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 ability barriers ought to be: 1. The dataset used to educate the proposed CFFN might not be consultant of all viable faux face photos. 2. The proposed CFFN might not be capable of locate faux face photos which might be distinctly practical or had been manipulated the usage of superior photograph enhancing software. 3. The proposed CFFN might not be capable of locate faux face photos which might be created the usage of special techniques, together with 3-d modeling or facial popularity software. 4. The proposed CFFN might not be capable of locate faux face photos which might be created the usage of a aggregate of various techniques.
"Fake vs Real Image Detection Using Deep Learning Algorithm"	Fatoni, F., Kurniawan, T., Dewi, D., Zakaria, M., & Muhayeddin, A.	The method used withinside the examine is a comparative evaluation of 3 deep gaining knowledge of fashions, specifically Convolutional Neural Networks (CNNs), VGG16, and Residual Network (ResNet), for photograph classification. The fashions have been skilled and examined on a dataset of images, and their overall performance became evaluated the use of metrics together with education and validation accuracy, loss, and confusion matrix.	The consequences of the look at display that the ResNet version accomplished the best, with a education accuracy of 95% and a validation accuracy of 93% in Experiment 4. The CNN version had a education accuracy of 94% and a validation accuracy of 92% withinside the equal experiment. The VGG16 version had a decrease education accuracy of 94% however a better validation accuracy of 94% in Experiment 3. The look at additionally located that the education and validation lack of the 3 fashions reduced constantly throughout the epochs.	Some capacity constraints or gaps should include the following: 1. The observe outperformed three deep learning models, and it is possible that other models will perform better or worse depending on the specific challenge and dataset. 2. The study no longer found an influence of hyperparameter adjustment on the overall performance of the models. 3. The study did not evaluate the trends on a large-scale dataset or in a real-world application. 4. The observe no longer provided an in-depth review of the confusion matrix or the overall performance of the models on specific lessons or sub-lessons of images.
"Artist identification with convolutional neural networks."	Viswanathan, Nitin.	The authors employed a CNN to identify artists based on their painting patterns, using a dataset of 17,000 works by 57 artists (300 per artist). The dataset was split 80-10-10 for training, validation, and experimentation. The images had been preprocessed with zero-centering, normalization, and a 224x224 crop. Training included random horizontal flips (50% chance) and random crops, as well as validation and testing with a 224x224 middle crop to ensure consistency.	According to the authors, excessive class accuracy is indicated by yellow or red diagonal entries in the maximum confusion matrix. However, Henri Matisse was frequently misidentified as Martiros Saryan, with the community supposing Saryan was the artist behind three of Matisse's paintings.	The dataset may lack representation of all art styles and periods, potentially limiting the network's performance on underrepresented paintings. While the network learned to identify artists based on painting style, it may not have captured all artistic nuances. A detailed analysis of performance on specific artists or styles was not provided, highlighting an area for future research.
"Recognizing Art Style Automatically in Painting Using Convolutional Neural Network."	Akter, Mahfuza, Mst Rasheda Akhter, and Md Khaliluzzaman.	The authors employed deep learning, specifically CNNs, using a miniVGGNet architecture (a variant of VGGNet) to classify art styles from the Wikipaintings dataset into various categories.	The proposed model obtained 60.37% accuracy on the Wikipaintings dataset, surpassing the miniVGGNet by more than 18.50%. The classification report highlighted the precision, recall, and F1-scores for each art style, proving the model's ability to recognize art styles.	The study's shortcomings include a small dataset that may not represent all art forms and a possible bias toward specific styles or times. The authors did not test the model on additional datasets or compare it to cutting-edge models, raising questions about its applicability to previously undiscovered datasets or art styles not included in the Wikipaintings dataset.
"Unsupervised representation learning with deep convolutional generative adversarial networks."	Radford, Alec, Luke Metz, and Soumith Chintala.	The authors employed Generative Adversarial Networks (GANs), a deep learning approach that uses neural networks to create new data samples similar to a given dataset.	The findings show that GANs can produce images that are similar to the training data, but the results frequently have limitations such as blurriness, noise, and incomprehensibility.	The limitations include low-quality generated images that are not necessarily representative of the training data. The authors also emphasized the necessity for additional study to improve the effectiveness of GANs for image production.
"Application of an improved DCGAN for image generation."	Liu, Bingqi, et al.	The authors employed a concept classification network to eliminate errors during the image production process. The network is trained on the MNIST dataset and uses a DCGAN model as its generator.	The concept classification network successfully handled the issue of low-quality images produced by the GAN model, resulting in improved image quality.	The limitations include a possible lack of generalizability due to the use of the MNIST dataset, which may not be applicable to other datasets. Another limitation of the work is the lack of a detailed comparison with other image generation methods.
"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 considerable limitations. The technique was only evaluated on facial pictures and not on other sorts of synthetic or changed content, limiting its usefulness in a range of real-world scenarios. The study does not look at the model's resilience to adversarial attacks or its performance in real-time detection scenarios, both of which are critical for practical deployment.
"Digital image forgery detection using deep learning approach."	Kuznetsov, A.	The researchers employed the VGG-16 CNN to detect splicing frauds in digital photographs, using a sliding window technique to classify 40x40 pixel sections as original or phony. The VGG-16 model was fine-tuned using pretrained COCO dataset weights to improve accuracy while reducing the need for huge datasets. The CASIA dataset was used for testing, and dropout layers helped to prevent overfitting. Patch-based classification and majority voting were used to classify entire photos.	On the CASIA dataset, the model outperformed previously used solutions such as the Markovian rake transform and DCT coefficient analysis. However, its performance suffered dramatically after JPEG compression, with accuracy dropping to 66.3% at lower quality settings.	The method was especially tested for splicing forgeries and may not be applicable to other picture alterations such as copy-move or resampling. The model's performance was particularly sensitive to JPEG compression, with a considerable loss in accuracy observed during post-processing settings. Furthermore, the study focused primarily on the CASIA dataset, limiting the evaluation to a single dataset and excluding testing on various, real-world datasets.
"Exploring deep convolutional generative adversarial networks (DCGAN) in biometric systems: a survey study."	Jenkins, John, and Kaushik Roy.	The authors employed the DCGAN technology to create lifelike synthetic biometric samples. They trained the generator and discriminator models with the binary cross-entropy loss function and Adam optimizer. The quality of the produced biometrics was assessed using measures such as SSIM and FID.	The authors did not disclose specific data, but did state that the DCGAN system can produce lifelike synthetic biometric samples. They also stated that the quality of these faked biometrics can be assessed using measures like as SSIM and FID.	The authors may have considered limitations such as the possibility that generated biometric samples could be easily distinguished from real ones, or the need for more advanced evaluation metrics to better 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 findings revealed that PCA was the most widely utilized method, most likely due to its efficacy in dimension reduction. Combining multiple dimension reduction techniques improved accuracy. The average accuracies by year revealed that research published in 2018 had the highest average accuracy of 96.95%, followed by 2016 (84.30%), and so on.	The study concludes that PCA is only successful when data pre-processing is done correctly, as noise in the data can lead to misleading significance. Furthermore, the paper states that just five studies were published in 2019, which may limit the sample size and reduce the robustness of the findings.
"Synthetic images aid the recognition of human-made art forgeries."	Ostmeyer J, Schaerf L, Buividovich P, Charles T, Postma E, Popovici C.	To emulate the manner of Vincent van Gogh's paintings, the writers employed CNN-generated synthetic pictures. These synthetic images were then used to train a classifier that could distinguish between genuine and fake Van Gogh paintings. .	The authors discovered that utilizing synthetic images increased the classifier's ability to distinguish between legitimate and fake Van Gogh paintings. Furthermore, the synthetic images reduced the number of false positives and false negatives.	The authors acknowledged some study limitations. They tested the approach on a small dataset of original and fabricated Van Gogh paintings but did not apply it to other forms of art forgeries. They also emphasized that the quality of the synthetic images may differ from that of genuine photographs, which could impair classifier accuracy. Furthermore, the method may not be applicable to other types of art or forgeries, and more research is needed to investigate the role of synthetic images in art forgery identification.