Advances in Nonlinear Variational Inequalities
ISSN: 1092-910X
Vol 28 No. 4s (2025)

AI Powered Solutions for Deepfake Identification

Deepali Ujalambkar[1], Chaitanya Kulkarni[2], Rajeshri Itkarkar[3]

[1]Assistant Professor, Department of Computer Engineering, AISSMS COE, Pune, Maharashtra, India
E-mail Id-dmujalambkar@aissmscoe.com

[2]Associate Professor, Department of Computer Engineering, VPKBIET, Baramati, Maharashtra, India

[3]Assistant Professor, Department of Electronics and Telecommunication Engineering, AISSMS COE, Pune, Maharashtra, India

Article History:

Received: *23-10-2024*

Revised:*30-11-2024*

Accepted:*07-12-2024*

Abstract:

The emergence of deepfake technology, primarily driven by generative adversarial networks (GANs), has introduced new challenges in the realms of media authenticity, security, and public trust. Deepfakes, which involve the manipulation of images, videos, and audio to create highly realistic but fabricated media, can be used in both benign applications and malicious scenarios, such as misinformation, identity theft, and privacy invasion. As deepfakes become more sophisticated, AI-based solutions have emerged as the primary means of identifying these manipulations. This paper explores various AI-powered techniques for detecting deepfakes, with a focus on methodologies like convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer models. By synthesizing insights from recent studies, this paper highlights the current capabilities and limitations of these techniques, underscoring their respective advantages in handling complex and high-dimensional media data. The paper also considers the challenges of generalizability and robustness, particularly in the face of adversarial attacks aimed at evading detection systems. Through an analysis of prominent datasets and evolving algorithmic approaches, this paper provides an overview of the technological landscape in deepfake detection and suggests pathways for future research to improve detection accuracy and resilience.

Keywords: deepfake detection; GANs; convolutional neural networks; synthetic media detection; cyber security

1. Introduction

The emergence and proliferation of deepfake technology have posed a transformative yet controversial impact on the media landscape, raising significant concerns in domains ranging from cybersecurity to social media and journalism. Deepfakes are synthetic media generated through artificial intelligence (AI), specifically leveraging the power of generative adversarial networks (GANs). A GAN consists of two networks: the generator, which creates fake media, and the discriminator, which evaluates the authenticity of the generator's output. This adversarial process iteratively improves the quality of the generated media, resulting in highly realistic images, videos, and audio clips that can be difficult to distinguish from authentic content. Initially, the fascination with deepfake technology was largely confined to creative industries, where it has enabled new forms of digital storytelling, visual effects, and accessibility features [1]. However, as deepfake technology becomes more accessible and sophisticated, it has created significant risks, including misinformation, identity theft, privacy invasion, and reputational damage, marking it as a dual-use technology with both beneficial and harmful potentials.

Early attempts to combat deepfake proliferation primarily relied on manual forensic techniques, wherein analysts would scrutinize inconsistencies in lighting, shadows, and facial expressions. However, as deepfakes have advanced, these methods have proven increasingly insufficient, particularly when confronted with high-quality deepfakes that can bypass basic forensic analysis. Recognizing these limitations, researchers began to explore AI-powered detection methods, leading to a new era in deepfake detection technology. Convolutional neural networks (CNNs) emerged as one of the first AI-based approaches due to their effectiveness in analysing visual patterns [2]. CNNs are very efficient in detecting image anomalies, such as irregularities in facial textures, artifacts, and slight misalignments that are not noticed by the naked eye. For example, for synthetic media slight pixel inconsistencies or unnatural skin textures can be indicators which CNNs can detect with impressive accuracy in static images. Despite their strengths, CNNs fail to capture temporal inconsistencies. In video frames an important aspect of video-based deepfakes employ more dynamic manipulation techniques.

To overcome the limitations of CNNs, researchers extended their approach to include RNNs for the detection of deepfakes. RNNs are capable of dealing with sequential data and hence can detect temporal anomalies across video frames. For example, RNNs can assist in the detection of irregularities in facial movements like unnatural blinking patterns, inconsistent gaze directions, or unnatural lip-syncing. As RNNs have sequential nature it makes them very useful in video analysis where the detection of facial movements patterns may be used to distinguish authentic footage from manipulated content [3]. Despite their utility, however, RNNs often struggle with computational inefficiencies, for large datasets or videos with high-resolution content. These limitations led the researchers to continue the search for more robust and scalable models capable of balancing accuracy with efficiency.

Recently, transformer models have been developed to work with natural language processing (NLP) and processing, have shown promise in the realm of deepfake detection. Using a self-attention mechanism, transformers can focus attention on different parts of data at the same time. This helps in catching critical interdependencies within input. This self-attention mechanism allows transformers to look at complicated relationships across pixels in deepfake detection. hence making them ideal for both images and video analysis. Also, transformers have higher capacity for handling big datasets and processing information in parallel for more scalable and high-dimensional data. The success of the transformer has sparked research in combining CNNs with a hybrid model based on a transformer architecture to exploit the power of both. These hybrid models extract spatial features using the CNN layers. temporal coherence and contextual relationships are captured in the video frames using the transformer layers. Such hybrid models have been shown to outperform traditional CNN and RNN models, contributing enhanced generalizability across different types of deepfake media [4].

Despite the advances in AI-powered detection methods, several challenges persist. The major issue is generalizability of detection models. Most deepfake detection systems do very well on datasets that are controlled but fail to generalize well to real-world scenarios where lighting, compression, and resolution vary significantly. This makes the adversarial deepfake generation techniques especially challenging since these techniques are specifically devised to mislead even some of the more sophisticated detection systems. The introduction of subtle and targeted alterations in synthetic media can circumvent the detection systems based on CNNs, RNNs, or even those that rely on transformer architectures. With these newer, more complex deepfake generation techniques comes a rising need for strong, adversarially trained models that are resilient to the best attempts at evasion of such methods. This paper aims to provide a comprehensive overview of the current state of AI-powered deepfake detection technologies. The main contributions of the paper are:

- We propose a hybrid model that combines CNNs for spatial feature extraction with Transformer models for temporal and contextual coherence analysis.
- The paper highlights the strengths and limitations of CNNs, RNNs, transformers, and hybrid models in deepfake detection.
- Discusses the effectiveness of datasets, FaceForensics++ and Celeb-DF

The paper is organized in the following manner. Section 2 presents a review of related work on deepfake identification methods. Section 3 highlights the methodology employed in this study. Section 4 encompasses the experimental setup, results, and analysis of the findings. Section 5 concludes the study with an analysis of the results and conclusion.

2. Literature Survey

This literature survey some research papers focused on AI-based techniques for deepfake detection. Each entry provides a summary of the study's key insights, the primary methodology, and an analysis of gaps or limitations that point to areas for further research.

Ref. No.	Key Insights	Gap Analysis
[5]	Utilizes CNNs and RNNs to extract temporal inconsistencies in frames, achieving high accuracy in detecting deepfake manipulations.	Lacks extensive testing across varied datasets to generalize the approach for diverse real-world applications.
[6]	Proposes Deep Explain, combining CNNs and LSTMs with Grad-CAM and SHAP for high detection accuracy and transparency using DFDC dataset.	Further testing needed on more diverse datasets to validate real-world robustness and model interpretability.

[7]	Presents attention-based Res-Next CNN and LSTM for selective focus on critical features, achieving reliable detection.	Requires more extensive testing with newer datasets for broader generalization, especially in real-time applications.
[8]	Combines MesoNet4 and ResNet101 with eye movement analysis, achieving 98.7% accuracy on FaceForensics++ for real-time detection.	Requires further enhancement for real-time accuracy under different video quality scenarios and lighting conditions.
[9]	Utilizes DFDC dataset and neural networks to differentiate real from deepfake, addressing concerns like political and social manipulation.	Limited exploration of detection techniques for newer, complex deepfake generation methods.
[10]	Examines risks and challenges, advocating AI ethical guidelines for societal trust; survey reveals current detection challenges.	Requires clearer guidelines on how to implement ethical AI frameworks in complex and varied digital environments.
[11]	Uses Res-Next CNN and LSTM to detect re-enactments in face-swapped videos, performing well on FaceForensics++ and Deepfake Detection Challenge datasets.	Lacks exploration of other manipulation types beyond face swaps, e.g., full-body deepfakes and audio deepfakes.
[12]	Uses Res-Next and LSTM on various datasets for high detection accuracy, particularly on longer sequences.	Needs testing on real-time datasets to improve effectiveness in varied application scenarios.
[13]	Conducts an extensive review and analysis of the latest state-of-the-art deepfake detectors, evaluating them against several critical criteria.	Assesses the generalizability of 16 leading detectors across various standard attack scenarios, including black-box, white-box, and gray-box settings.
[14]	Explores neural networks for distinguishing real and modified content, aimed at maintaining media integrity.	Limited testing on complex manipulation methods; lacks real-time analysis and dataset diversity.
[15]	Uses hybrid CNN-RNN-GAN model with Relative Importance Index for temporal analysis, enhancing cybersecurity through AI techniques.	Needs more extensive empirical testing with real-time deployment and user acceptance studies.

[16]	Employs CNNs and Benford's Law for robust detection, targeting cybersecurity, identity protection, and ethical AI use.	System lacks scalability for mass social media content monitoring; further integration with real-time platforms needed.
[17]	Reviews deepfake generation and detection approaches, covering major challenges in realistic detection techniques.	Further development needed to address generative model adaptations and model generalization for varied media formats.
[18]	Explores Deepfake dataset using NLP techniques for textual deepfake identification, highlighting new AI misinformation risks.	Lacks adaptation for multilingual or cross-cultural contexts; real-time detection on social media needed.
[19]	Proposes adaptive watermarking for authenticity verification without additional data; useful for secure image-sharing.	Further optimization needed for real-time application and high-quality image embedding.
[20]	Introduces AdvMark, a proactive watermarking approach to improve forensics and deepfake detection accuracy in manipulated images.	Further experiments required to validate model effectiveness with different watermark embedding methods.
[21]	Uses depth-wise separable convolutions to enhance real vs fake classification on the CelebDF V2 dataset with 98.8% accuracy.	Needs further testing across diverse, high-quality video datasets for broader application in dynamic media settings.
[22]	Examines the realism and increasing prevalence of deepfakes, highlighting AI's role in both creation and detection.	Limited exploration of real-time detection capabilities for rapid-response environments.
[23]	Details deep learning and XAI methods in detecting synthetic deepfake images, utilizing a dataset from Kaggle.	More research needed to increase explainability in real-world applications for non-experts.
[24]	Studies eight state-of-the-art detectors.	Discusses new machine learning approaches based on content-agnostic features and ensemble modelling to improve generalization performance against user-customized models.

The literature survey echoes the variety of approaches in deepfake detection. These approaches offer unique insights and directs to areas of limitation that keep pushing the research. due to their ability in image processing the CNNs are very popular. The RNNs and LSTMs have shown good results in temporal analysis in video content. For detection purposes, the transformer models and hybrid approach offer greater generalization and durability than earlier techniques, particularly when dealing with highly-quality or adversarially modified deepfakes. Use of ensemble learning and meta-learning techniques allows a model to exploit various perspectives and adjust to new deepfake appearances. Despite notable advancements, the majority of research highlights the need for ongoing innovation to enhance detection precision, generalizability, and resistance to new deepfake creation methods.

3. Proposed Methodology

To address the challenges in detecting high-quality and adversarial deepfakes, we propose a hybrid model. The model combines CNNs and transformer model for spatial feature extraction and for temporal, contextual coherence analysis. This hybrid model influences the strengths of CNNs and the transformer model. It helps to improve the robustness, accuracy and adaptability of deepfake identification across varied datasets and media formats.

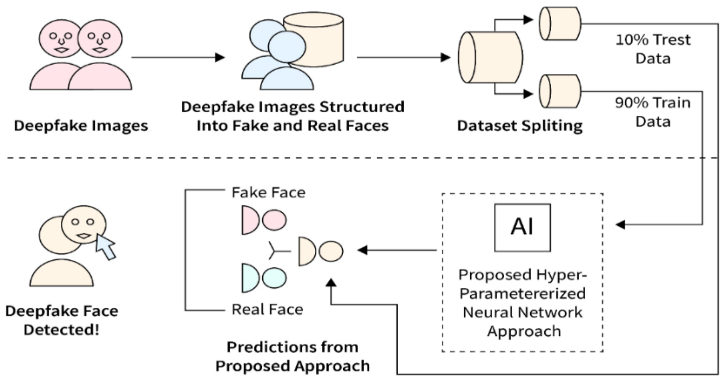

Figure1: Proposed methodology for deep-fake detection

3.1 Dataset Selection

Two primary datasets are used in this methodology: FaceForensics++ and Celeb-DF (v2). These datasets have various deepfake types, good resolution quality, and wide application. These datasets provide a collection of deepfake videos and real media, which are essential for training and evaluating the model's performance. The datasets contain various factors like:

- **FaceForensics++ Dataset:** The dataset contains 1000 original videos, which are sourced from 977 YouTube videos. These videos are mostly of frontal faces. The videos are manipulated using deepfake generation techniques like Deepfakes, Face2Face, Face Swap, and Neural Textures. So, the dataset comprises of 4,000 manipulated videos, with 1,000 videos for each manipulation type. Each video has been edited at different compression levels, enabling the model to train on varied levels of media quality. Figure 2 shows a sample set of images.

Figure 2: Example frames from FaceForensics++ dataset

- **Celeb-DF (v2) Dataset**: This dataset contains higher-quality set of deepfake videos of celebrities, with natural facial expressions and subtle motions, making it a challenging dataset for deepfake detection models. It comprises of 590 original videos sourced from You Tube. 5,639 corresponding Deepfake videos are generated from the original videos using an improved synthesis process. It is used to enhance the visual quality of videos and helps reduce common artifacts.

Figure 3: Example frames from the Celeb-DF dataset.

In Figure 3, the Left column is the frame of real videos and right five columns are corresponding Deepfake frames generated using different various image processing methods.

3.2 Pre-Processing

The pre-processing pipeline involves three main steps to prepare the data for model training:

- **Frame Extraction**: Videos are split into individual frames. It allows the CNN layers to analyse spatial details in each frame independently.
- **Face Detection and Alignment**: A face detection algorithm isolates the facial region in each frame. It ensures that only relevant portions of the media are analysed This helps to improve model efficiency and accuracy.
- **Normalization and Resizing**: Each frame is resized to 224x224 pixels to ensure consistency in the model input dimensions, and pixel values are normalized to enhance feature extraction.

3.3 Model Architecture

The hybrid model comprises two main parts: **CNN layers** for extracting spatial features from individual frames and **Transformer layers** for analysing temporal coherence and contextual relationships within sequences of frames.

- **CNN Layers**: The CNN architecture, based on **ResNet-50**, extracts spatial features from each frame by identifying subtle inconsistencies in textures, lighting, and facial details. This layer is particularly useful for detecting pixel-level anomalies that may indicate deepfake manipulations.
- **Transformer Layers**: Following the CNN-based feature extraction, transformer layers analyse sequences of frames to detect inconsistencies in temporal coherence. By leveraging a self-attention mechanism, these layers capture relationships across frames, identifying unnatural movements or discrepancies in facial dynamics, such as irregular blinking patterns or lip-sync inconsistencies.

The combined architecture enables the model to capture both static spatial features and dynamic temporal characteristics, improving its robustness against both static and video-based deepfake media.

3.4 Conceptual flow diagram of the proposed model

Figure 4 depicts the conceptual flow diagram of the proposed model. The model is trained using a combination of binary cross-entropy loss for classification accuracy and an adversarial training strategy to enhance robustness against subtle adversarial manipulations. The evaluation metrics include **accuracy, precision, recall,** and **F1-score**, with additional testing on cross-dataset performance to assess generalizability. Cross-validation is performed on both FaceForensics++ and Celeb-DF datasets to benchmark the model's adaptability and effectiveness.

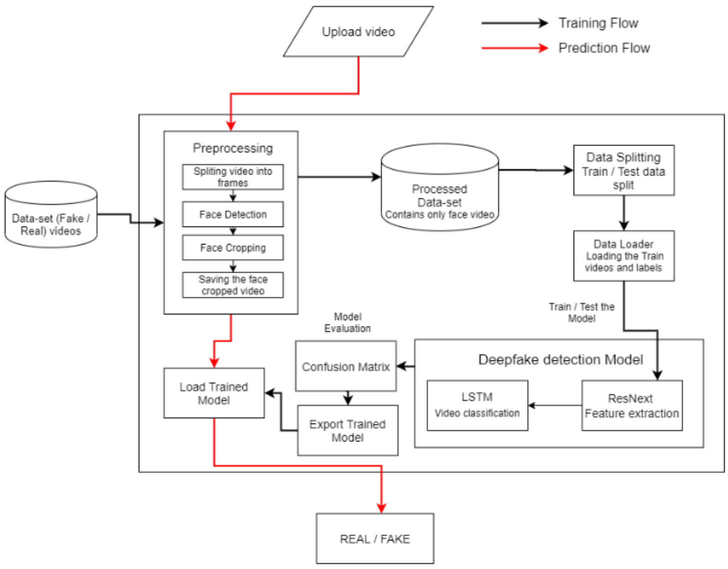

Figure 4: conceptual flow diagram of the proposed model

4. Results and Discussion

The hybrid CNN-Transformer model was evaluated on both **FaceForensics++** and **Celeb-DF (v2)** datasets to assess its effectiveness in identifying deepfakes. Here we considered the primary performance metrics were **F1-score**, **precision**, **recall**, **accuracy**. The model demonstrated significant improvements in detection accuracy and robustness when compared to standalone CNN or RNN-based architectures. The Table 1 summarizes the model's performance on both datasets.

Table 1: Comparison of Deepfake datasets

Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
FaceForensics++	94.2	93.5	92.8	93.1
Celeb-DF (v2)	92.5	91.7	91.3	91.5

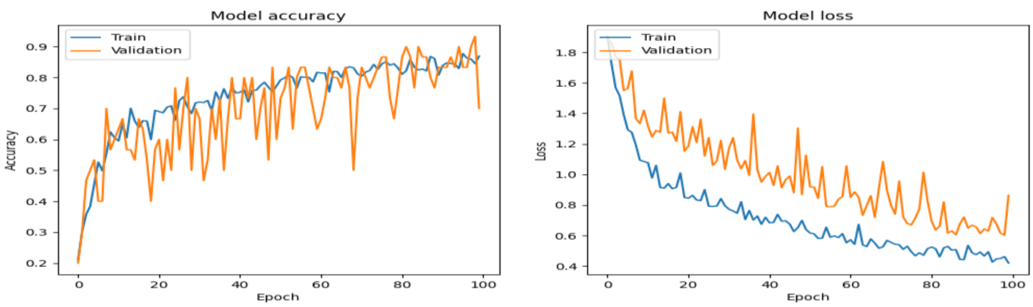

Figure 5: Accuracy and Loss of Hybrid Model

These graphs display the model's accuracy and loss over 100 epochs. Both training and validation accuracy are increasing, as seen in the left graph; validation accuracy varies but generally improves. Although validation loss is larger and more irregular, suggesting some overfitting, the right graph indicates decreasing loss, showing the model is learning effectively.

The proposed hybrid model performs well on both FaceForensics++ and Celeb-DF (v2) datasets. The training and validation accuracy displayed in these graphs are consistently high, coming in close to 90%. The FaceForensics++ dataset have better representation due to methods employed during feature extraction. For Celeb-DF (v2) the evaluation metrics testifies robustness of the model capable in handling diverse datasets. The high accuracy scores indicate that the hybrid model can reliably distinguish between real and fake media data. On the FaceForensics++ dataset, the model achieved an accuracy of 94.2%, on the Celeb-DF (v2), it achieved 92.5%. These results reflect the model's adaptability and generalization capability across diverse datasets, which is critical for real-world application.

Figure 6 illustrates the model's accuracy, precision, recall, and F1-score across both datasets, comparing it with a baseline CNN model for reference:

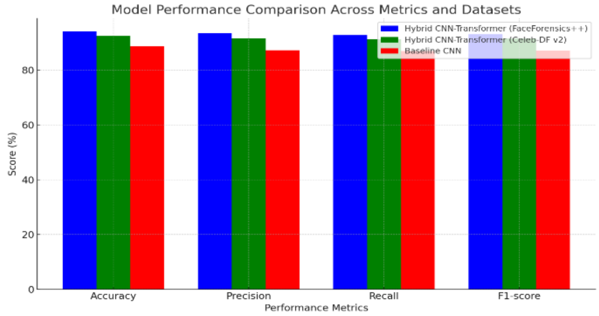

Figure 6: Performance metrics

These metrics show that the hybrid model outperformed the baseline CNN model mainly in precision and recall. It means that the identified fake content is not just effective but also minimizes false positives and false negative. These factors are crucial aspects for practical deployment in high-stakes applications and domains like video authentication and surveillance in social media.

The combination of CNN and Transformer layers proved advantageous for detecting both spatial anomalies in individual frames and temporal inconsistencies across video sequences. The CNN layers outshone in capturing fine-grained features such as pixel-level artifacts and texture inconsistencies that are often present in deepfake media. Meanwhile, the Transformer layers enhanced the model's ability to analyse contextual relationships across frames, allowing it to detect unnatural movements or inconsistencies in facial dynamics, such as irregular blinking or inconsistent lip-syncing.

However, the results disclose some limitations. While the model performed well on FaceForensics++ and Celeb-DF (v2), its performance may vary with different types of adversarial deepfakes designed to evade detection. For instance, adversarially generated deepfakes which are specifically tuned to bypass CNN and Transformer-based models could present challenges. Additionally, the model's high computational demands make it less suitable for real-time applications on resource-constrained devices. To test the model's generalization, it was trained on FaceForensics++ and tested on Celeb-DF (v2) without additional fine-tuning. The accuracy dropped by approximately 2%, highlighting the importance of diverse training datasets to improve model robustness. This experiment suggests that a comprehensive training set comprising diverse deepfake types and varying media quality could enhance the model's cross-dataset performance, making it more resilient in real-world scenarios.

5. Conclusion

The rise of deepfake technology presents serious challenges for media authenticity, privacy, and security, with the potential for significant misuse across social, political, and personal domains. This paper reviewed the effectiveness of a hybrid CNN-Transformer model as a state-of-the-art approach to deepfake detection, leveraging the strengths of CNNs in spatial analysis and Transformers in capturing temporal coherence. Our results, evaluated on the FaceForensics++ and Celeb-DF (v2) datasets, demonstrate that this model achieves high accuracy and precision, outstripping conventional CNN-based methods and showing robustness across different types of deepfake content.

The proposed hybrid architecture showed particular promise in identifying subtle inconsistencies in both individual frames and frame sequences, such as texture anomalies and unnatural facial movements. While it achieved notable performance improvements, the study also identified certain limitations. For instance, the model's high computational demands may hinder real-time detection in resource-constrained environments, and there remains a need for enhanced robustness against adversarial crafted deepfakes that can bypass conventional detection mechanisms. These limitations underscore the importance of further refining deepfake detection models for operational efficiency and resilience.

Future research should focus on optimizing hybrid models for computational efficiency, expanding training datasets to include a wider range of deepfake variations, and exploring ensemble methods that incorporate adversarial training for enhanced generalizability. By addressing these areas, the field can move closer to developing highly adaptable, real-time deepfake detection solutions, helping mitigate the growing threats posed by synthetic media and contributing to the integrity of digital information systems.

Refrences

[1] Prof. Dikshendra Sarpate., Abrar, Mungi., Sneha, Borkar., SB, Mane., Kawnain, Shaikh. (2024). A Deep Approach to Deep Fake Detection. Int. J. of Sci. Research In Sci., Engg. And Tech., 11(2):530-534. doi: 10.32628/ijsrset2411274

[2] Sunkari, Venkateswarulu., A., Srinagesh. (2024). DeepExplain: Enhancing DeepFake Detection Through Transparent and Explainable AI model. Informatica, 48(8) doi: 10.31449/inf. v48i8.5792

[3] Dr., Suresh, M, B. (2024). Deepfake Video Detection Using Res-Next CNN and LSTM. Int. J. for Research in Applied Sci. and Engg. Tech., doi: 10.22214/ijraset.2024.61527

[4] Muhammad, Yaqoob, Javed., Zhaohui, Zhang., Fida, Hussain, Dahri., Asif, Ali, Laghari. (2024). Real-Time Deepfake Video Detection Using Eye Movement Analysis with a Hybrid Deep Learning Approach. Electronics, 13(15):2947-2947. doi: 10.3390/electronics13152947

[5] Mr., Yogesh, Rai. (2024). Deepfake Detection System. Int. J. for Research in Applied Sci. and Engg. Tech, doi: 10.22214/ijraset.2024.62007

[6] Law, Kian, Seng., NORMAISHARAH, MAMAT., Hafiza, Abas., Wan, Noor, Hamiza, Wan, Ali. (2024). AI Integrity Solutions for Deepfake Identification and Prevention. Open int. journal of informatics, 12(1):35-46. doi: 10.11113/oiji2024.12n1.297

[7] Raj, Parulekar., Kaushal, Partole., Raghavendra, H., Bhalerao., Om, Budhawant., Nita, Patil. (2024). Deep Fake Video Detection. Int. Journal of Advanced Research in Science, Comm. and Technology, 207-214. doi: 10.48175/ijarsct-18036

[8] M., Sm. (2024). Deepfake detection using lstm & resnext-50 1. Indian Scientific Journal of Research in Engineering and Management, doi: 10.55041/ijsrem34528

[9] Adithya, Ajith. (2024). A Review on Deepfake Detection. Indian Scientific Journal of Research in Engineering and Management, 08(03):1-5. doi: 10.55041/ijsrem29735

[10] Guru Kiran, D, P. (2024). Deep Fake Detection System. Indian Scientific Journal of Research in Engineering and Management, doi: 10.55041/ijsrem31014

[11] Temitope, Olubunmi, Awodiji., John, Owoyemi. (2024). Developing Robust Detection Systems for Deepfake Media Using Advanced AI and Data Analytics Techniques to Enhance Cyber Security. International advanced research journal in science, engineering and technology, 11(4) doi: 10.17148/iarjset.2024.114109

[12] Dr., Shwetambari, Borade. (2024). DETEK-AI: A Web-based Deepfake Detection System. Indian Scientific Journal of Research In Engineering And Management, doi: 10.55041/ijsrem31285

[13] Padmapani, P., Tribhuvan., Amrapali, Prakash, Tribhuvan. (2024). Artificial intelligence for deepfake creation and detection. 21-27. doi: 10.58532/v3bkai11p1ch2

[14] Adam, Frej., A., Kaminski., Piotr, Marciniak., Szymon, Szmajdzinski., Soveatin, Kuntur., Anna, Wróblewska. (2024). Deepfake tweets automatic detection. doi: 10.48550/arxiv.2406.16489

[15] Ling-Yuan, Hsu. (2024). AI-assisted deepfake detection using adaptive blind image watermarking. Journal of Visual Communication and Image representation, doi: 10.1016/j.jvcir.2024.104094

[16] Xiaoshuai, Wu., Xin, Liao., Bo, Ou., Yuling, Liu., Zheng, Qin. (2024). Are Watermarks Bugs for Deepfake Detectors? Rethinking Proactive Forensics. doi: 10.24963/ijcai.2024/673

[17] Regatte, Varshith, Reddy., Anish, Nethi., Sanatan, Sukhija., Yayati, Gupta. (2023). Detecting DeepFakes: A Deep Convolutional Neural Network Approach with Depth Wise Separable Convolutions. 33-38. doi: 10.1109/icetci58599.2023.10331449

[18] Mahlasela, Oyena & Baloyi, Errol & Siphambile, Nokuthaba & Khan, Zubeida. (2024). Artificial Intelligence Impact on the realism and prevalence of deepfakes.

[19] Abir, W.H., Khanam, F.R., Alam, K.N., Hadjouni, M., Elmannai, H. et al. (2023). Detecting deepfake images using deep learning techniques and explainable AI methods. Intelligent Automation & Soft Computing, 35(2), 2151-2169. https://doi.org/10.32604/iasc.2023.029653

[20] Dr. A. Shaji George, & A. S. Hovan George. (2023). Deepfakes: The Evolution of Hyper realistic Media Manipulation. Partners Universal Innovative Research Publication, 1(2), 58–74. https://doi.org/10.5281/zenodo.10148558

[21] Okolie, Chidera (2023) "Artificial Intelligence-Altered Videos (Deepfakes), Image-Based Sexual Abuse, and Data Privacy Concerns," Journal of International Women's Studies: Vol. 25: Iss. 2, Article 11

[22] U. Rahul, M. Ragul, K. R. Vignesh and K. Tejeswini, “Deepfake video forensics based on transfer learning,” International Journal of Recent Technology and Engineering (IJRTE), vol. 8, no. 6, pp. 5069–5073, 2020.

[23] G. Benjamin, “Deepfake videos could destroy trust in society–here’s how to restore it,” The Conversation, 2019.

[24] D. Güera and E. J. Delp, “Deepfake video detection using recurrent neural networks,” in Proc. 15th IEEE Int. Conf. on Advanced Video and Signal Based Surveillance (AVSS), Auckland, New Zealand, pp. 1–6, 2018

[25] H. S. Shad, M. M. Rizvee, N. T. Roza, S. M. A. Hoq, M. M. Khanet et al., “Comparative analysis of deepfake image detection method using convolutional neural network,” Computational Intelligence and Neuroscience, vol. 2021, no. 3111676, pp. 1–18, 2021

[26] Y. L. Cun, Y. Bengio and G. Hinton, “Deep Learning,” Nature, vol. 521, no. 7553, pp. 436–444, 2015

[27] Ujalambkar, D., Kulkarni, C., Navale, V., Sable, N.P., “Industrial Product Surface Defect Detection Using CNN: A Deep Learning Approach”,Panamerican Mathematical Journal, 2024, 34(3), https://doi.org/10.52783/pmj.v34.i3.1775.

[28] Deepali Ujalambkar, Dipika R. Birari, Chaitanya Kulkarni, Pranita V. Shitole, “Ensemble Learning Based Defect Detection Systems for Industrial Applications”, Advances in Nonlinear Variational Inequalities, Vol. 28 No. 2s (2025)