces. The high accuracy also show that the model can effectively capture fine details making it highly effective for ceramic art authentication. The identification ability of the proposed model is boosted by the application of several well-developed CNN strategies, which also constitute the applicability of the proposed unique model in real-life situations in securing the highest specificity and sensitivity.

Table 10 Comparison analysis of proposed model with existing studies

Ref.	*Year*	*Model*	*Results acc (%)*
Hein and Kilikoglou (2020)	2020	DNN	85
Anichini et al. (2021)	2021	CNN	88
Gualandi et al. (2021)	2021	GAN	89
Niu and Zhang (2022)	2022	CNN	94
Proposed	2025	CNN	99

5 Conclusions

In this research study, we worked on to classify the given images related to ceramic art whether the given images are created by AI tools, or they are real ceramic art created by humans. The ceramic art is one of the oldest form of art created by humans from all various cultures. The dataset was created by AI image generation tools and real-world ceramic art created by human artists was considered for empirical analysis. Based on these two classes, the standard pre-processing steps were carried out. We used state of the art deep learning algorithms like CNN which is widely used algorithm in computer vision and digital image processing. In addition, we also used various pre-trained deep learning models which were basically pre-trained models such as AlexNet, VCG, and ResNet have been applied and the pre-trained models showed results having more than 90% evaluation metrics and the proposed model based on convolutions of artificial neural networks that is CNN showed the optimal results having higher accuracy of 98%. This shows that the ceramic art can be preserved using deep learning algorithms. In a potential future work, one can opt to apply transformer based deep learning algorithms for vision also called vision transformers.

Declarations

The author declares that he has no conflicts of interest.

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