RESEARCH PAPER

A Hybrid Spatial–Frequency Learning Framework for Medical Deepfake Detection

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Abstract

Medical deepfakes present considerable threats to healthcare systems by altering diagnostic images, such as Magnetic Resonance Imaging (MRI) and Chest X-ray scans. The majority of current deepfake detection techniques are primarily tailored for natural images and frequently struggle to generalize effectively across various medical imaging types. To tackle this issue, this paper introduces a hybrid deep learning framework that integrates DenseNet121-based spatial feature extraction with Fast Fourier Transform (FFT)-based frequency-domain analysis for effective medical deepfake detection. The suggested architecture captures both anatomical visual features and concealed spectral artifacts that arise during image manipulation. Experiments were performed on a multi-modal medical imaging dataset that includes both genuine and altered MRI and Chest X-ray images. Spatial and frequency-domain features are combined through a hybrid feature fusion strategy and classified using fully connected layers. The experimental results indicate that the proposed framework achieves a classification accuracy of around 99%, surpassing traditional Convolutional Neural Networks (CNNs), DenseNet121-only,
and FFT-only methods. These results suggest that the integration of spatial and These results indicate that the proposed hybrid framework successfully utilizes complementary spatial and frequency-domain features to identify subtle manipulation artifacts, thus achieving enhanced detection accuracy, increased robustness, and improved cross-domain generalization across various medical imaging modalities**.**

Keywords Deepfake Detection, Medical Imaging, DenseNet121, FFT, MRI, Chest X-ray, Feature Fusion.

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1. Introduction

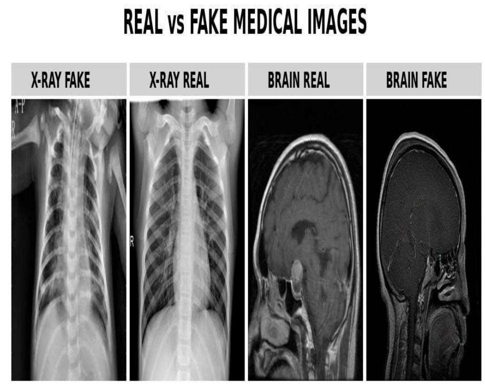
Medical imaging plays an important role in modern healthcare, aiding in the diagnosis of diseases, planning of treatments, and making medical decisions. Techniques such as Magnetic Resonance Imaging and Chest X-ray are commonly used to detect neurological disorders, lung diseases, and various other pathological conditions. Recent growth in AI and deep learning have considerably improved the analysis and explanation of medical images, enabling automated diagnoses with descent accuracy. Although, the rapid progress in image generation technologies, especially Generative Adversarial Networks and diffusion-based models, has introduced a new security concern known as medical deepfake

Medical deepfakes refer to artificially created or modified medical images that seem visually authentic but contain altered diagnostic information. These modifications can lead to misdiagnosis, inappropriate treatment choices, and considerable risks to patient safety. Unlike natural image deepfakes, forgeries in medical imaging are often more difficult to detect due to gradual alterations in anatomical structures and pathological patterns that may not be readily apparent to physicians or standard image analysis methods.

to detect due to gradual alterations in anatomical structures and pathological patterns that may not be readily apparent to physicians or standard image analysis methods.

Deepfake detection methods now use spatial distortions and visual anomalies to primarily target facial photos and videos. These techniques have shown promising results, but the complexity of medical data and the distinctive features of different modalities limit their usefulness to medical imaging. Moreover, a lot of existing methods rely solely on spatial-domain or frequency-domain data, which might lead to inadequate feature representation and lower detection effectiveness.

In today's healthcare system, medical imaging is essential for disease diagnosis, treatment planning, and clinical decision-making. Neurological illnesses, lung ailments, and other pathological conditions are frequently detected using methods like magnetic resonance imaging and chest X-rays. Recent developments in deep learning and artificial intelligence have greatly enhanced the analysis and interpretation of medical pictures, allowing for very accurate automated diagnosis. However, a new security issue known as medical deepfakes has emerged because to the quick development of image generating technologies, particularly Generative Adversarial Networks and diffusion-based models.



(Fig.1. Real and Fake medical images of Brain and X-ray)

2. Literature Review

Table 1. Literature survey

Year	Authors	Method/ Model	Dataset	Focus Area	Key Contribution
2024	C. Tan et al.	Frequency Space Learning	Multi-dataset	Frequency-aware Detection	Improved generalization using frequency-domain learning
2024	V.N. Convertini et al.	Discrete Fourier Transform (DFT)	Deepfake Image Dataset	Frequency Analysis	Used DFT for identifying hidden forgery artifacts
2024	J. Gao et al.	High-Frequency Enhancement Network	General Deepfake Dataset	Frequency-based Detection	Enhanced detection using high-frequency feature learning
2023	B. Wang et al.	Frequency Domain Filtered Residual Network	General Dataset	Frequency Detection	Improved robustness using residual frequency filtering
2022	Y. Jeong et al.	FrePGAN	Multi-dataset	Robust Deepfa	Introduced frequency-level perturbation learning

				keDetection	
2021	Y. Mirsky and W. Lee	Survey	—	DeepfakeSurvey	Comprehensive overview of deepfake generation and detection
2021	S. Solaiyappan and Y. Wen	MachineLearningModels	Medical Magnetic Resonance Imaging Data set	MedicalDeepfake	Comparative study on medical image deepfake detection
2021	J. Wang et al.	M2TR Transformer Framework	Multi-modal Data set	Multi-modal Detection	Transformer-based deepfake detection framework
2021	L. Jiang et al.	F^3-Net	FaceForensics++	FrequencyDetection	Learned local frequency statistics for deepfake detection
2021	X. Xu et al.	High-Frequency Convolutional Neural Network	Face Dataset	FrequencyFeatures	Improved generalization using high-frequency information

2021	T. Zhao et al.	Multi-Attentional Network	Face Dataset	Attention-based Detection	Used attention mechanism for deepfake localization
2020	Q. Wang et al.	Convolutional Neural Network + Frequency Artifact Analysis	GAN-generated Images	Frequency Detection	Detected GAN artifacts using Convolutional Neural Network analysis
2020	Z. Qian et al.	Frequency-aware Detection Model	Face Forgery Dataset	Frequency Analysis	Introduced frequency clue mining for forgery detection
2020	R. Verdoliva	MediaForensics Survey	—	MediaForensics	Discussed deepfake detection and forensic analysis
2020	L. Durall et al.	Spectral Analysis	GAN-generated Images	Frequency Analysis	Demonstrated spectral inconsistencies in GAN images
2020	H. Tolosana et al.	Survey	—	DeepfakeSurvey	Review of face manipulation and detection techniques
2020	L. Li et al.	Face X-Ray	FaceForensics++	Forgery Localization	Detected forgery boundaries in manipu

					lated images
2020	S. Agarwal et al.	Co-occurrence Matrix Analysis	GAN-generated Images	GAN Detection	Used co-occurrence matrices for fake image detection
2020	U. Ciftci et al.	FakeCatcher	Video Dataset	Biological Signal Detection	Detected deepfakes using biological signals
2019	B. Yi et al.	GAN-based Medical Imaging	Medical Dataset	Medical GAN	Review of GAN applications in medical imaging
2018	M. Frid-Adar et al.	GAN-based Augmentation	Liver Lesion Dataset	Medical Augmentation	Improved medical classification using synthetic images
2018	A. Madani et al.	Semi-supervised GAN	Chest X-ray Dataset	Medical GAN	GAN-based chest X-ray image generation

3.Proposed Methodology

This work introduces a hybrid deep learning system that simultaneously uses both spatial-domain and frequency-domain data to detect deepfake medical images.

By combining DenseNet121 for spatial feature extraction with Fast Fourier Transform (FFT) for frequency analysis, the framework is carefully designed to identify changed MRI and Chest X-ray. Dataset preparation, image preprocessing, spatial feature extraction, frequency-domain analysis, hybrid feature fusion, and binary classification are all included in the comprehensive procedure.

3.1. Dataset Preparation

Publicly accessible datasets from three distinct sources were utilized in this research study, which includes Brain MRI, Chest X-ray Pneumonia datasets. The Brain MRI dataset consists of four original classes which include glioma, meningioma, pituitary, and no tumor. The first three classes were merged into a single "Tumor" class for this study while "No Tumor" was treated as the "Normal" class resulting in a binary classification problem. The final dataset contained 4200 tumor images and 1400 normal images.

1.The Chest X-ray Pneumonia dataset consists of chest radiographs classified into pneumonia and normal categories A total of 3875 pneumonia images and 1341 normal images were used

2. The images were combined with the pneumonia dataset to create a three-class X-ray dataset which includes Normal, Pneumonia categories

The training process began after all images were converted to 128 × 128pixel dimensions and underwent normalization. The datasets were divided into training and testing sets using an 80:20 ratio.

To create the fake image dataset, authentic Brain MRI and Chest X-ray images were synthetically manipulated using a generative image synthesis approach. The generated images preserved the overall anatomical appearance while introducing subtle visual and frequency-domain artifacts characteristic of deepfake generation. These manipulated images were labeled as Fake, whereas the original images were labeled as Real. The resulting dataset provided a balanced set of authentic and manipulated medical images, enabling the proposed hybrid DenseNet121–FFT framework to effectively learn both spatial and spectral forgery patterns for accurate deepfake detection.

3.2. Image Preprocessing

Prior to feature extraction, all images undergo preprocessing to ensure consistency across different datasets. The images are resized to 128 × 128 pixels and normalized to a pixel intensity range of [0,1]. This normalization process enhances numerical stability and accelerates model convergence during training. For frequency-domain analysis, grayscale versions of the images are generated before applying the FFT transformation. These preprocessing steps reduce computational complexity while preserving essential anatomical details.

3.3. Spatial Feature Extraction Using DenseNet121

The spatial aspect of the proposed framework employs DenseNet121 as its backbone network to extract deep visual features from medical images. DenseNet121 is selected for its dense connectivity strategy, efficient feature reuse, and strong performance in medical image analysis tasks. The pretrained DenseNet121 model, initialized with weights from ImageNet, is adept at learning distinctive spatial features such as anatomical structures, texture patterns, lesion boundaries, and anomalies within images. Global Average Pooling (GAP) is utilized to generate a compact feature representation that captures the critical visual characteristics required for deepfake detection.

3.4. Frequency -Domain Feature Extraction Utilizing FFT

Although altered images may appear visually convincing, the methods employed for image generation often introduce subtle frequency artifacts that are difficult to detect in the spatial domain. To reveal these artifacts, the Fast Fourier Transform (FFT) is applied to each medical image. The FFT converts the image from the spatial domain to the frequency domain, producing a magnitude spectrum that highlights spectral discrepancies, high-frequency artifacts, checkerboard patterns, and indications of manipulation. The resulting FFT feature maps are subsequently processed through convolutional layers to create discriminative frequency-domain representations that enhance the spatiat121.

3.5. Hybrid Feature Fusion

The proposed framework combines spatial and frequency-domain features to improve medical deepfake detection. DenseNet121 extracts spatial features such as anatomical structures and texture patterns, while the FFT branch captures hidden frequency artifacts introduced during image manipulation. The extracted features are merged convert images into the frequency domain, facilitating the detection of concealed spectral artifacts and inconsistencies that arise during deepfake generation [2], [4], [13].

using a feature concatenation operation to form a unified feature representation:

$$\square_{\text{Hybrid}} = \square_{\text{Spatial}} \oplus \square_{\text{Frequency}}$$

where $\square_{\text{Spatial}}$and $\square_{\text{Frequency}}$represent the spatial and frequency feature vectors, respectively, and $\oplus$denotes feature concatenation. The fused features are then passed through fully connected layers for binary classification. By combining information from both domains, the proposed framework effectively identifies subtle forgery patterns and improves detection accuracy and cross-domain generalization.

3.6 Binary Classification

The hybrid feature vector undergoes processing through fully connected dense layers for classification purposes. To reduce overfitting and improve generalization performance, a dropout layer is incorporated. Ultimately, a sigmoid activation function is utilized to classify each image as either Real or Fake. The Binary Cross-Entropy (BCE) loss functions as the objective function, while the Adam optimizer is used to ensure efficient model training. The network aims to minimize classification errors by optimizing the combined feature representations.

3.7. Performance Evaluation

The effectiveness of the proposed framework is assessed using standard classification metrics, including Accuracy, Precision, Recall, F1-Score, Area Under Curve (AUC), Receiver Operating Characteristic (ROC), and Confusion Matrix analysis. These metrics provide a comprehensive evaluation of detection performance and the model's ability to generalize across various domains. Experimental results demonstrate that the DenseNet121-FFT hybrid framework surpasses traditional Convolutional Neural Network -based and single-domain approaches in detecting medical deepfakes.

4.System Architecture

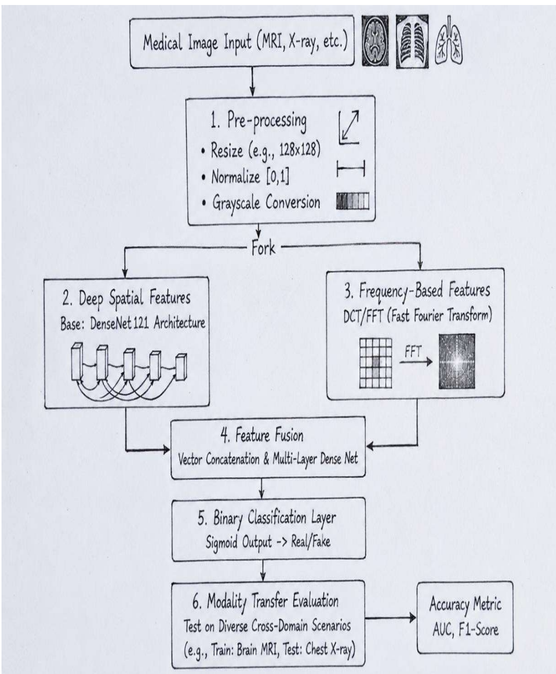
The proposed system architecture is a hybrid deep learning framework aimed at detecting deepfake medical images by utilizing both spatial-domain and frequency-domain information. This framework integrates DenseNet121-based spatial feature extraction with Fast Fourier Transform (FFT)-based frequency analysis to identify manipulated Magnetic Resonance Imaging and Chest X-ray images [2], [13], [23].

Initially, the input medical images undergo preprocessing, which includes resizing and normalization to ensure consistency across the dataset. Following this, the pre-processed images are processed through two parallel branches. In the first branch, DenseNet121 extracts deep spatial features that represent anatomical structures, texture patterns, and

The spatial and frequency-domain features are then merged through feature fusion to create a comprehensive representation of the input image. By integrating complementary information from both domains, the framework effectively captures both visual and spectral forgery patterns [1], [3], [9].

The fused feature vector is subsequently processed through fully connected layers, followed by a sigmoid activation function for binary classification. The classifier determines whether the input medical image is categorized as Real or Fake. To assess the robustness and generalization capability of the proposed framework, cross-domain experiments are conducted.

(Fig.2. Proposed hybrid spatial-frequency

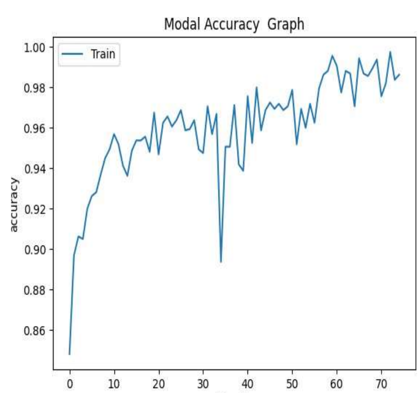


deepfake detection architecture)

5. Result and Analysis

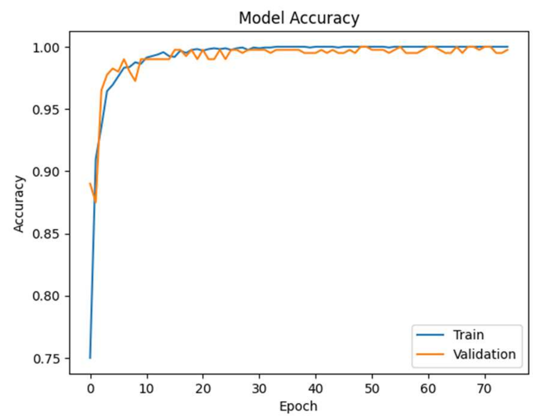
5.1. Proposed Hybrid DenseNet121 + FFT Model Accuracy

Fig. 3. depicts the training and validation accuracy curves for the proposed DenseNet121–FFT hybrid model over a duration of 70 epochs. The training accuracy showed a steady increase from approximately 85% to nearly 99%, indicating

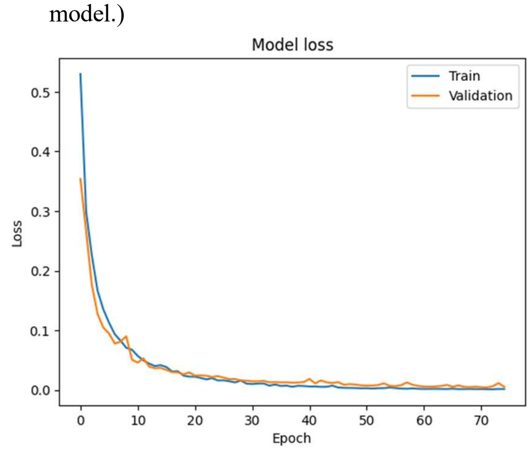


effective feature learning and stable convergence. During the training phase, the validation accuracy remained high, frequently reaching values between 97% and 100%, although some fluctuations were observed due to the limitations of the small validation dataset and batch size.

The close correspondence between training and validation accuracies underscores the strong generalization ability of the proposed model, suggesting minimal overfitting. The integration of DenseNet121-based spatial features with FFT-based frequency features significantly improved the model's capability to distinguish between authentic and deepfake medical images. In conclusion, the model achieved a final validation accuracy of around 99% and a test accuracy of 98.25%, thereby confirming its effectiveness in detecting medical deepfakes.



(Fig.3. Training and validation accuracy curves of the proposed DenseNet121–FFT hybrid model.)



(Fig.4. Training and validation Loss curves of the proposed DenseNet121–FFT hybrid)

5.2 Performance Metrics Analysis of the Proposed Hybrid Model

The performance of the proposed DenseNet121–FFT hybrid model was evaluated using four standard classification metrics: accuracy, precision, recall, and F1-score. These metrics provide a reliable measure of the model's ability to distinguish between real and manipulated medical images.

As shown in Figure X, the proposed model achieved an accuracy of 99.75%, indicating

(Fig .5. Cross-Domain Training Accuracy Curve of the Proposed DenseNet121–FFT Hybrid Model Trained on Magnetic Resonance Imaging Images.)

that it correctly classified almost all test images. The model obtained a precision of 100%, which means that every image predicted as fake was actually fake, with no false positive predictions. The recall reached 99.50%, showing that the model successfully detected nearly all manipulated images while missing only a very small number of cases. In addition, the F1-score of 99.75% demonstrates a good balance between precision and recall, confirming the consistency of the model's performance.

These results indicate that combining DenseNet121 with Fast Fourier Transform (FFT) improves the detection of deepfake medical images. DenseNet121 learns meaningful spatial features such as anatomical structures and texture patterns from MRI and Chest X-ray images, while FFT captures frequency-domain artifacts that are often introduced during image manipulation. By combining information from both domains, the proposed framework can effectively identify subtle differences between real and fake images, leading to high classification performance across the test dataset.

5.3. Cross-Domain Evaluation Analysis

To assess the generalization ability of the proposed hybrid deepfake detection framework, a cross-domain experiment was carried out. This experiment involved training the model solely on Brain Magnetic Resonance Imaging images while evaluating it on a markedly different medical imaging modality, specifically Chest X-ray images. This evaluation approach is crucial, as models trained on one modality frequently exhibit a decrease in performance when applied to another unfamiliar modality, owing to variations in image characteristics, anatomical structures, textures, and acquisition methods.

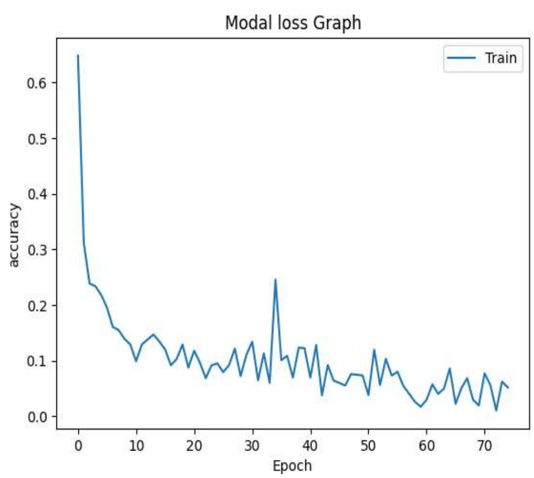
The aim of this experiment was to ascertain whether the proposed DenseNet121–FFT hybrid framework could identify modality-independent deepfake features and sustain high detection performance across previously unencountered medical image domains.

Fig.6. illustrates the training accuracy achieved throughout the cross-domain learning process. The proposed DenseNet121–FFT hybrid model demonstrated effective learning of distinguishing features from Magnetic Resonance Imaging images over the span of 75 training epochs. The training accuracy began at approximately 84.9% and rapidly increased beyond 99% during the initial epochs, indicating successful extraction of both spatial and frequency-domain features.

As training progressed, the accuracy consistently improved and remained above 95% for the majority of the epochs, signifying stable convergence and effective feature learning. Several epochs approached near-perfect performance, with training accuracy reaching a peak of 1, highlighting the model's capability to learn highly discriminative representations of both genuine and fabricated medical images.

Fig .7 The training loss curve, which is derived from the cross-domain learning process, is illustrated here. Initially, the loss value showed a rapid decrease from about 0.65 in the first epoch to below 0.20 during the early training phases, indicating an effective acquisition of discriminative features from Magnetic Resonance Imaging images. As training progressed, the loss continued to decline swiftly and remained at a consistently low level for most of the training period, suggesting stable optimization and successful convergence of the model. Several epochs achieved near-zero loss values, reflecting highly confident and accurate predictions. Although minor fluctuations were observed during a few epochs, the model quickly regained stability, demonstrating robust learning behaviour without significant instability.

The final training loss was approximately 0.0086, while the cross-domain test loss on the Chest X-ray dataset was around 0.0080. These low loss values confirm the ability of the proposed DenseNet121–FFT hybrid architecture to learn generalized representations and effectively transfer knowledge across different medical imaging modalities.



(Fig.6. Training loss curve of the proposed DenseNet121–FFT hybrid model during cross-domain learning.)

5.4. Cross -Domain Confusion Matrix Analysis

Fig .8. The confusion matrix presented here is derived from the cross-domain evaluation of the proposed DenseNet121–FFT hybrid model. Training was conducted using Magnetic Resonance Imaging images, while testing was performed on an unseen Chest X-ray dataset. The model successfully classified 500 genuine images and 496 counterfeit images, with only 4 counterfeit images misclassified as genuine. Importantly, no genuine images were incorrectly classified as counterfeit, resulting in zero false positives.

The confusion matrix indicates 496 True Positives (TP), 500 True Negatives (TN), 0

False Positives (FP), and 4 False Negatives (FN).

These findings highlight the model's exceptional ability to differentiate between authentic and manipulated medical images across various imaging modalities.

The proposed framework achieved a cross-domain accuracy of approximately 99.60%, accurately classifying 996 out of 1000 test images. This impressive performance suggests that the model has learned generalized features of manipulation rather than characteristics specific to any one modality. The integration of DenseNet121 for spatial feature extraction and FFT for frequency analysis has significantly enhanced the model's robust cross-domain generalization and effective deepfake detection.

6. Conclusion and Future Scope

The increasing use of deep learning techniques for generating realistic medical image deepfakes has raised serious concerns regarding the reliability of computer-aided diagnosis and the security of healthcare systems. Detecting manipulated medical images has therefore become an important research problem. In this work, a hybrid deepfake detection framework was developed by combining DenseNet121 for spatial feature extraction with Fast Fourier Transform **(**FFT**)** for frequency-domain analysis. The integration of these two feature representations enables the model to capture both visual characteristics and hidden frequency artifacts introduced during image manipulation.

The proposed framework was evaluated on Brain MRI and Chest X-ray datasets containing both real and fake images. The experimental results demonstrate that the model performs consistently well, achieving an accuracy of 99.75%**,** precision of 100.00%**,** recall of 99.50%**,** and an F1-score of 99.75%**.** These results indicate that the proposed approach can accurately distinguish genuine medical images from manipulated ones while maintaining a balanced performance across both classes. The high precision and recall further confirm the effectiveness and reliability of the model for medical image deepfake detection.

Although the proposed framework shows promising results, there is scope for further improvement. Future work will focus on evaluating the model using a wider range of medical imaging modalities, such as CT scans, ultrasound, and retinal images. The framework can also be extended to detect deepfakes generated by advanced generative models and diffusion-based techniques. In addition, reducing computational complexity, improving cross-domain generalization, and validating the model on real-world clinical datasets will help enhance its practical applicability. These improvements could make the proposed framework more suitable for deployment in secure and trustworthy medical imaging systems.

Cross-domain evaluations further illustrated strong generalization performance, highlighting the model's ability to detect manipulated images across different medical imaging modalities. These results validate that the proposed DenseNet121–FFT hybrid architecture provides a robust, accurate, and reliable solution for detecting medical deepfakes, significantly improving the integrity and trustworthiness of healthcare imaging systems.

To address this issue, this study presents a hybrid framework for deepfake detection that combines DenseNet121-based spatial feature extraction with Fast Fourier Transform (FFT)-based frequency-domain analysis. By integrating both spatial and frequency-domain information, the model effectively identifies subtle manipulation artifacts present in counterfeit medical images.

References

[1] C. Tan et al., "Frequency-Aware Deepfake Detection: Improving Generalizability through Frequency Space Learning," arXiv preprint arXiv:2403.07240, 2024.

[2] V. N. Convertini et al., "Discrete Fourier Transform in Unmasking Deepfake Images," *Information*, vol. 15, no. 11, 2024.

[3] J. Gao et al., "DeepFake Detection Based on High-Frequency Enhancement Network," *Expert Systems with Applications*, vol. 252, 2024.

[4] B. Wang et al., "Frequency Domain Filtered Residual Network for Deepfake Detection," *Mathematics*, vol. 11, no. 4, 2023.

[5] Y. Jeong et al., "FrePGAN: Robust Deepfake Detection Using Frequency-level Perturbations," arXiv preprint arXiv:2202.03347, 2022.

[6] J. Wang et al., "M2TR: Multi-modal Multi-scale Transformers for Deepfake Detection," in *Proc. ACM International Conference on Multimedia*, 2021.

[7] Y. Mirsky and W. Lee, "The Creation and Detection of Deepfakes: A Survey," *ACM Computing Surveys*, vol. 54, no. 1, 2021.

[8] S. Solaiyappan and Y. Wen, "Machine Learning based Medical Image Deepfake Detection: A Comparative Study," arXiv preprint arXiv:2109.12800, 2021.

[9] L. Jiang et al., "F³-Net: Learning Local Frequency Statistics for Deepfake Detection," in *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2021, pp. 2871–2880.

[10] X. Xu et al., "Generalizing Face Forgery Detection with High-Frequency Features," in *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2021, pp. 16317–16326.

[11] T. Zhao et al., "Multi-Attentional Deepfake Detection," in *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2021, pp. 2185–2194.

[12] Q. Wang et al., “Convolutional Neural Network -Generated Images Are Surprisingly Easy to Spot... for Now,” in *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020, pp. 8695–8704.

[13] Z. Qian et al., “Thinking in Frequency: Face Forgery Detection by Mining Frequency-aware Clues,” in *Proc. European Conference on Computer Vision (ECCV)*, 2020, pp. 86–103.

[14] L. Durall et al., “Watch Your Up-Convolution: Convolutional Neural Network Based Generative Deep Neural Networks Are Failing to Reproduce Spectral Distributions,” in *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020, pp. 7890–7899.

[15] H. Tolosana et al., "Deepfakes and Beyond: A Survey of Face Manipulation and Fake Detection," *Information Fusion*, vol. 64, pp. 131–148, 2020.

[16] R. Verdoliva, "Media Forensics and DeepFakes: An Overview," *IEEE Journal of Selected Topics in Signal Processing*, vol. 14, no. 5, pp. 910–932, 2020.

[17] L. Li et al., "Face X-Ray for More General Face Forgery Detection," in *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020, pp. 5001–5010.

[18] S. Agarwal et al., "Detecting GAN Generated Fake Images Using Co-occurrence Matrices," arXiv preprint arXiv:1912.11759, 2020.

[19] U. Ciftci et al., "FakeCatcher: Detection of Synthetic Portrait Videos Using Biological Signals," in *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020, pp. 5381–5390.

[20] B. Yi et al., "Generative Adversarial Networks in Medical Imaging: A Review," *IEEE Access*, vol. 7, pp. 184–205, 2019.

[21] M. Frid-Adar et al., "GAN-based Synthetic Medical Image Augmentation for Increased Convolutional Neural Network Performance in Liver Lesion Classification," *Neurocomputing*, vol. 321, pp. 321–331, 2018.

[22] A. Madani et al., "Semi-supervised Learning with Generative Adversarial Networks for Chest X-ray Classification with Ability of Data Domain Adaptation," in *Proc. International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, 2018.

[23] G. Huang et al., "Densely Connected Convolutional Networks," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017, pp. 4700–4708.

[24] F. Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017, pp. 1251–1258.