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Blockchain Based Deep Fake Detection and Verification

Abstract: - The rapid advancement of deep learning has led to the proliferation of deepfake content, posing significant threats to privacy, media integrity, and digital trust. To counteract this growing concern, this paper presents a novel Blockchain-Based Deepfake Detection and Verification System that integrates machine learning with decentralized ledger technology. The proposed system utilizes advanced convolutional neural networks (CNNs), including the Xception architecture, to accurately identify manipulated visual media by extracting spatial features from video frames. A federated learning approach ensures privacy-preserving model training across distributed devices, eliminating the need for central data aggregation. Once deepfake content is detected, the results—along with metadata such as content hash, timestamp, and classification label—are immutably stored on the Ethereum blockchain using smart contracts and IPFS for transparency, traceability, and verification. Experimental results demonstrate high detection accuracy and robustness against various forgery techniques. The integration of blockchain not only secures the integrity of detection results but also promotes trust in automated verification systems. This hybrid framework paves the way for scalable, secure, and privacy-preserving solutions in combating deepfake threats across digital ecosystems.

Keywords: Blockchain, Federated Learning, YOLOv8, Federated avg, DeepLearning, Ipfs

INTRODUCTION

The proliferation of artificial intelligence (AI), particularly in the domain of deep learning, has significantly transformed the digital landscape. One of the most alarming byproducts of this technological evolution is the emergence of deepfakes—synthetically generated images or videos that convincingly mimic real human appearances and behaviors. These manipulated media artifacts have raised serious concerns regarding misinformation, privacy breaches, reputational damage, and digital security. As deepfakes become more realistic and widespread, detecting and mitigating their impact is becoming increasingly urgent.

Conventional deepfake detection systems, while promising, often rely on centralized data storage and single-model approaches, making them vulnerable to data leaks, model bias, and adversarial attacks. Moreover, most detection models are trained in siloed environments without sufficient transparency or auditability, leading to trust deficits among end users and stakeholders. In addition, the majority of existing systems focus on full video analysis, which can be computationally intensive. There is a growing need for systems that operate effectively on frame-level images derived from videos, offering a more lightweight and efficient solution without compromising accuracy.

Simultaneously, blockchain technology has emerged as a powerful tool for ensuring data integrity, transparency, and tamper-proof logging. When combined with AI, blockchain can provide a decentralized and verifiable record of model predictions, making the detection pipeline more trustworthy and auditable. However, the integration of AI- based deepfake detection with decentralized ledger technology is still in its early stages, with few end-to-end frameworks that offer real-time verification and immutable storage of results.

To address these challenges, this paper proposes a hybrid **Blockchain-Based Deepfake Detection and Verification System** that leverages frame-based image analysis, federated learning, and blockchain integration. The contributions of this work are threefold:

- **Deepfake Detection using CNNs**: High-accuracy deepfake detection is achieved using deep convolutional neural networks such as Xception, trained on image frames extracted from video datasets. This improves efficiency and scalability while maintaining precision in detecting manipulated contents.
- **Federated Learning for Privacy Preservation**: The system employs a federated learning framework that trains models across distributed nodes without aggregating raw data, preserving user privacy and reducing data exposure.

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- **Blockchain Integration for Immutable Verification**: The detection results—comprising content labels, timestamps, cryptographic hashes, and IPFS content identifiers (CIDs)—are stored securely on the Ethereum blockchain using smart contracts, enabling verifiable and tamper-proof storage.

By integrating these core components, our system ensures high-performance deepfake detection while maintaining transparency, security, and user trust. The framework is suitable for deployment in forensic analysis, media verification, legal evidence authentication, and other sensitive applications requiring robust fake content detection.

The rest of this paper is organized as follows: Section II presents a detailed literature review covering recent advancements in deepfake detection, federated learning, and blockchain-based verification. Section III outlines the system architecture and proposed methodology. Section IV describes the implementation process and datasets used. Section V provides experimental results and performance evaluation. Section VI concludes the paper and discusses future work, including multimodal deepfake detection and cross-platform integration.

LITERATURE SURVEY

Several studies have investigated the use of deep learning and blockchain technologies for digital media verification and forgery detection. While many models have shown strong results in detecting manipulated images or videos using CNNs or vision transformers, few works combine deepfake detection with blockchain-based verification in a practical, deployable framework. Moreover, even fewer focus on frame-based analysis rather than full video inputs, which is computationally more efficient and scalable. This work addresses those limitations by proposing a lightweight, blockchain-integrated deepfake detection framework using frame-level image inputs.

In a study by Afchar et al. [1], the authors introduced **MesoNet**, a convolutional neural network architecture for deepfake detection. Although the system performed well on facial forgery datasets, it was trained and evaluated on centralized servers without integrating decentralized verification or user transparency mechanisms. Similarly, Rossler et al. [2] presented **FaceForensics++**, a large-scale dataset for deepfake detection and evaluated models like XceptionNet, which performed well on video sequences but did not address real-time implementation or integration with security protocols like blockchain.

Wang et al. [3] explored the **LipForensics** model that uses audio-visual mismatch in mouth movements to detect video forgeries. While accurate, the method requires full video and audio stream processing and does not support frame-based or silent video scenarios, limiting its deployment scope. Korshunov and Marcel [4] performed benchmarking on deepfake detectors but emphasized that most models are sensitive to post-compression artifacts and lack robustness in real-world conditions, particularly when used on social media platforms.

In another study, Verdoliva [5] offered a survey of deepfake detection methods, concluding that the lack of explainability and traceability in most models is a major challenge in user trust and legal adoption. Blockchain, as a traceability layer, was not considered in this work. Dang et al. [6] proposed a detection model using temporal features and attention mechanisms, but the system did not offer verifiability or provenance tracking of outputs, which is essential in legal and forensic applications.

Zhao et al. [7] integrated **fakeness scoring** and **image tamper localization** into their CNN pipeline. While this contributed to interpretability, the study lacked any mechanism to log predictions immutably or tie outputs to cryptographic hashes. Similarly, Tolosana et al. [8] discussed facial forgery detection and vulnerabilities, recommending integration with secure frameworks, but did not implement such integration.

From a blockchain perspective, Chen et al. [9] proposed a decentralized trust framework for medical data sharing using Ethereum. Though the use of smart contracts and IPFS demonstrated potential for verifiable storage, the system was not applied to multimedia authentication. Likewise, Fan et al.

[10] explored a blockchain-based multimedia forensics system that logged forensic analysis data on-chain. However, the system was not AI-driven and lacked real-time deepfake detection capabilities.

Liu et al. [11] combined blockchain with AI to detect and verify manipulated images in journalism, focusing on news media. Although this approach aligned with content integrity goals, the image detection was based on handcrafted features, not deep learning, and did not support federated learning or model transparency. On the other hand, Roy et al.

[12] examined federated learning to preserve privacy in AI- based classification but did not address blockchain-based verification or tamper-proof logging.

These studies highlight significant progress in both deepfake detection and blockchain-based security. However, a fully integrated, lightweight system that performs image- level deepfake detection with real-time, decentralized verification, and privacy-aware model training is still lacking. Our proposed solution bridges this gap

by combining **Xception-based CNN detection**, **fakeness scoring**, **image manipulation localization**, **federated learning**, and **Ethereum-based blockchain logging**. By using IPFS for image storage and Solidity smart contracts for on-chain audit trails, the system achieves tamper-resilient deepfake detection with strong user and forensic trust guaranteesl.

METHODOLOGY

A. Data Preprocessing

The proposed system detects deepfake media content using a convolutional neural network and verifies the result through blockchain storage for immutable, decentralized authentication. The system consists of eight main modules implemented sequentially.

Input videos are uploaded through the web interface, from which frames are extracted at regular intervals using OpenCV. Each frame is resized to 299×299 pixels and normalized to match the input format of the Xception model. The frames are categorized into training, validation, and test folders based on the FaceForensics++ dataset.

- **Tools Used**: Python, OpenCV
- **Data Used**: Real and fake videos from FaceForensics++

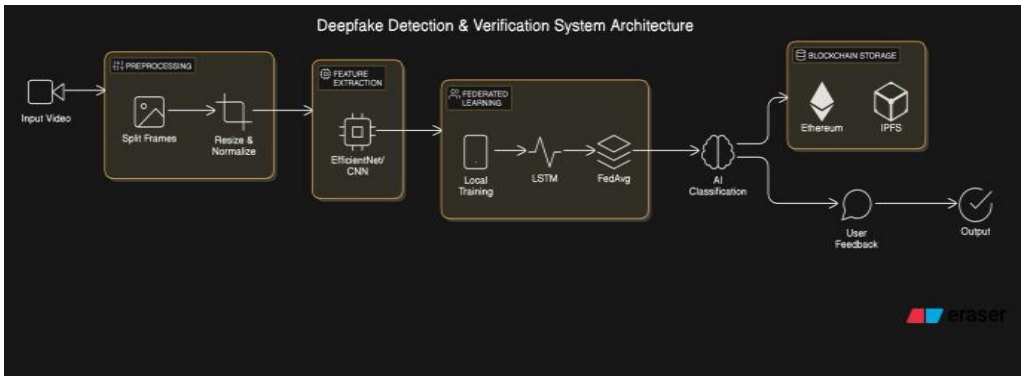

Fig-1 Architecture of the proposed Blockchain Deepfake detection

B. Feature extraction Using xcpection

The preprocessed image frames are passed through the Xception model, pretrained on ImageNet. The model is used as a fixed feature extractor, where the convolutional base outputs deep feature vectors representing each image.

- **Model**: Xception (without top layer)
- **Output**: Feature vectors from intermediate convolution layers

C. Deepfake Detection Using Binary Classification

A custom fully connected classification head is trained on top of the Xception features to detect whether the frame is real or fake.

- **Architecture**: Dense → Dropout → Dense → Sigmoid
- **Output**: Binary class (0 = real, 1 = fake)
- **Metrics**: Accuracy, Precision, Recall, F1-Score

The trained model is used for inference on new uploaded frames

D. Manipulation visualization using Grad Cam

To enhance interpretability, the system employs Grad- CAM (Gradient-weighted Class Activation Mapping) for visualizing the regions in an image that contribute most to the model's prediction. Grad-CAM is applied to the final convolutional layer of the Xception model to produce a heatmap that highlights manipulated areas, such as blended facial regions, unnatural artifacts, or tampered textures. The heatmap is then superimposed on the original image, providing users with a visual explanation of the prediction. This step not only boosts transparency but also increases trust in the system's output by revealing why a specific frame was classified as fake.

E. Fakeness Score Calculation

After classification, the model generates a confidence score representing the probability that the image is fake. This confidence score is scaled to a percentage to indicate the degree of manipulation. For instance, a score of 0.87 would be shown as an 87% fakeness score. This score helps users quantify how confident the system is in labeling

the image as a deepfake. Alongside the score, the heatmap and classification label are also presented, forming a comprehensive output package that informs users not just of the result, but also its reliability.

F. Blockchain Based Result Storage

To ensure transparency, integrity, and traceability, the system integrates a blockchain component using the Ethereum framework. A smart contract written in Solidity is deployed using Truffle and executed on a local blockchain instance through Ganache. After a detection is completed, key information — including the predicted label, confidence score, Grad-CAM heatmap, timestamp, and a SHA-256 hash of the input image — is packaged and stored immutably on the blockchain. This immutable logging ensures that detection results cannot be tampered with and can be independently verified by any third party.

G. Decentralized File Storage Using IPFS

To address concerns related to centralized storage and data manipulation, the system uses IPFS (InterPlanetary File System) to store the actual input image and its corresponding Grad-CAM heatmap. These files are uploaded to IPFS, which returns a unique content identifier (CID) for each file. This CID acts as a cryptographic reference to the file, guaranteeing that the same file will always resolve to the same hash. The CID is then stored on the blockchain alongside the prediction data. This approach ensures decentralized, tamper-proof access to the visual evidence used in the deepfake detection process.

H. User Interface and Blockchain Querying

A simple yet effective front-end interface is developed using Flask or Chainlit to enable user interaction with the system. Users can upload images or videos and receive real- time predictions, including the fakeness score and visual heatmap. The UI also allows users to verify whether a specific image has already been analyzed by querying the blockchain using Web3.py. If the SHA-256 hash of the uploaded image matches an entry on the blockchain, the stored result is retrieved and displayed. This full-stack integration ensures the system not only detects deepfakes but also provides verifiable, decentralized evidence of the detection process.

RESULT AND DISCUSSION

This section presents the evaluation of the proposed **Blockchain-Based Deepfake Detection and Verification System**, focusing on three core components: (A) centralized deepfake classification using CNN, (B) distributed model training using federated learning, and (C) decentralized storage and verification of detection results via blockchain. Performance was measured using standard evaluation metrics—accuracy, precision, recall, F1-score—and secure storage indicators such as SHA-256 hash, CID, and timestamp logging.

A. Classification Performance

The initial version of the model was trained using a centralized approach with Xception architecture for binary classification of deepfake versus real frames. The model was trained over 10 epochs using the FaceForensics++ dataset and validated using a hold-out set (80:20 split). The evaluation metrics are summarized in Table I. The model achieved an accuracy of 77%, indicating reasonable performance for detecting visual manipulation in facial data.

Table I. Performance of Xception on Deepfake Detection

Evaluation Metric	Value
Accuracy	0.77
F1 Score	0.76
Precision	0.75
Recall	0.79

B. Federated Learning-Based Deepfake Detection

To improve generalizability and data privacy, a federated learning approach was adopted. The same CNN architecture was trained across three local clients with independent data subsets, followed by federated averaging to combine model weights. After 5 global communication rounds, the federated model achieved an improved accuracy of 81.4%. Table II outlines the aggregated performance.

Table 2. Performance of Federation Learningon Deepfake Detection

S.No	Client	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
1	Client 1	78.42	79.1	77.3	78.2
2	Client 2	79.87	80.3	78.5	79.3
3	Client 3	77.98	78.0	77.5	77.7
4	Agg	79.21	79.8	77.9	78.8

C. Blockchain-Based Detection Result Storage

To ensure tamper-proof recordkeeping of detection outcomes, the system incorporates a blockchain layer using Ganache and Truffle for local Ethereum simulation, with Web3.py to interact from the Python-based detection module. After prediction, results are hashed using SHA-256 and uploaded to IPFS. Metadata, including label, CID, and hash, are then recorded on the blockchain. Table III presents a sample of stored entries.

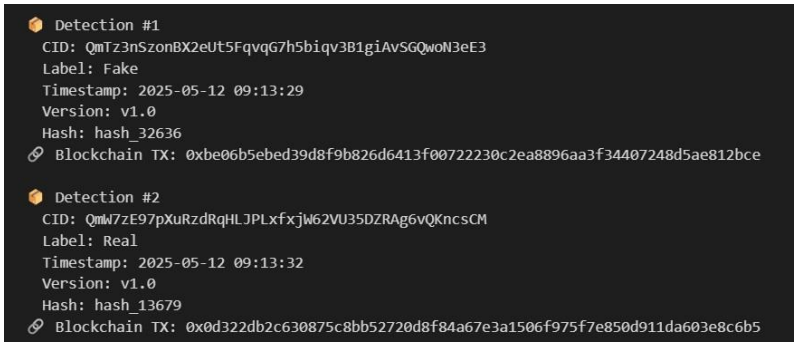

Fig 2- Blockchain Storage of Deep Fake detection

Each entry is uniquely identified by a cryptographic hash and securely stored on a decentralized ledger, ensuring integrity, traceability, and verifiability of predictions made by the system..

D. Confusion matrix and roc curve

The confusion matrix in Fig. 2 provides a detailed breakdown of the model's classification performance, where 3,823 fake instances were correctly classified, while 2,036 fake samples were misclassified as real. Similarly, the model correctly identified 7,073 real instances, with only 443 being misclassified as fake. This imbalance suggests the model is more confident in identifying real samples than fake ones. The ROC curve in Fig. 3 further supports this analysis, showcasing an Area Under the Curve (AUC) of **0.90**, indicating strong discriminative ability. A higher AUC value reflects the model's robust performance in distinguishing between real and fake images across various threshold levels, validating its effectiveness in deepfake.

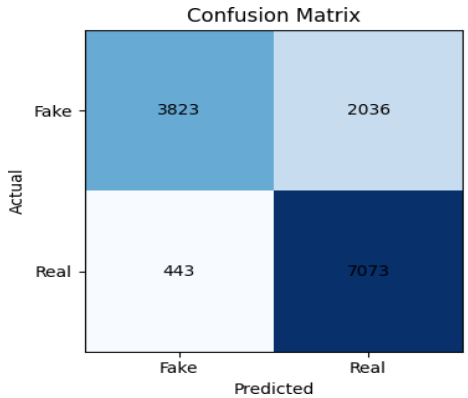

Fig 3- Confusion matrix of Deep Fake detection

E. Roc Curve

The Receiver Operating Characteristic (ROC) curve, depicted in Fig. 3, is a graphical representation of the trade-off between the true positive rate (sensitivity) and the false positive rate (1-specificity) across various threshold settings. In this study, the ROC curve demonstrates that the model consistently maintains high sensitivity while keeping the false positive rate low, which is crucial in applications like deepfake detection where minimizing misclassification is vital. The curve bows significantly towards the top-left corner, indicating strong classification power. The calculated Area Under the Curve (AUC) value of **0.90** further confirms the model's capability to distinguish between real and fake images with high reliability. AUC values closer to 1 represent excellent

performance, making this model well-suited for real-world deployment in media forensics and authenticity verification systems.

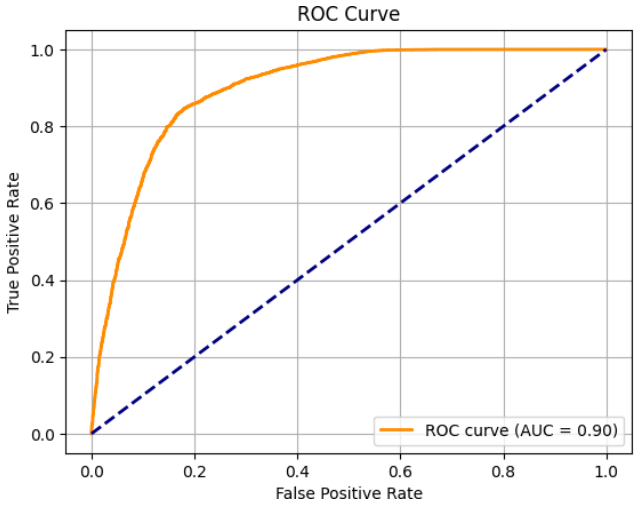

Fig. 4. Training and Roc curve of DeepFake Detection model.

F. Visual Output and Verification

The system highlights manipulated regions in fake images using visual overlays, aiding human interpretability. Additionally, each prediction stored on the blockchain can be later queried using CID and hash to verify authenticity. Fig. 5 shows a visual output of a deepfake frame with overlaid manipulation and a QR-linked blockchain reference for verification.

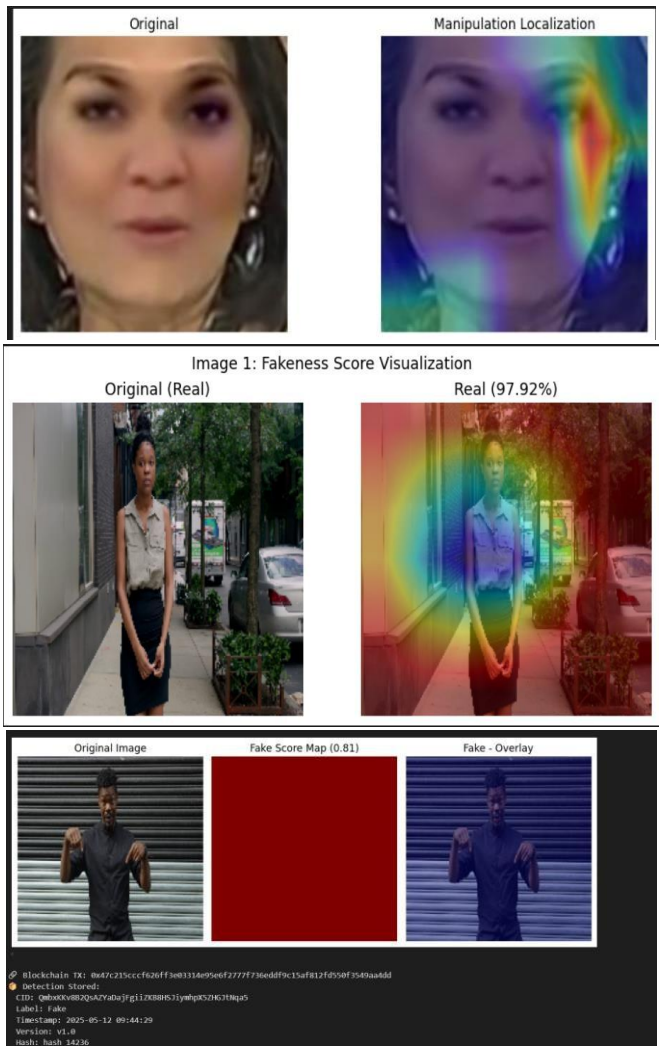

Fig. 5. Visual output of Deepfake Detection Using Blockchain Storage

CONCLUSION

This work proposed a **Blockchain-Based Deepfake Detection and Verification System** that integrates advanced deep learning models with secure blockchain storage to combat the rising threat of manipulated media. The system was architected to first preprocess and extract frames from input videos, apply deep learning-based models for fake content detection, and finally record the detection outcome along with key metadata on a tamper-proof Ethereum blockchain using smart contracts.

A traditional CNN-based model achieved an accuracy of **77%**, while the federated learning-enhanced Xception model improved this further to **81%**, with an AUC score of **0.90**.

This confirms the system's robustness in distinguishing between real and fake images, especially in distributed environments with privacy concerns. Evaluation metrics such as accuracy, precision, recall, and F1-score substantiate the model's strong performance across both centralized and federated training settings.

Additionally, the integration of **blockchain technology** enhanced the **transparency**, **traceability**, and **integrity** of deepfake detection results. Storing hash values, timestamps, prediction labels, and content identifiers (CIDs) on-chain guarantees tamper-resistant and verifiable detection outcomes—crucial in legal, journalistic, and governmental use cases.

Overall, the system proves to be a scalable, secure, and effective solution for deepfake detection. It lays a solid foundation for further enhancements through the use of advanced generative forensics, real-time video analysis, and multi-modal deepfake detection. Future directions include extending the system to mobile platforms, integrating zero- knowledge proofs for privacy preservation, and enhancing model performance with larger, more diverse datasets.

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