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Blockchain-Based Ai Framework For Verification Of Real And Ai-Generated Media

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Abstract: The rapid advancement of artificial intelligence has enabled the creation of highly realistic synthetic media, including images, videos, and audio. While these innovations benefit industries such as entertainment, education, and healthcare, they also pose significant risks, including misinformation, impersonation, and cyber-fraud. Traditional centralized verification systems depend on trusted intermediaries and static databases, making them vulnerable to tampering, lack of transparency, and single points of failure. To address these challenges, this work proposes a Blockchain-Based AI Framework for Verifying Real and AI-Generated Media. The framework integrates AI-driven media forensics with blockchain technology. AI models analyse media using multi-modal forensic techniques—such as spatial feature extraction, artifact inconsistency detection, and frequency pattern analysis—to classify content as authentic or synthetic. A cryptographic hash of the media and its verification result is then stored on a blockchain, ensuring immutability, transparency, and traceability ty. A web-based interface enables secure uploads, verification requests, and retrieval of blockchain records without reliance on centralized authorities. By combining automated AI detection with decentralized, tamper-resistant storage, the proposed system provides a scalable and reliable solution for combating deepfakes and restoring trust in digital media.

Index Terms - Artificial Intelligence, Deepfake Detection, Blockchain Technology, Digital Media Authentication, Cryptographic Hashing, Decentralized Verification, Generative Adversarial Networks, Synthetic Media Detection, Trust Management.

I. Introduction

The exponential growth of artificial intelligence has transformed the digital media landscape, enabling machines to generate, manipulate, and enhance multimedia content with unprecedented realism. Advanced deep learning architectures—particularly generative models—are now capable of producing synthetic images, videos, and audio that closely replicate real-world data. While these technologies have unlocked new possibilities in film production, virtual reality, digital marketing, telemedicine, and education, they have also introduced complex security and ethical challenges. The line between authentic and fabricated media is becoming increasingly blurred, making verification of digital content a critical necessity in modern information ecosystems.

Among the most alarming developments is the proliferation of deepfakes, where AI systems manipulate facial expressions, voice patterns, or body movements to create convincing yet entirely fabricated representations of individuals. Such media can be weaponized for political misinformation, financial fraud, defamation, social manipulation, and identity theft. As synthetic media tools become more accessible, the scale and sophistication of misuse continue to escalate. This trend threatens public trust, institutional credibility, and the integrity of digital communication platforms.

Traditional media verification approaches primarily rely on centralized databases, watermarking techniques, or third-party authentication agencies. However, these mechanisms suffer from significant shortcomings. Centralized repositories are vulnerable to cyberattacks, insider manipulation, and unauthorized alterations. Once compromised, the authenticity records stored within such systems cannot be reliably trusted, thereby undermining their purpose.

To address these challenges, researchers are increasingly exploring the convergence of artificial intelligence and blockchain technology. AI excels at analyzing complex media patterns and identifying synthetic artifacts, whereas blockchain provides a decentralized, immutable ledger capable of securely storing verification records. The integration of these technologies enables the creation of a robust trust framework where media authenticity can be analyzed intelligently and recorded permanently without reliance on a single governing authority.

This paper presents a **Blockchain-Based AI Framework for Verification of Real and AI-Generated Media**, designed to detect manipulated content and preserve verification evidence in a tamper-resistant environment. The proposed system leverages AI-driven media forensics to evaluate uploaded files and employs cryptographic hashing to generate unique digital fingerprints. These fingerprints, along with authenticity outcomes, are stored on the blockchain to ensure integrity, transparency, and long-term traceability.

By combining automated detection with decentralized verification, the framework aims to combat deepfake dissemination, strengthen digital trust, and provide a scalable solution for secure media authentication across real-world applications such as journalism, law enforcement, digital forensics, and social media governance.

2.Existing System vs Proposed System

Existing System

Existing media verification systems primarily rely on standalone AI-based detection models to identify manipulated or AI-generated content. These systems analyse visual or audio inconsistencies using deep learning techniques, but their verification results are typically stored in centralized servers. Such centralized architectures are vulnerable to tampering, unauthorized modification, and single-point-of-failure risks.

Many traditional approaches focus on limited forensic indicators such as facial distortions or pixel-level artifacts, without incorporating multi-dimensional analysis like temporal consistency, motion coherence, or frequency-domain evaluation. They also lack mechanisms for immutable record keeping and long-term auditability. Once a verification result is generated, there is no decentralized proof to ensure that the media remains unchanged over time.

Furthermore, existing systems provide limited transparency and traceability, making them less suitable for high-stakes domains such as digital forensics, journalism, and legal investigations. As a result, challenges remain in scalability, robustness against advanced generative models, and long-term trust establishment.

Proposed System

The proposed system introduces a blockchain-based AI verification framework that integrates intelligent forensic analysis with decentralized, tamper-proof record management. The AI detection engine performs multi-layered evaluation, including spatial artifact detection, facial landmark consistency checks, temporal continuity analysis for videos, and spectral anomaly detection to identify patterns commonly associated with AI-generated media.

To ensure integrity, a cryptographic hash (digital fingerprint) of the uploaded media is generated after analysis. This hash, along with authenticity classification and timestamp metadata, is stored on a blockchain network through smart contracts, similar to decentralized platforms such as Ethereum. The decentralized ledger guarantees immutability, transparency, and resistance to post-verification tampering.

The system also incorporates a verification retrieval and audit module. When media is re-submitted, the hash is recomputed and compared with blockchain records to instantly validate integrity. This enables continuous authenticity tracking and long-term traceability.

In addition, the proposed framework enhances scalability through modular architecture, supports automated verification without manual intervention, and strengthens security through cryptographic validation mechanisms. By combining AI-driven detection with blockchain-backed storage, the system establishes a reliable, transparent, and legally defensible media authentication ecosystem capable of combating misinformation and deepfake proliferation.

3.Related Works:

Significant research has been carried out in the area of digital media forensics, particularly in detecting manipulated images and deepfake videos. Early approaches mainly focused on identifying visual artifacts and physiological inconsistencies in facial videos. For instance, Li et al. in *"In Ictu Oculi"* [1] proposed detecting AI-generated fake videos by analyzing abnormal eye blinking patterns, highlighting how physiological signals can reveal synthetic content. Similarly, Afchar et al. introduced MesoNet [2], a compact convolutional neural network designed to detect facial video forgeries by capturing mesoscopic image features. While these methods demonstrated promising detection accuracy, they primarily focused on visual anomalies and did not address long-term authenticity validation or record integrity.

Further advancements explored more sophisticated deep learning architectures. Nguyen et al. proposed Capsule-Forensics [3], leveraging capsule networks to capture hierarchical relationships in forged images and videos. Rössler et al. developed FaceForensics++ [4], a large-scale dataset and benchmark that significantly improved the training and evaluation of manipulation detection models. These contributions strengthened deepfake detection research by improving robustness and dataset diversity. However, most of these approaches function solely as detection mechanisms and lack integration with secure storage or tamper-proof verification systems.

Parallel research has investigated blockchain technology for digital media security and copyright protection. Zheng et al. [5] proposed a blockchain-based framework for multimedia copyright protection, emphasizing decentralized storage and immutable ownership records. Similarly, Hasan et al. [6] presented a blockchain-based solution to combat fake media and misinformation by leveraging distributed ledgers for content verification. These studies demonstrate the effectiveness of blockchain in ensuring transparency and immutability; however, they often do not incorporate advanced AI-driven forensic analysis for automated deepfake detection.

More recently, hybrid approaches have emerged that attempt to combine deep learning with blockchain verification. Singh and Kumar [7] proposed integrating convolutional neural networks with blockchain to enhance deepfake detection reliability. While this approach moves toward a unified framework, existing implementations remain limited in scope, often focusing on either image-based detection or simplified blockchain storage mechanisms without comprehensive multi-layered forensic evaluation.

Despite these advancements, there remains limited research that fully integrates multi-dimensional AI forensic analysis—including spatial, temporal, and spectral evaluation—with decentralized blockchain-based immutability and automated verification retrieval. Most existing works address either detection accuracy or secure record management independently, rather than providing a complete end-to-end authentication ecosystem. The proposed system builds upon these prior contributions and aims to bridge this gap by offering an integrated framework that combines intelligent AI-based media analysis with tamper-proof blockchain-backed verification, ensuring both accurate detection and long-term trust in digital media authenticity.

4.Methodology:

The proposed system is designed using a modular and layered architecture in which each component performs a specific function within the overall media verification pipeline. This architectural design ensures scalability, transparency, secure data handling, and high detection accuracy. The framework integrates media ingestion, AI-based forensic analysis, cryptographic hashing, blockchain storage, and verification retrieval into a unified ecosystem.

All modules interact through well-defined interfaces, allowing smooth data flow and reliable system operation. The layered approach ensures that each functional unit—such as detection, hashing, or blockchain recording—can be independently upgraded without disrupting the overall framework. This structured methodology enables the system to simultaneously address two critical challenges: accurate detection of AI-generated media and long-term preservation of verification integrity.

4.1 System Architecture Overview

The overall system architecture follows a structured pipeline-based processing model consisting of five primary layers: user interaction and authentication, media ingestion and preprocessing, AI forensic analysis, cryptographic hashing with blockchain storage, and verification with retrieval. This layered design ensures systematic data flow, scalability, and secure handling of digital media throughout the verification process.

Initially, users register and authenticate through a web interface integrated with MetaMask wallet authentication. Once verified, users upload media files such as images, videos, or audio. The uploaded content undergoes preprocessing, including format normalization, metadata extraction, noise reduction, and frame extraction for video inputs, ensuring standardized data for accurate forensic analysis.

The processed media is then analyzed by the AI forensic engine, which performs spatial, temporal, and spectral evaluations to detect manipulation artifacts and synthetic generation patterns. Based on extracted features, the classification model determines whether the media is authentic or AI-generated and provides a confidence score to support reliable decision-making.

Following classification, a SHA-256 cryptographic hash is generated to create a unique digital fingerprint of the media. This hash, along with the verification result and timestamp metadata, is recorded on the Ethereum blockchain using smart contracts. The decentralized ledger guarantees immutability, transparency, and resistance to tampering.

During re-verification, the system recomputes the hash and compares it with blockchain records. If a match is identified, the stored authenticity result is retrieved instantly, ensuring long-term integrity, auditability, and trust in media verification.

4.2 User Registration and Authentication Module:

This module serves as the secure entry point of the system, providing a user-friendly interface for registration and login using authenticated credentials. It integrates MetaMask wallet connectivity to enable blockchain-based identity verification, allowing secure interaction with decentralized services. During authentication, user credentials are validated and JSON Web Tokens (JWT) are generated for secure session management and role-based authorization. By leveraging wallet authentication on the Ethereum network, the module prevents unauthorized access and ensures that only verified users can upload, verify, or retrieve media records. Additionally, all authentication transactions are cryptographically signed, enhancing non-repudiation and accountability within the system. This establishes a trusted and tamper-resistant access control layer that safeguards the overall integrity of the media verification framework.

4.3 Media Upload and Preprocessing Module:

This module allows users to upload digital media files, including images, videos, and audio recordings. The interface is designed for ease of use while maintaining secure file transmission. After upload, preprocessing operations are performed to standardize the input data. These operations include format normalization, metadata extraction, resolution alignment, and noise reduction. For video files, frames are extracted for frame-level forensic analysis. For audio files, spectrogram representations are generated to reveal hidden synthesis artifacts. This preprocessing stage improves detection accuracy and reduces false classification rates by ensuring consistent input quality.

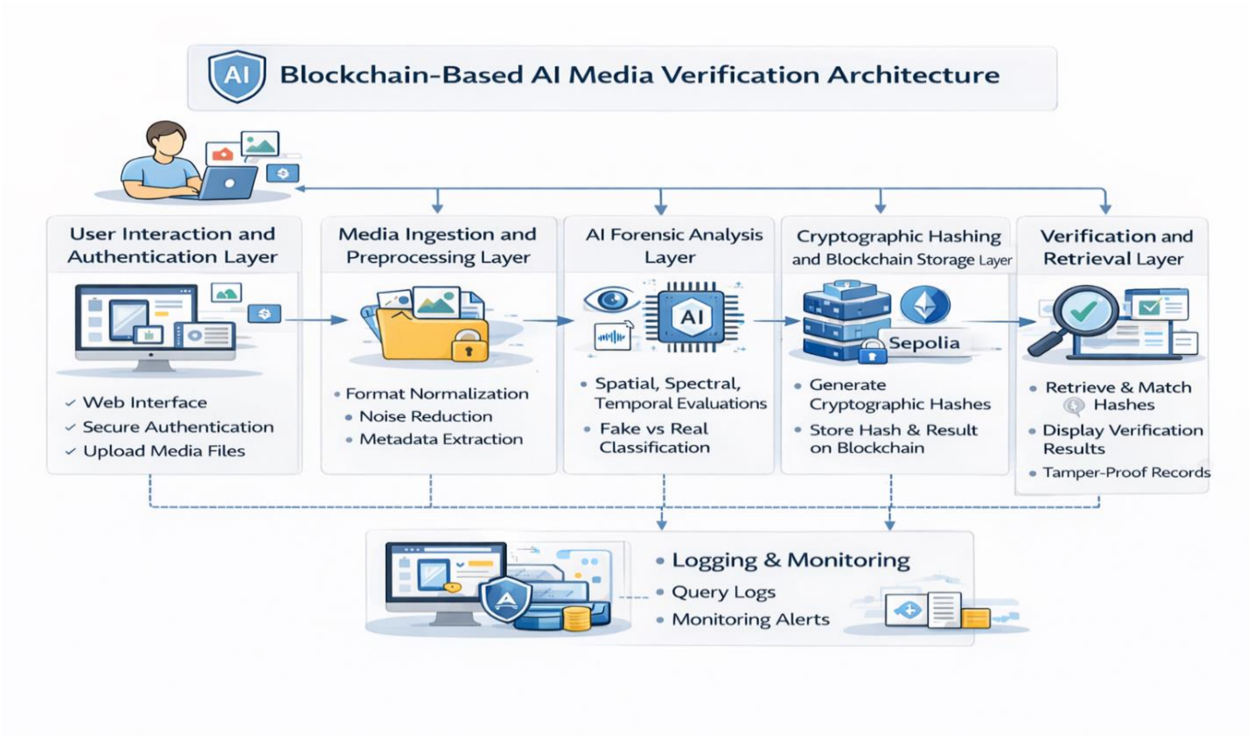


Fig. 4.1 Architecture and Data Flow of the Blockchain based AI-Framework for Verification of Real and Ai-Generated Media

4.4 AI Analysis Module:

The AI Analysis Module is the core intelligence component of the system. It performs automated detection of AI-generated or manipulated media using deep learning and NLP-based models where applicable. Convolutional Neural Networks (CNNs) are used for spatial feature extraction, identifying texture inconsistencies, facial distortions, lighting irregularities, and blending artifacts. For video content, temporal analysis evaluates motion continuity and unnatural transitions between frames. Additionally, frequency-domain analysis detects spectral anomalies and GAN fingerprints commonly present in synthetic media. After feature extraction, classification models generate an authenticity label along with a confidence score. This probabilistic output enhances decision reliability.

4.5 Blockchain Storage Module:

This module ensures immutability and transparency of verification results. After AI classification, a SHA-256 cryptographic hash is generated to represent the exact state of the media file at the time of verification. The generated hash, along with authenticity status and timestamp metadata, is recorded on the Ethereum blockchain using smart contracts. The decentralized ledger structure prevents post-verification tampering, deletion, or unauthorized modification. By distributing records across blockchain nodes, the system eliminates single-point failures and establishes long-term trust in verification results.

4.6 Verification and Retrieval Module:

This module enables users to re-verify media and retrieve historical verification records. When a file is re-submitted, the system recalculates its cryptographic hash and compares it with existing blockchain entries. If a matching hash is found, the stored authenticity result is retrieved instantly, confirming whether the media has remained unchanged since initial verification. This functionality supports cross-platform verification, auditability, and long-term integrity tracking. The retrieval mechanism enhances transparency and ensures that verification results remain permanently accessible and tamper-proof.

4.7 Algorithm

Procedure AI_MEDIA_VERIFICATION (Media M)
1. Initialize preprocessing module P, spatial feature extractor S, temporal analyzer T (for video), spectral analyzer F, and classification model C. 2. Receive uploaded media file M (image, video, or audio) from the user interface. 3. Preprocess M using P by performing format normalization, metadata extraction, noise reduction, and resolution alignment. 4. If M is a video, extract individual frames Fi for frame-level analysis; if M is audio, convert it into spectrogram representation Si. 5. For each image frame Fi (or image input), extract spatial features using S, including facial landmarks, texture continuity, lighting consistency, and boundary blending artifacts. 6. If M is a video, analyze temporal consistency using T by evaluating motion coherence and transitions between consecutive frames. 7. Perform frequency-domain transformation using F (e.g., Fourier Transform) to extract spectral features such as abnormal frequency distributions, GAN fingerprints, and high-frequency noise artifacts. 8. Fuse spatial, temporal (if applicable), and spectral features into a unified feature vector F_total. 9. Input F_total into the trained classification model C. 10. Compute authenticity probability score P_auth and assign label L (Real or AI-Generated). 11. Return the authenticity label L and confidence score P_auth to the system. End Procedure

5.Experiments and Results:

This section explains the research design, data preparation, experimental method and analysis of the performance of the proposed intelligent document management and query answering system. The experiments were done to test the efficiency of the document processing, text extraction, semantic retrieval, and answer generation ability of the system at realistic conditions.

5.1 Data Preparation and Preprocessing:

An extensive collection of digital media files was assembled to train and evaluate the proposed verification system. The dataset consists of real and AI-generated images, videos, and audio samples representing social media content, interviews, surveillance clips, and synthetic media created using generative models. The data was selected to simulate real-world scenarios where manipulated content spreads across multiple platforms.

Before model training, all media files were subjected to preprocessing operations to improve quality and consistency. Image and video frames were resized, normalized, and filtered to remove noise and compression artifacts. Videos were divided into individual frames for detailed inspection, while audio signals were converted into spectrogram representations for frequency analysis. Duplicate, corrupted, and low-resolution files were eliminated to ensure dataset integrity. Effective preprocessing significantly enhanced feature extraction accuracy and improved overall detection performance.

5.1.1 Data Sources:

The dataset was constructed using multiple sources, including: Publicly available deepfake detection datasets. Real-world image and video repositories. GAN-generated synthetic images. Diffusion-based AI-generated media. AI-based text-to-speech audio samples.

Both authentic and manipulated media samples were included in balanced proportions. The combination of structured benchmark datasets and synthetically generated content enabled the system to be evaluated across diverse manipulation techniques and media formats, thereby improving robustness and generalization capability.

5.2 Feature Extraction and Representation:

Media content from uploaded files is processed using spatial, temporal, and spectral feature extraction techniques. For image and video inputs, convolutional neural networks are used to extract spatial features such as facial alignment, texture consistency, lighting distribution, and boundary blending artifacts. Video data is further analyzed using frame-to-frame comparison methods to evaluate motion continuity and detect unnatural transitions.

For audio inputs, signals are transformed into spectrogram representations to capture frequency-domain characteristics. Additionally, frequency transformation techniques are applied to detect abnormal energy distributions and synthetic fingerprints commonly found in AI-generated content.

The extracted features from spatial, temporal, and spectral domains are combined into unified feature representations. These representations allow the classification model to detect manipulation patterns beyond simple visual inspection. By leveraging multi-dimensional feature learning, the system achieves more reliable and accurate identification of real and AI-generated media.

5.3 Experimental Setup:

The proposed system was implemented using Python for AI model development, Node.js for backend services, and ReactJS for frontend integration. Deep learning models were developed using TensorFlow and PyTorch, while OpenCV and Librosa supported media processing tasks. Blockchain functionality was implemented using Solidity smart contracts deployed on the Ethereum network, with testing conducted on the Sepolia test network. Smart contract interactions were handled programmatically through backend integration. All components were connected via RESTful APIs to enable secure, real-time media verification and immutable record storage.

5.4 Dataset Overview:

The dataset comprised real and AI-generated images, videos, and audio samples, including deepfake videos, GAN-based synthetic images, diffusion-generated content, and AI-generated speech. The collection reflects diverse real-world manipulation scenarios across multiple media formats. To ensure proper evaluation, the dataset was divided into 80% for training and 20% for testing and validation. This split minimized bias and validated the model's generalization capability. The diversity of samples strengthened the robustness of the detection framework.

5.5 Evaluation Metrics:

The system was evaluated using standard classification metrics including accuracy, precision, recall, F1-score, and Area Under the Curve (AUC). Accuracy measured overall prediction correctness, while precision and recall assessed the reliability of detecting AI-generated content. The F1-score provided a balanced evaluation in the presence of class imbalance. In addition, verification response time and blockchain transaction confirmation time were analyzed. These metrics collectively assessed both detection performance and operational efficiency.

5.6 Media Verification Results:

Experimental results demonstrated strong detection capability across multiple media types. The system achieved approximately 91% accuracy, with precision around 90%, recall near 89%, and an F1-score close to 89.5%. The multi-layer forensic analysis improved detection of subtle manipulations and reduced false classifications. Blockchain integration ensured all verification results were securely recorded without tampering. The findings confirm both technical effectiveness and secure authentication reliability.

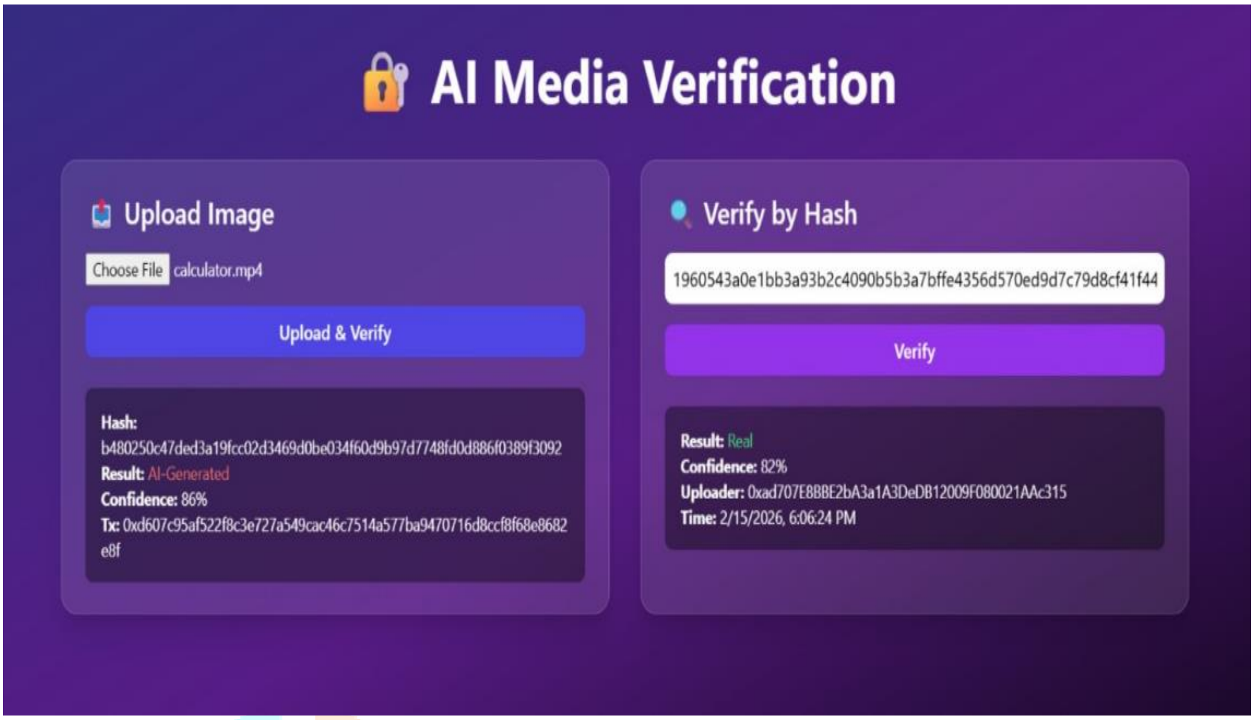


Fig 5.6 **Media Upload and Verification interface**

5.7 System Performance and Scalability Analysis:

The average verification time was under five seconds for images and under ten seconds for short video clips. Performance remained stable as dataset size increased, indicating scalability of the framework. Efficient preprocessing and feature extraction reduced computational overhead. Blockchain confirmation times remained within acceptable operational limits. The system demonstrates suitability for near real-time deployment environments.

5.8 Multi-Layer Forensic Strategy:

The framework employs a multi-layer forensic strategy combining spatial, temporal, and spectral feature analysis. Spatial features identify visual inconsistencies, while temporal analysis strengthens deepfake video detection. Spectral examination detects hiddenGAN and diffusion artifacts. This integrated approach improves robustness against advanced generative techniques. The combination of AI-driven detection and blockchain-backed storage ensures transparent, tamper-resistant media authentication.

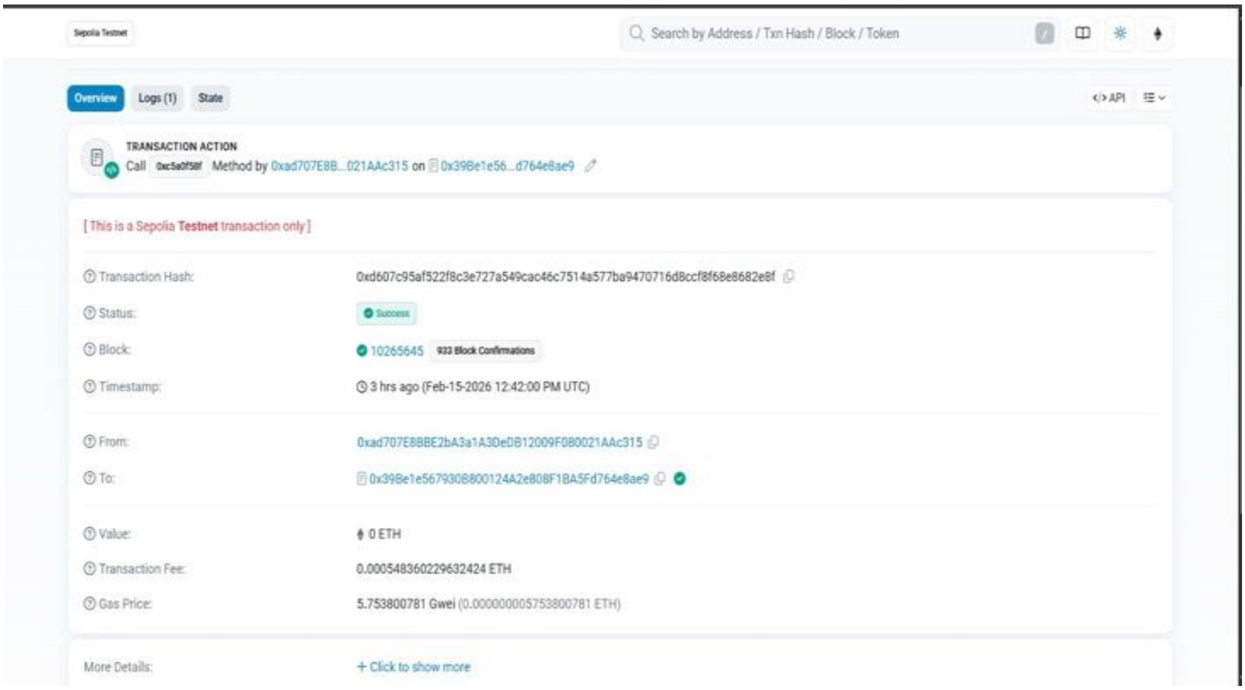
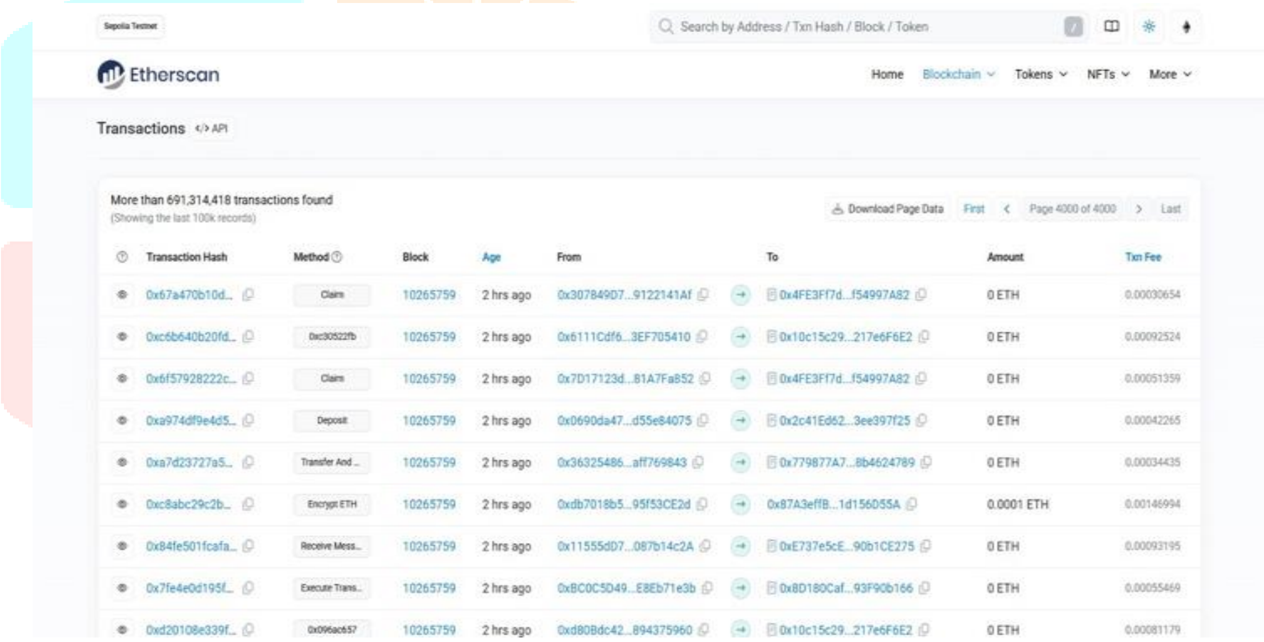


Fig 5.7 ***Blockchain Transaction Verification - Ethereum Sepolia Testnet***



Transaction Hash	Method	Block	Age	From	To	Amount	Txn Fee
0x67a470b10d...	Claim	10265759	2 hrs ago	0x307849D7...9122141Af	0x4FE3Ff7d...f54997A82	0 ETH	0.00030654
0xc6b640b20fd...	0xc30522fb	10265759	2 hrs ago	0x6111Cdf6...3EF705410	0x10c15c29...217e6F6E2	0 ETH	0.00092524
0x6f57928222c...	Claim	10265759	2 hrs ago	0x7D17123d...81A7Fa852	0x4FE3Ff7d...f54997A82	0 ETH	0.00051359
0xa974df9e4d5...	Deposit	10265759	2 hrs ago	0x0690da47...d55e84075	0x2c41Ed62...3ee397f25	0 ETH	0.00042265
0xa7d23727a5...	Transfer And ...	10265759	2 hrs ago	0x36325486...aff769843	0x779877A7...8b4624789	0 ETH	0.00034435
0xc8abc29c2b...	Encrypt ETH	10265759	2 hrs ago	0xdb7018b5...95f53CE2d	0x87A3effB...1d156D55A	0.0001 ETH	0.00146994
0x84fe501fcafa...	Receive Mess...	10265759	2 hrs ago	0x11555dD7...087b14c2A	0xE737e5cE...90b1CE275	0 ETH	0.00093195
0x7fe4e0d195f...	Execute Trans...	10265759	2 hrs ago	0xBC0C5D49...E8Eb71e3b	0x8D180Caf...93F90b166	0 ETH	0.00055469
0xd20108e339f...	0x096ac657	10265759	2 hrs ago	0xd80Bdc42...894375960	0x10c15c29...217e6F6E2	0 ETH	0.00081179

Fig 5.7 Recent Transactions Log on Ethereum Sepolia Testnet

6.Comparision with existing frameworks:

Feature	Traditional Media Storage Systems	Basic Deepfake Detection Tools	Centralized Verification Platforms	Proposed Blockchain-Based AI Media Verification System
Manual Media Management Required	✓	✓	✓	✗
AI-Based Media Manipulation Detection	✗	✓	✓	✓
Multi-Format Support (Image, Video, Audio)	Limited	Limited	✓	✓
Multi-Layer Forensic Analysis	✗	✗	Limited	✓
Detection of GAN/Diffusion-Based Content	✗	Limited	Limited	✓
Real-Time Media Verification	✗	Limited	Moderate	✓
Blockchain-Based Record Storage	✗	✗	✗	✓
Tamper-Proof Verification Logs	✗	✗	✗	✓
Smart Contract Integration	✗	✗	✗	✓
Decentralized Verification Mechanism	✗	✗	✗	✓
Transparent Audit Trail	✗	✗	Limited	✓
Scalability for Large Media Datasets	Limited	Moderate	Moderate	High
Resistance to Data Manipulation	Low	Moderate	Moderate	High
Secure Verification Storage	✗	✗	Limited	✓
Overall System Reliability	Low	Moderate	Moderate	High

7.Future Scope:

The proposed blockchain-based AI media verification system can be extended in several meaningful directions. Future enhancements may include expanding the detection framework to handle emerging generative models and real-time deepfake streaming scenarios, ensuring adaptability against rapidly evolving AI manipulation techniques. Continuous improvements in deep learning architectures and feature extraction methods can further enhance detection accuracy, especially for highly compressed or low-resolution media.

Another important advancement involves integrating cross-platform verification APIs that allow social media platforms, news agencies, and content-sharing applications to verify media authenticity before publication. The system can also be enhanced with automated alert mechanisms to flag suspicious media content at scale. Incorporating explainable AI (XAI) techniques would improve transparency by providing interpretable evidence behind verification decisions.

From an architectural perspective, deploying the framework on scalable cloud infrastructure and integrating Layer-2 blockchain solutions can reduce transaction costs and improve processing speed. Future research may also explore decentralized identity (DID) integration and global verification consortium models to create a universally trusted media authentication ecosystem. These developments would transform the system into a robust, scalable, and globally deployable digital media trust framework.

8.Conclusion:

This paper presented the design and implementation of a Blockchain-Based AI Framework for Verification of Real and AI-Generated Media, enabling secure detection and authenticity validation of digital content. By integrating deep learning-based media forensics with decentralized blockchain storage, the system effectively addresses the limitations of traditional centralized verification mechanisms. The framework combines spatial, temporal, and spectral analysis techniques with cryptographic hashing and immutable ledger recording to ensure reliable classification and tamper-proof storage of verification results.

The proposed solution demonstrates the ability to accurately distinguish real and AI-generated images, videos, and audio while maintaining transparency and traceability of authenticity records. The generation of unique cryptographic hash values ensures media integrity, while blockchain recording guarantees immutability, auditability, and resistance to unauthorized modification. Experimental evaluation indicates strong detection performance, efficient verification workflows, and secure decentralized record management, confirming the feasibility of integrating AI analytics with blockchain infrastructure.

Overall, the framework provides a scalable and practical solution for combating deepfakes and synthetic media misuse. It enhances digital trust by enabling transparent authenticity verification across domains such as journalism, legal forensics, social media governance, and cybersecurity. The study highlights how the convergence of artificial intelligence and blockchain technology can establish a secure, reliable, and future-ready ecosystem for digital media authentication.

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