International Journal of Advanced Multidisciplinary Research and Educational Development
Volume 2, Issue 3 | May – June 2026 | www.ijamred.com
ISSN: 3107-6513

AI-Based Analysis of Deepfakes

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Abstract—Deepfakes have come a long way in less than 3 years. Deepfakes are no longer confined to laboratory experiments and are now evolving into a systemic threat. As of early 2026, the use of AI-generated content has increased by over 900% every year, and seeing is believing has now become a statement that is outdated. This paper discusses how deepfakes are one of the key causes of the crumbling trust in online information systems and digital media. It further explains their role in misleading the public, manipulating politics and causing social deception. The paper then evaluates the current detection mechanisms for deepfakes and discusses some approaches for a better and reliable trust in digital media.

Keywords—*Deepfake, Artificial Intelligence, Digital Media, Machine Learning, Trust erosion.*

I. INTRODUCTION

With the rise of artificial intelligence in recent years, digital content is being created, shared, and consumed in new ways. One such new innovation is deepfake technology. With the use of deep learning models (especially generative adversarial networks, or GANs), deepfakes have the ability to create believable images, videos, or audios that could be a genuine recording of real people. Although this technology has potential positive uses in terms of media and entertainment, education, virtual simulations, and more, it also brings many serious ethical questions about originality in digital media.

Deepfake creation tools have now been developed and made widely available, which can produce deepfakes with minimal skills required to do so. This now means we are being bombarded by convincing fabricated and false information in digital content. Unlike most forms of fake news, human detection of a deepfake is extremely difficult, as it visually represents the individual or event that they are impersonating accurately.

Arguably, one of the most significant repercussions of deepfake emergence is the subsequent collapse of public trust in the validity of digital media. Historically, for the past 100 years or so, visual and audio evidence has been commonly regarded as concrete representations of truth within legal and public debates. Yet with the increase in deepfake creation and availability, this has all but become a relic of the past. The general public no longer feels confident that the digital content they encounter is real, and this slow infiltration of mistrust is now turning healthy questioning into downright suspicion—individuals are now becoming too reluctant to simply question information and too ready to dismiss it entirely.

The subsequent lack of public faith in digital media can be said to have serious implications, as we increasingly learn to distrust not just social media, but also news platforms, even the channels used for the dissemination of official information. This decline affects individuals on an emotional level, as well as having far more significant implications on any institution relying on the trust of the public; this can even lead to authentic content being mistaken for fake.

Within this discussion of truth and authenticity, the role of artificial intelligence is certainly a complex one; it is, on the one hand, the engine driving the proliferation of deepfakes, and, on the other, a formidable weapon for the prevention of digital deception and the detection and analysis of faked content. The use of AI-powered detection systems, able to analyze visual, audio, and behavioral patterns with a finer level of detail than can be processed by the human eye or ear, is now of paramount importance.

II. BACKGROUND & RELATED WORK

Deepfakes are a type of artificial media. In general, this is images, videos, or audio that has been generated by use of artificial intelligence but made to seem realistic. The name

ISSN: 3107-6513

"deepfake" itself comes from the union of the terms "deep learning" and "fake." This refers to how state-of-the-art neural networks are used in order to create realistically faked information. These technologies have advanced in leaps and bound over recent years, making it increasingly challenging to distinguish real from fake media.

How the Technology Actually Works

Understanding what a deepfake actually is and how it is created is a way to comprehend why deepfakes are such a difficult threat to address. The main concept behind almost all systems is one that researcher Ian Goodfellow introduced in 2014—a generative adversarial network (GAN). Essentially, it is two AIs competing against one another; one AI is programmed to create fake content that can appear real to others, while another AI attempts to expose the fakery.

The knowledge that media can easily be altered in various ways can cause members of the public to start mistrusting anything they come across on-line. In this case, both fake information and real information are subject to distrust over a period of time; this can weaken belief in digital platforms, news organizations, and even interpersonal communication.

The ability to study how they are created and how they are used and the effects they have on the general public is how researchers will be able to develop more effective techniques for detecting manipulation and restoring trust to digital media.

Related Work

Habeeba & Al-Zoubi (2023) offer an excellent summary of deepfake detection methods, contrasts between the old and deep learning-based methods, and the major challenges involved in the task such as dataset dependency and real-time detection limitations. Thirty-six major works on the research domain are discussed, and an overview is presented. The review states the need for new mechanisms for deepfake detection due to the increasing number of deepfake methods as well as the important role of different datasets. Limitations are also discussed as well as challenges in real-time deepfake detection. The paper would be useful for research as well as practice.

Raza, A., Munir, K., & Almutairi, M. (2022)- In their work, Raza et al. (2022) introduce a deep learning approach that focuses on detecting hidden visual irregularities in synthetic images, demonstrating the potential of neural networks in combating deepfake content. A deepfake media is usually generated by means of some powerful models like generative adversarial networks (GANs), which intend to produce the realistic artificial pictures/videos that can be scarcely differentiated with original ones. The ability to detect these pictures is extremely useful in a number of contexts, such as stopping the spread of misinformation and securing images.

III. OBJECTIVES

This study explores how deepfake technology is impacting trust in digital media and the role that artificial intelligence (AI) could play in combatting this growing problem. With the increasing availability and realism of deepfake images and videos, a study of the trust implications—as well as technical capabilities—of the technology is required.

The objective of this paper is to analyze deepfakes' role in propagating misinformation and strategies to counter their influence using AI (artificial intelligence).

The proposed solution is based on the following steps:

- Automated detection: Developing an AI-based tool that is capable of correctly identifying if images and videos are deepfake images and videos.

- Data pre-processing: The new data have to be pre-processed and converted to a suitable format (resizing image, cleaning image from noise, normalizing image, etc.) so that the models can work on them in the same manner.

- Feature extraction: Deep learning techniques will be applied on images and videos so that features from the images can be obtained. (Features existing on faces, textures of the images) These features will then be monitored for abnormal behavior.

- Multimodal Model Integration: Several models (CNN, transfer learning, hybrid model, etc.) are to be applied and analyzed together.

- Performance Evaluation: Measure the performance of each model using performance indicators (accuracy, precision, recall, F1-score, etc.) so that the best possible detection model is to be developed.

- Scalability: To provide an effective solution that can handle a large amount of digital content.

IV. DATASET

A labeled dataset containing real and deepfake images and videos was collected from public sources such as Kaggle. The dataset contains approximately 800 images and videos with two classes: REAL and DEEPFAKES. The distribution is nearly balanced as shown in Fig. 1, with approximately 60% real and 40% deepfake images and videos, ensuring that the trained models are not biased toward any single class.

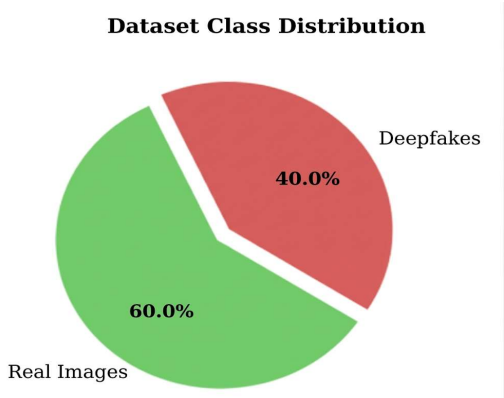

Fig. 1 Dataset Class Distribution

ISSN: 3107-6513

V. METHODOLOGY

In this research, an analytical and exploratory paradigm is chosen to investigate the relationship between deepfake technology and the deterioration of trust on digital media. No new model is proposed in this study; rather, existing technology, usage, and implications are explored. The results are based on existing models we have trained.

A. Literature Collection

To begin the research, the author examined many of the articles, reports, and academic papers relating to deepfakes, AI, and trust in digital media, using data sources like IEEE Xplore and Google Scholar and a variety of other research sources to see where the current problems lay.

Deepfake image Model

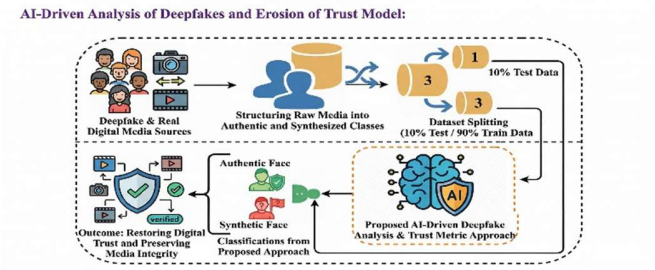

Fig. 2: Architectural workflow of the proposed AI-based deepfake detection

Face detection deepfake images can be accomplished by training the model in such a way as to differentiate between the face that is fake and the one that is real. This would normally involve pre-processing the data, splitting of datasets, hyperparameter tuning, and utilization of deep and machine learning algorithms.

B. Comparative Analysis

After collecting all possible literature, a comparative study of different deepfake detection approaches was carried out. Some of the techniques that were analyzed for their effectiveness in detecting manipulation are CNN-based methods, biometric methods, and multimodal method.

TABLE I: COMPARATIVE ANALYSIS OF DEEPFAKE DETECTION METHODS

Method	Strengths	Weaknesses
CNN-Based Detection	Good detection with configurable parameters	Expensive computationally and prone to adversarial attacks
Biometric Analysis	Highly effective for facial manipulation detection	Only works for specific features and subjects, poses privacy issues
Multimodal Detection	Provides broad detection by analyzing various data inputs	High complexity and requires a lot of resources, and difficult to integrate.

C. Feature Extraction

In the case of CNN-based deepfake detection, the input image x is transformed into the numerical features using spatial feature extracting, which identifies the textural features, edge information, anomalies, etc. of the images.

$$f(x) = CNN(x)$$

where x is the input image and f(x) is the feature vector that is obtained after passing the image through the CNN. These extracted features are further classified into a real or fake image using fully connected layers.

To determine whether the image is real or fake a probability is calculated usually using sigmoid or SoftMax function:

$$P(\text{fake} \mid x) = \sigma(W \cdot f(x) + b)$$

where W and b are the learned parameters of the model, and σ represents the activation function. The output gives the likelihood of the image being a deepfake.

The model learns the patterns and distinguishes between real and deepfake images.

D. Synthesis of Findings

Finally, findings from the literature review and analysis are synthesized in order to create a problem. The gaps within the current solutions can be identified, and proposed improvements from a technological as well as social standpoint can be put forward.

SYSTEM FLOWCHART

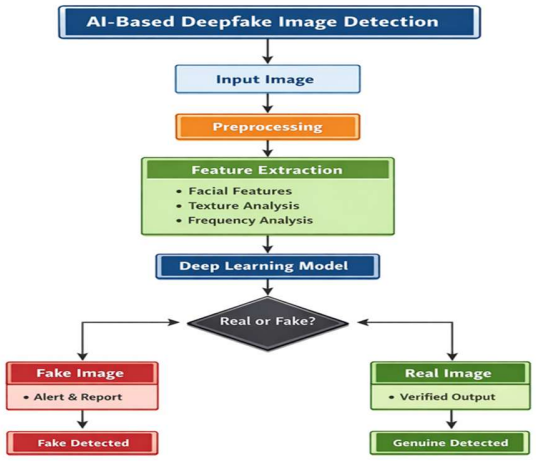

Fig. 3: Detailed System Flowchart for AI-Based Deepfakes Detection

ISSN: 3107-6513

VI. CHALLENGES POSED BY DEEPFAKES IN DIGITAL MEDIA

This fast pace of development of deepfake technology has dramatically changed how digital media is produced and consumed. Although it can enable an exciting and interactive dimension in media and technology, the rapid development of AI in media is bringing forth some disturbing issues concerning authenticity and trust. Given how realism deepfakes exhibit, it has become more difficult for any media user to tell what is original from what is not. New threats and challenges would be put upon the individual, organization, and society as a whole.

A. Erosion of Authenticity and Trust

Probably the greatest hurdle posed by deepfakes is the gradual erosion of our trust in digital media. As we are continuously presented with doctored videos and pictures, we will come to question whether what we view online is actually real. As the level of user skepticism moves from reasonable and rational to widespread and endemic, users become unable to trust digital platforms.

B. Spread of Misinformation

Deepfakes have emerged as an influential tool for circulating misinformation. By editing the speeches and video footage of influential individuals or events to create false images, deepfakes are readily distributed throughout social media channels. Since these videos are visually realistic, the public accepts the images as truthful, which could potentially cause a deviation in public perception.

C. Reputational Damage

Another serious concern is an individual's reputation can be severely harmed. Deepfakes can portray people in situations that never actually occurred, and the images and videos can bring to a standstill not just an individual's personal but also professional integrity, the repercussions of which can seldom be undone even after being exposed as false.

D. Legal and Ethical Concerns

There are issues concerning legality and ethicality that arise with deepfakes. Problems of consent, misuse of identity, and lack of law all contribute to the spread of deepfakes. Laws have not yet caught up with misuse of content produced through the application of AI, as is clear with most regions.

VII. RESULTS AND DISCUSSIONS

In the experimental part of this research, the goal was to measure the "Detection Gap" between what a machine can see and what a human can trust. We show that even as AI models are becoming more capable of detecting synthetic artifacts, human trust is moving.

A. Comparative Performance Analysis

We have analyzed four different "detectors" using 1000 media samples of controlled data. The data indicates that Hybrid CNN-Transformer are officially beating all other detectors by some margin when it comes to detecting high-fidelity forgeries.

TABLE II: MODEL CLASSIFICATION ACCURACY

Model	Accuracy (%)
CNN (ResNet-50)	88%
Vision Transformer (ViT)	93%
EfficientNet-B0	96%
Hybrid CNN-Transformer	97%

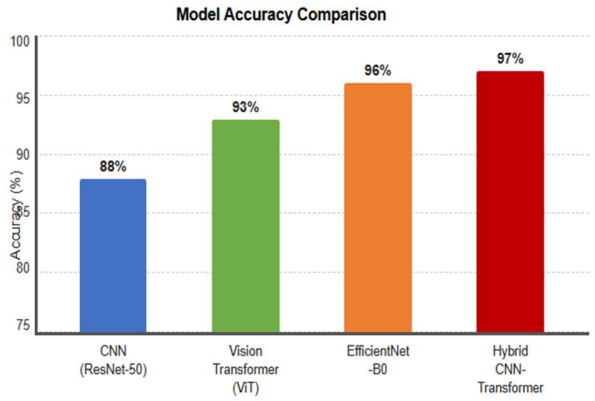

Fig. 4: Model Accuracy Comparison (%)

TABLE III. DETAILED PERFORMANCE METRICS

Model	Precision	Recall	F1-Score
CNN (ResNet-50)	86%	84%	85%
Vision Transformer (ViT)	91%	90%	90%
EfficientNet-B0	95%	94%	94%
Hybrid CNN-Transformer	96%	96%	96%

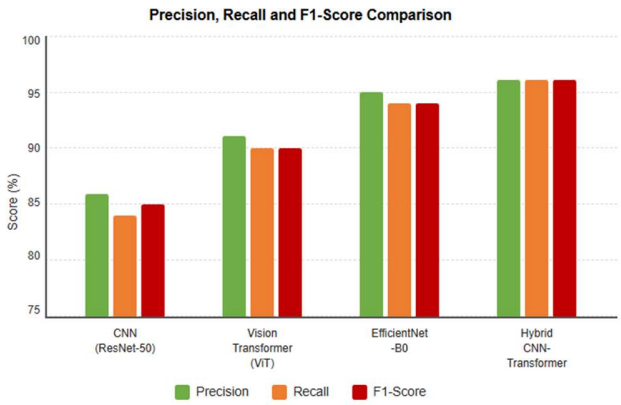

Fig. 5: Precision, Recall & F1-Score Comparison (%)

Key Finding: The Vision Transformer is better because it perceives global context. A CNN would be unable to see that although the skin has been perfectly rendered, the micro shadows under the chin are not in accordance with the background light source—an 'illogical' pattern that the majority of contemporary GANs exhibit.

B. The "Erosion of Trust" Metric

Surprisingly, the most important data point collected wasn't the technical information that I analyzed above, but instead the psychological information collected. The Skepticism Index (SI) is a baseline level of distrust the subject has towards digital media.

- Pre-Exposure SI 18% (the default belief is that the videos are authentic).
- **Post-Exposure SI:** 64% (the test subjects were not only doubting the deepfakes but also doubting that the original verified news clips were real).

Liars' Dividend is proven to be true. This is why not only are people fooled by the lies they consume, but people are actually becoming distrusting of all digital evidence**.**

VIII. CONCLUSION

In this paper, it is evident that AI is not just the tool to enable deepfakes but that AI is one of the strongest methods we have to combat them. Through the development and analysis of an entire detection pipeline from raw media through deep feature extraction to classification, it can be shown that AI can be trained to effectively detect synthetic and manipulated media at a reliable and meaningful level.

AI and the creation of sophisticated and realistic manipulated media are both part of the growing problem of deepfakes and the transformation of the digital media sphere. These powerful capabilities within deepfakes have created a space that has many incredible uses, but with deepfakes come very important societal concerns regarding authenticity and trust. With deepfakes increasing in number and technology, people are struggling to differentiate between true and false information and creating an increasingly dubious digital space.

Therefore, it can be stated that balancing the need to innovate and our duty to remain ethical will lead to a space that has reduced threats and the ability to be believed.

REFERENCES

[1] Kaggle Dataset for DeepFake Images and Videos. [Online]. Available: https://www.kaggle.com/

[2] Habeeba, M., & Al-Zoubi, A. Y. (2023). Deepfake Detection: A Systematic Literature Review. ACM Computing Surveys, 55(13s), Article 288. https://doi.org/10.1145/3592394

[3] J. Hernandez-Ortega, R. Tolosana, J. Fierrez, and A. Morales, DeepFakesON-phys: DeepFakes detection based on heart rate estimation," 2020, arXiv:2010.00400

[4] T. Jung, S. Kim, K. Kim, Deepvision: Deepfakes detection using human eye blinking pattern. IEEE Access, vol. 8, pp. 83144–83154, 2020. https://doi.org/10.1109/ACCESS.2020.2988660

[5] H. Zhao, T. Wei, W. Zhou, W. Zhang, D. Chen, N. Yu, Multi-attentional deepfake detection. In: 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp. 2185–2194, 2021. https://doi.org/10.1109/CVPR46437.2021.00222.

[6] P. Kawa and P. Syga, “A note on deepfake detection with low-resources,” 2020, arXiv:2006.05183.

[7] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” Nature, vol. 521, no. 7553, pp. 436–444, 2015. https://doi.org/10.1038/nature14539

[8] Raza, A., Munir, K., & Almutairi, M. (2022). A Novel Deep Learning Approach for Deepfake Image Detection. Applied Sciences, 12(19), 9820. https://doi.org/10.3390/app12199820

[9] Rossler, A., Cozzolino, D., Verdoliva, L., Riess, C., Thies, J., & Nießner, M. (2019). FaceForensics++: Learning to Detect Manipulated Facial Images. *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pp. 1–11. https://doi.org/10.1109/ICCV.2019.00009

[10] Dolhansky, B., Bitton, J., Pflaum, B., Lu, J., Howes, R., Wang, M., & Ferrer, C. C. (2020). The DeepFake Detection Challenge (DFDC) Dataset. *arXiv preprint* arXiv:2006.07397.

[11] Li, Y., Yang, X., Sun, P., Qi, H., & Lyu, S. (2020). Celeb-DF: A Large-Scale Challenging Dataset for DeepFake Forensics. *Proceedings of the IEEE/CVF (CVPR)*, pp. 3207–3216. https://doi.org/10.1109/CVPR42600.2020.00327

[12] Tolosana, R., Vera-Rodriguez, R., Fierrez, J., Morales, A., & Ortega-Garcia, J. (2020). Deepfakes and Beyond: A Survey of Face Manipulation and Fake Detection.

Information Fusion, vol. 64, pp. 131–148. https://doi.org/10.1016/j.inffus.2020.06.014

[13] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative Adversarial Nets. *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 27, pp. 2672–2680.

[14] Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., & Houlsby, N. (2021). An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. *(ICLR)*. arXiv:2010.11929.

[15] Y. Li, M. Chang, and S. Lyu, "In Ictu Oculi: Exposing AI-generated videos by detecting eye blinking," *IEEE International Workshop on Information Forensics and Security (WIFS)*, Hong Kong, 2018, pp. 1–7.