Title	Authors	Method/Approach	Results/Findings	Limitations/Gaps
"Deep fake image detection based on pairwise learning."	*Hsu,Chih-Chung, Yi-Xiu Zhuang, and Chia-Yen Lee.*	*The method used in the research paper is a deep convolutional neural network (CNN) called the "proposed CFFN" (Convolutional Face Forgery Detection Network). The proposed CFFN is a multi-layered neural network that uses a combination of convolutional and fully connected layers to learn features from images and detect fake face images.*	*The results or findings of the research paper are presented in Table, which shows the objective performance comparison of the proposed CFFN with other fake face detectors. The proposed CFFN outperforms the other methods in terms of precision and recall, with a precision of 0.986 and a recall of 0.751.*	*Some potential limitations could be:* *1. The dataset used to train the proposed CFFN may not be representative of all possible fake face images.* *2. The proposed CFFN may not be able to detect fake face images that are highly realistic or have been manipulated using advanced image editing software.* *3. The proposed CFFN may not be able to detect fake face images that are created using different techniques, such as 3D modeling or facial recognition software.* *4. The proposed CFFN may not be able to detect fake face images that are created using a combination of different techniques.*
"Fake vs Real Image Detection Using Deep Learning Algorithm"	*Fatoni, F., Kurniawan, T., Dewi, D., Zakaria, M., & Muhayeddin, A.*	*The approach used in the study is a comparative analysis of three deep learning models, namely Convolutional Neural Networks (CNNs), VGG16, and Residual Network (ResNet), for image classification. The models were trained and tested on a dataset of images, and their performance was evaluated using metrics such as training and validation accuracy, loss, and confusion matrix.*	*The results of the study show that the ResNet model performed the best, with a training accuracy of 95% and a validation accuracy of 93% in Experiment 4. The CNN model had a training accuracy of 94% and a validation accuracy of 92% in the same experiment. The VGG16 model had a lower training accuracy of 94% but a higher validation accuracy of 94% in Experiment 3. The study also found that the training and validation loss of the three models decreased continuously across the epochs.*	*Some potential limitations or gaps could include:* *1. The study only compared three deep learning models, and it is possible that other models may perform better or worse depending on the specific task and dataset.* *2. The study did not explore the impact of hyperparameter tuning on the performance of the models.* *3. The study did not evaluate the models on a large-scale dataset or in a real-world application.* *4. The study did not provide a detailed analysis of the confusion matrix or the performance of the models on specific classes or sub-classes of images.*
"Artist identification with convolutional neural networks."	*Viswanathan, Nitin.*	*The authors used a convolutional neural network (CNN) to identify artists based on their painting styles. They used a dataset of 17,000 paintings from 57 artists, with 300 paintings per artist. The dataset was split into training, validation, and test sets using an 80-10-10 split per artist. The authors preprocessed the images by zero-centering and normalizing them, then taking a 224x224 crop of each image. During training, they randomly horizontally flipped the input images with a 50% probability and took a random crop of the painting. For validation and test images, they took a 224x224 center crop of the image to ensure stable and reproducible results*	*The authors reported that most paintings were correctly classified, with the diagonal entries in the confusion matrix being yellow or red. However, they noted that one artist, Henri Matisse, was particularly confused with Martiros Saryan, with the network predicting Saryan as the artist for 3 of Matisse's paintings.*	*It can be inferred that the dataset may not be representative of all art styles and periods, and that the network may not perform well on paintings that are not well-represented in the dataset.* *1. The network was able to learn a representation of painting style that allowed it to identify artists, but it may not have captured all the nuances and complexities of artistic style.* *2. The authors did not provide a detailed analysis of the network's performance on specific artists or styles, which may be an area for future research.*
"Recognizing Art Style Automatically in Painting Using Convolutional Neural Network."	*Akter, Mahfuza, Mst Rasheda Akther, and Md Khaliluzzaman.*	*The method or approach used by the authors is deep learning, specifically convolutional neural networks (CNNs), to recognize art styles from the Wikipaintings dataset. The authors used a miniVGGNet architecture, which is a variant of the VGGNet architecture, to classify the art styles into different categories.*	*Their results or findings show that the proposed model achieved an accuracy of 60.37% on the Wikipaintings dataset, which is more than 18.50% better than the miniVGGNet model. The authors also presented a classification report, which shows the precision, recall, and F1-score for each art style category. The results suggest that the proposed model is effective in recognizing art styles from the Wikipaintings dataset.*	*Limitations or gaps in their work include the following:* *1. The authors used a relatively small dataset, which may not be representative of all art styles.* *2. The dataset may be biased towards certain art styles or periods.* *3. The authors did not evaluate the model on other datasets or compare it with other state-of-the-art models.* *4. The model may not generalize well to other datasets or art styles that are not present in the Wikipaintings dataset.*
"Unsupervised representation learning with deep convolutional generative adversarial networks."	*Radford, Alec, Luke Metz, and Soumith Chintala.*	*The method or approach they used is Generative Adversarial Networks (GANs), which is a type of deep learning algorithm that uses a neural network to generate new data samples that are similar to a given dataset.*	*Their results or findings are that GANs are able to generate images that are similar to the training data, but with some limitations. The authors found that the generated images often suffer from being blurry, noisy, and incomprehensible.*	*The limitations or gaps in their work are that the generated images are not always of high quality and may not always be representative of the training data. Additionally, the authors note that there is still much to be learned about how to effectively use GANs for image generation.*
"Application of an improved DCGAN for image generation."	*Liu, Bingqi, et al.*	*The method or approach used is a concept classification network, which is proposed to eliminate errors in the image generation process. The network is trained on the MNIST dataset and uses a DCGAN model as the generator.*	*The results or findings mentioned in the text include the ability of the concept classification network to effectively solve the problem of low-quality images being output by the GANs model, and achieving good results.*	*limitations or gaps in their work are:* *1. It can be inferred that the use of the MNIST dataset may limit the generalizability of the results to other datasets.* *2. Additionally, the text does not provide a detailed comparison with other image generation methods, which could be a limitation.*
"Fake Image Detection Using Deep Learning."	*Khudeyer, Raidah Salim, and Noor Mohammed Almoosawi.*	*Three versions of the model were proposed:* *Model 1 used transfer learning with the pre-trained EfficientNetB0, and the model weights were fine-tuned for the binary classification task of identifying real and fraudulent photos.* *Model 2 added two more dense layers to the fully linked component of the architecture, which, when combined with dropout and batch normalization approaches, reduced overfitting and improved convergence.* *Model 3 improved upon the strategy by introducing a learning rate scheduling technique, which allows the model to dynamically modify the learning rate during training, resulting in faster convergence and more exact weight alterations..*	*The experimental findings showed that the proposed changes to EfficientNetB0 considerably improved performance. Model 1 obtained a test accuracy of 51.88%, whereas Model 2 increased it to 65.88%. Model 3 produced the greatest results, scoring 99.06% accuracy on the test set, 99.37% on the validation set, and 100% on the training set. This high accuracy and low error rate (0.0569) demonstrate the efficacy of the upgraded EfficientNetB0 architecture and the learning rate scheduling method.*	*The study has significant drawbacks.* *The technique was only tested on facial photos and not on other types of synthetic or modified content, which limits its application in a variety of real-world circumstances.* *The study does not explore the model's robustness to adversarial attacks or its performance in real-time detection settings, both of which are crucial for practical deployment.*
"Digital image forgery detection using deep learning approach."	*Kuznetsov, A.*	*Using the VGG-16 convolutional neural network (CNN), the researchers attempted to detect splicing frauds in digital photos. The suggested algorithm examined images using a sliding window approach, categorizing areas of a set size (40x40 pixels) as original or faked. The VGG-16 architecture was fine-tuned with pretrained weights from the COCO dataset to improve accuracy and eliminate the need for large-scale training datasets. The CASIA dataset was used for the studies, and dropout layers were used to prevent overfitting. The method used patch-based classification and majority voting to classify full images.*	*The model outperformed existing solutions like Markovian rake transform and DCT coefficient analysis on the CASIA dataset. However, the performance significantly degraded under JPEG compression, with accuracy dropping to 66.3% at lower quality settings.*	*The method was specifically tested for splicing forgeries and may not generalize to other types of image manipulations like copy-move or resampling.* *The model's performance was highly sensitive to JPEG compression, with a substantial drop in accuracy under post-processing conditions.* *The study relied on the CASIA dataset, limiting the evaluation scope to a single dataset without testing on diverse, real-world datasets.*
"Exploring deep convolutional generative adversarial networks (DCGAN) in biometric systems: a survey study."	*Jenkins, John, and Kaushik Roy.*	*The authors used the DCGAN (Deep Convolutional Generative Adversarial Network) framework to generate photorealistic synthetic biometric samples. They employed the binary cross-entropy loss function with the Adam optimizer to train the generator and discriminator models. The quality of the fabricated biometrics was evaluated using metrics such as SSIM and FID.*	*The authors did not present specific results or findings in the provided context. However, they mentioned that the DCGAN framework can be used to generate photorealistic synthetic biometric samples, and that the quality of the fabricated biometrics can be evaluated using metrics such as SSIM and FID.*	*In this case, the authors may have considered the limitations of their approach, such as the potential for generated biometric samples to be easily distinguishable from real biometric samples, or the need for more advanced evaluation metrics to assess the quality of the fabricated biometrics.*
"Recent Advances in Counterfeit Art, Document, Photo, Hologram, and Currency Detection Using Hyperspectral Imaging."	*Huang SY, Mukundan A, Tsao YM, Kim Y, Lin FC, Wang HC.*	*The method or approach used is Principal Component Analysis (PCA) and combining multiple dimension reduction algorithms.*	*The results or findings are:* *PCA was the most commonly used algorithm, possibly due to its effectiveness in dimension reduction.* *Combining multiple dimension reduction algorithms yielded higher accuracy.* *Computing the average accuracies for each year the studies were published, studies published in 2018 had the highest average accuracy of 96.95%, followed by 2016 with 84.30% accuracy, and so on.*	*The research does mention that PCA is only effective when the pre-processing of data is completed correctly, and that noises inherent in data may result in false significance. Additionally, the research notes that only five studies were published in 2019, which may be a limitation in terms of the sample size.*
"Synthetic images aid the recognition of human-made art forgeries."	*Ostmeyer J, Schaerf L, Buividovich P, Charles T, Postma E, Popovici C.*	*The authors used synthetic images to aid the recognition of human-made art forgeries. They used a convolutional neural network (CNN) to generate synthetic images that mimic the style of Vincent van Gogh's paintings. They then used these synthetic images to train a classifier to distinguish between authentic and forged Van Gogh paintings.*	*The authors found that the use of synthetic images improved the accuracy of the classifier in distinguishing between authentic and forged Van Gogh paintings. They also found that the synthetic images were effective in reducing the number of false positives and false negatives.*	*The authors noted that their study had some limitations. For example, they only used a small dataset of authentic and forged Van Gogh paintings, and they did not test their method on other types of art forgeries. They also noted that the quality of the synthetic images may not be as high as the quality of the real images, which could affect the accuracy of the classifier. Additionally, they mentioned that the method may not be applicable to other types of art or forgeries, and that further research is needed to explore the potential of synthetic images in art forgery detection.*