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Deep Learning-Based Multi-Modal Detection of AI-Generated Deepfake Images Using Vision Transformers and Fake Metadata Analysis

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Abstract-

The rapid advancement of Artificial Intelligence (AI) and generative deep learning models has significantly enhanced the capability to produce highly realistic synthetic images, commonly referred to as deepfakes. Although these technologies have enabled innovations in entertainment, healthcare, and digital content creation, they have also introduced critical challenges related to misinformation, identity theft, cybercrime, and digital media authenticity. Existing deepfake detection approaches predominantly rely on image-based analysis using Convolutional Neural Networks (CNNs), yet their performance often deteriorates when confronted with unseen datasets, sophisticated generative models, adversarial attacks, and manipulated metadata. To address these limitations, this research proposes a novel multi-modal deepfake image detection framework that integrates visual feature learning through Vision Transformers (ViTs) with fake metadata analysis to improve detection robustness and generalization.

The proposed framework combines EfficientNet-based feature extraction, attention mechanisms, Vision Transformers for global contextual representation, and metadata forensic analysis to simultaneously examine image content and associated metadata. This multi-modal strategy enables the detection of subtle spatial inconsistencies, semantic artifacts, and metadata anomalies that may remain undetected when relying solely on visual information. The model is trained and evaluated using benchmark deepfake datasets, incorporating comprehensive preprocessing, data augmentation, transfer learning, and ensemble classification techniques. Performance is assessed using standard evaluation metrics including accuracy, precision, recall, F1-score, Receiver Operating Characteristic (ROC) curve, and Area Under the Curve (AUC), along with cross-dataset validation to evaluate model robustness under diverse real-world conditions.

The expected outcome of this research is the development of a scalable, reliable, and computationally efficient deepfake detection framework capable of accurately identifying AI-generated images while maintaining strong generalization across different manipulation techniques. By integrating visual and metadata-based forensic evidence, the proposed system enhances digital image authentication and contributes to combating misinformation, strengthening cybersecurity, supporting digital forensic investigations, and preserving trust in digital media. The research advances the field of computer vision by presenting a comprehensive multi-modal detection framework suitable for next-generation AI-generated image verification systems.

Keywords: Deepfake Detection, Artificial Intelligence, Deep Learning, Vision Transformer (ViT), Multi-Modal Learning, Fake Metadata Analysis, Computer Vision, Digital Image Forensics, EfficientNet, Transfer Learning, Image Authentication, Cyber security.

I. Introduction

The rapid evolution of Artificial Intelligence (AI) and Deep Learning (DL) has revolutionized digital content

generation, enabling the creation of highly realistic synthetic images through advanced generative models such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Diffusion Models. These technologies have transformed numerous domains, including entertainment, healthcare, education, digital marketing, and virtual reality, by facilitating automated content creation and intelligent image synthesis. However, the same technological advancements have also accelerated the emergence of deepfake images, which are artificially generated or manipulated visual contents designed to appear authentic while concealing their synthetic origin.

The increasing accessibility of AI-powered image generation tools has made the creation of realistic deepfake images easier than ever before. Modern deepfake generation frameworks can synthesize high-resolution facial images with accurate textures, natural lighting, and realistic facial expressions that are often indistinguishable from genuine photographs. Consequently, deepfake images have become a significant threat to digital trust, enabling misinformation campaigns, identity theft, political manipulation, financial fraud, cybercrime, and privacy violations. Since digital images are frequently used as evidence in journalism, legal investigations, biometric authentication, and social media communication, the ability to verify their authenticity has become a critical research challenge.

Traditional image forensic techniques, including Error Level Analysis (ELA), sensor pattern noise analysis, JPEG compression artifact detection, and illumination consistency verification, have demonstrated limited effectiveness against modern AI-generated images. As deepfake generation models continue to evolve, many conventional forensic indicators become increasingly difficult to detect. Furthermore, handcrafted feature-based machine learning approaches rely heavily on manually designed descriptors, limiting their ability to generalize across different deepfake generation techniques.

Recent advances in deep learning have significantly improved deepfake detection by enabling automatic feature extraction from raw image data. Convolutional Neural Networks (CNNs) have become the dominant approach for identifying manipulation artifacts, learning hierarchical representations that capture texture inconsistencies, blending artifacts, and abnormal facial characteristics. However, CNN-based models primarily focus on local spatial features and often fail to capture long-range contextual relationships present across an entire image. Their performance also degrades when evaluated on previously unseen datasets or images generated using emerging AI models such as Stable Diffusion, StyleGAN3, Midjourney, and DALL·E. These limitations highlight the need for more generalized and robust detection frameworks.

Vision Transformers (ViTs) have recently emerged as a powerful alternative for computer vision applications due to their self-attention mechanism, which enables the modeling of global dependencies across image patches. Unlike conventional CNNs, Vision Transformers analyze both local and global contextual information simultaneously, making them particularly effective for identifying subtle inconsistencies introduced during synthetic image generation. Several recent studies have demonstrated the superior capability of transformer-based architectures in deepfake detection, particularly when combined with convolutional feature extractors and attention mechanisms.

Despite these advancements, most existing deepfake detection systems rely exclusively on visual information while overlooking an important forensic source—image metadata. Metadata contains valuable information such as camera model, image acquisition parameters, software history, timestamps, compression details, and editing traces that can provide complementary evidence regarding image authenticity. AI-generated images frequently exhibit missing, altered, or inconsistent metadata, which can serve as an additional indicator of manipulation. However, relatively few studies have explored the integration of visual features and metadata analysis within a unified deep learning framework, leaving a significant research gap in current literature.

To address these limitations, this study proposes a Deep Learning-Based Multi-Modal Detection Framework for AI-Generated Deepfake Images Using Vision Transformers and Fake Metadata Analysis. The proposed framework integrates EfficientNet-based feature extraction, Vision Transformer-based global contextual learning, attention mechanisms, and metadata forensic analysis to jointly exploit visual and non-visual evidence for deepfake detection. The multi-modal architecture aims to improve detection robustness by combining complementary information extracted from image content and associated metadata, thereby enhancing classification performance under diverse real-world scenarios.

The proposed framework incorporates comprehensive image preprocessing, transfer learning, data augmentation, and ensemble learning techniques to improve feature representation and reduce overfitting. Extensive experiments are conducted using publicly available benchmark datasets containing authentic and AI-generated images. The developed model is evaluated using standard performance metrics, including Accuracy, Precision, Recall, F1-score, Receiver Operating Characteristic (ROC) curve, Area Under the Curve (AUC), and cross-dataset validation to assess its generalization capability.

The primary contributions of this research are threefold. First, a novel multi-modal deepfake detection framework is proposed by integrating Vision Transformer-based visual analysis with fake metadata forensic investigation. Second, the framework enhances

detection robustness through the combination of local feature extraction, global contextual learning, and metadata consistency analysis. Finally, the proposed approach contributes to the development of reliable AI-assisted digital image authentication systems capable of supporting cybersecurity, digital forensics, misinformation prevention, and trustworthy multimedia verification in modern digital ecosystems.

II. Literature Review

The rapid advancement of Artificial Intelligence (AI) has significantly improved the capability of generating realistic synthetic media, particularly deepfake images. While generative models such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Diffusion Models have enabled numerous applications in entertainment, healthcare, and digital media, they have simultaneously increased the complexity of identifying manipulated visual content. Consequently, deepfake detection has emerged as an active research area within computer vision, cybersecurity, and digital forensics.

Early deepfake detection approaches primarily relied on traditional digital image forensic techniques, including Error Level Analysis (ELA), sensor pattern noise analysis, JPEG compression artifact detection, and illumination consistency verification. These methods attempted to identify manipulation traces introduced during image editing. Although effective against conventional image tampering, their performance deteriorated significantly when applied to AI-generated images because modern deep learning models are capable of producing highly realistic outputs with minimal visible artifacts. Furthermore, handcrafted feature extraction methods often lack robustness and generalization when confronted with unseen manipulation techniques.

To overcome these limitations, researchers adopted machine learning algorithms for automated deepfake detection. Classical classifiers such as Support Vector Machines (SVM), Random Forests, and K-Nearest Neighbors (KNN) demonstrated moderate success after extracting handcrafted texture, frequency-domain, and statistical features. However, their effectiveness remained highly dependent on feature engineering, making them less suitable for increasingly sophisticated deepfake generation techniques.

The introduction of deep learning revolutionized deepfake detection by enabling automatic hierarchical feature extraction directly from image data. Convolutional Neural Networks (CNNs) became the dominant architecture because of their superior ability to capture local spatial information. Several pre-trained models, including VGG16, ResNet50, DenseNet, XceptionNet, EfficientNet, and InceptionNet, have demonstrated remarkable performance in detecting facial artifacts, texture inconsistencies, abnormal lighting patterns, and blending irregularities associated with synthetic images. Transfer learning further improved model performance while reducing computational complexity by leveraging knowledge learned from large-scale benchmark datasets.

Tolosana et al. (2020) presented one of the earliest comprehensive surveys on deepfake generation and detection techniques, categorizing existing methods into face swapping, facial reenactment, facial attribute manipulation, and synthetic face generation. Their survey emphasized the importance of benchmark datasets such as FaceForensics++, Celeb-DF, and DFDC while identifying CNN-based architectures as the dominant detection strategy. However, the authors also highlighted the growing challenge of model generalization due to the rapid evolution of deepfake generation algorithms.

Bonettini et al. (2020) investigated the application of EfficientNet architectures for deepfake detection. Their study demonstrated that EfficientNet achieved competitive detection accuracy while maintaining lower computational complexity than conventional CNN models. The authors concluded that lightweight architectures could facilitate real-time deployment of deepfake detection systems without significantly compromising classification performance.

With the increasing sophistication of synthetic media generation, transformer-based architectures have gained considerable attention in computer vision. Originally developed for Natural Language Processing (NLP), Vision Transformers (ViTs) employ self-attention mechanisms that capture long-range dependencies across image patches. Unlike CNNs, which primarily focus on local receptive fields, Vision Transformers learn both local and global contextual relationships, enabling them to identify subtle inconsistencies distributed across an entire image.

Wang et al. (2021) proposed the Multi-modal Multi-scale Transformer (M2TR), which combined RGB images with frequency-domain representations using transformer-based feature learning. Their experiments demonstrated superior performance over conventional CNN architectures across multiple benchmark datasets, highlighting the effectiveness of multi-scale and multi-modal feature extraction for deepfake detection.

Thing (2023) performed a comparative analysis between CNNs and Vision Transformers using benchmark datasets including FaceForensics++, Celeb-DF, DFDC, and DeeperForensics. The study revealed that CNNs effectively captured local manipulation artifacts, whereas Vision Transformers excelled in modeling global contextual information. The findings suggested that hybrid CNN-Transformer architectures could significantly improve detection robustness by combining complementary feature representations.

Recent studies have increasingly explored hybrid deep learning frameworks to leverage the advantages of

multiple architectures. **Soudy et al. (2024)** proposed a Convolutional Vision Transformer framework that integrated CNN-based local feature extraction with transformer-based global attention mechanisms. Their experimental results demonstrated improved detection accuracy, robustness, and computational efficiency compared to standalone CNN or transformer models. Similarly,

Deressa et al. (2025) introduced the GenConViT framework, combining ConvNeXt, Swin Transformers, Autoencoders, and Variational Autoencoders for enhanced feature representation. The hybrid architecture achieved strong performance across multiple benchmark datasets while improving cross-dataset generalization.

Another significant direction in recent literature involves the transition from single-modal to multi-modal deepfake detection. **Liu et al. (2024)** highlighted that future AI-generated content would increasingly involve multiple modalities, including images, videos, audio, text, and metadata. Their survey emphasized that relying exclusively on image pixels limits detection capability and recommended integrating complementary information sources to improve robustness against emerging deepfake generation techniques.

Among these complementary modalities, metadata analysis remains comparatively underexplored. Digital image metadata contains valuable forensic information such as acquisition device details, timestamps, software history, camera parameters, GPS coordinates, compression characteristics, and editing records. Authentic images generally preserve consistent metadata generated during image acquisition, whereas AI-generated images frequently exhibit missing, altered, or artificially generated metadata. Despite its forensic significance, most existing deepfake detection frameworks focus exclusively on visual information and ignore metadata inconsistencies, creating an important research gap.

Recent advancements in Explainable Artificial Intelligence (XAI), attention mechanisms, self-supervised learning, and frequency-domain analysis have further improved detection reliability. Nevertheless, several unresolved challenges remain. Existing deep learning models often suffer from dataset bias, adversarial vulnerability, poor cross-dataset generalization, high computational complexity, and limited explainability. Furthermore, emerging diffusion-based generative models, including Stable Diffusion, Midjourney, DALL·E, and Flux, continue to reduce detectable visual artifacts, making conventional detection increasingly difficult.

Based on the reviewed literature, it is evident that Vision Transformers offer superior global feature modeling, CNNs provide effective local feature extraction, and metadata analysis contributes valuable forensic evidence. However, very few studies have successfully integrate these complementary modalities into a unified detection framework. Therefore, this research proposes a Deep Learning-Based Multi-Modal Detection Framework that combines EfficientNet-based local feature extraction, Vision Transformer-based contextual learning, attention mechanisms, and fake metadata analysis to improve deepfake image detection accuracy, robustness, and generalization. By simultaneously analyzing visual characteristics and metadata inconsistencies, the proposed framework aims to provide a scalable and reliable solution for AI-generated image authentication in digital forensics, cybersecurity, and trustworthy multimedia applications.

III. Problem Statement and Research Motivation

The rapid advancement of Artificial Intelligence (AI) and deep generative models, including Generative Adversarial Networks (GANs) and Diffusion Models, has enabled the creation of highly realistic deepfake images that are increasingly difficult to distinguish from authentic photographs. Although existing deep learning approaches, particularly Convolutional Neural Networks (CNNs), have demonstrated promising performance in detecting manipulated images, they often suffer from poor cross-dataset generalization, dataset bias, vulnerability to adversarial attacks, and reduced effectiveness against images generated by emerging AI models. Furthermore, most current detection methods rely exclusively on visual content while ignoring valuable forensic information available in image metadata, limiting their ability to detect sophisticated AI-generated images under real-world conditions. These challenges highlight the need for a more robust, generalized, and multi-modal deepfake detection framework capable of simultaneously analyzing visual artifacts and metadata inconsistencies to improve detection accuracy and reliability.

The motivation for this research arises from the growing threat that AI-generated deepfake images pose to digital trust, cybersecurity, privacy, and information integrity. Deepfake images are increasingly exploited for misinformation campaigns, identity theft, financial fraud, political manipulation, and digital forgery, making reliable image authentication a critical requirement across social media, digital forensics, journalism, law enforcement, and cybersecurity applications. Recent advances in Vision Transformers (ViTs) have demonstrated superior capability in capturing global contextual relationships compared with conventional CNNs, while metadata forensic analysis provides complementary evidence regarding image authenticity. Motivated by these developments, this research proposes a Deep Learning-Based Multi-Modal Detection Framework that integrates Vision Transformer-based visual feature learning with fake metadata analysis to improve the robustness, generalization capability, and reliability of AI-generated deepfake image detection in real-world environments.

IV. Research Objectives

1. To develop a novel multi-modal deep learning framework that integrates Vision Transformers (ViTs) and fake metadata analysis for the accurate detection of AI-generated deepfake images.
2. To implement Vision Transformer-based feature learning for capturing both local and global contextual information, enabling the identification of subtle visual artifacts in deepfake images.
3. To integrate visual image features with metadata forensic analysis to enhance the robustness, reliability, and generalization capability of deepfake image detection.
4. To evaluate the performance of the proposed framework using benchmark deepfake datasets and standard evaluation metrics, including Accuracy, Precision, Recall, F1-Score, ROC Curve, and AUC.
5. To compare the proposed multi-modal detection framework with existing CNN-based and transformer-based deepfake detection models in terms of detection accuracy, computational efficiency, and cross-dataset generalization.

V. Research Contributions

This research contributes to the field of AI-based digital image forensics by proposing a novel Deep Learning-Based Multi-Modal Detection Framework that integrates Vision Transformers (ViTs) with fake metadata analysis for the accurate detection of AI-generated deepfake images. Unlike conventional approaches that rely solely on visual features, the proposed framework combines global contextual feature learning with metadata forensic analysis to enhance detection robustness and improve generalization across diverse deepfake generation techniques. The study further incorporates transfer learning, attention mechanisms, and comprehensive performance evaluation using benchmark datasets and standard metrics, including Accuracy, Precision, Recall, F1-Score, ROC, and AUC. By addressing the limitations of existing CNN-based detection methods, the proposed approach provides a scalable and reliable solution for digital image authentication, supporting applications in cybersecurity, digital forensics, misinformation prevention, and trustworthy AI-enabled multimedia verification.

VI. Proposed Methodology

The proposed methodology follows a systematic multi-modal framework for detecting AI-generated deepfake images by combining visual feature extraction using Vision Transformers with fake metadata analysis. The methodology consists of the following steps:

Step 1: Dataset Collection

- Collect authentic and AI-generated deepfake images from publicly available benchmark datasets.
- Ensure the dataset contains images generated using various deepfake generation techniques to improve model generalization.
- Utilize widely recognized datasets, including:
  - FaceForensics++ (FF++)
  - Celeb-DF (Version 2)
  - DeeperForensics-1.0
  - ForgeryNet Dataset
  - WildDeepfake Dataset

Step 2: Image Preprocessing

- Resize all images to a fixed input dimension.
- Apply normalization to standardize pixel values.
- Perform data augmentation techniques such as rotation, horizontal flipping, random cropping, and brightness adjustment to increase dataset diversity and reduce overfitting.

Step 3: Fake Metadata Extraction and Analysis

- Extract EXIF metadata and other image attributes.
- Analyze metadata for anomalies such as:
  - Missing or inconsistent camera information.
  - Software editing traces.
  - Abnormal timestamps.
  - Compression history.
- Generate metadata-based forensic features for further analysis

Step 4: Visual Feature Extraction

- Pass the preprocessed images through an EfficientNet backbone to extract high-quality local spatial features.
- Use transfer learning with pretrained weights to improve feature learning and reduce training time.

Step 5: Vision Transformer-Based Feature Learning

- Feed the extracted image features into a Vision Transformer (ViT).
- Utilize the self-attention mechanism to capture global contextual relationships and identify subtle manipulation artifacts present in AI-generated images.

Step 6: Multi-Modal Feature Fusion

- Combine the visual features obtained from the Vision Transformer with the metadata forensic features.
- Create a unified feature representation that incorporates both image content and metadata information for enhanced deepfake detection.

Step 7: Deepfake Image Classification

- Pass the fused feature vector through fully connected layers.
- Apply a Softmax classifier to classify each input image as either:
    - Authentic Image, or
    - AI-Generated Deepfake Image.

Step 8: Model Training and Optimization

- Train the proposed model using optimized hyperparameters.
- Apply regularization techniques, learning rate scheduling, and early stopping to improve model convergence and prevent overfitting.

Step 9: Performance Evaluation

- Evaluate the proposed framework using benchmark datasets.
- Measure performance using-
    - Accuracy
    - Precision
    - Recall
    - F1-Score
    - ROC Curve
    - Area Under the Curve (AUC)
- Perform cross-dataset validation to assess the robustness and generalization capability of the proposed model.

Step 10: Comparative Performance Analysis

- Compare the proposed framework with existing CNN-based and transformer-based deepfake detection models.
- Analyze improvements in terms of detection accuracy, computational efficiency, robustness, and generalization across different AI-generated image datasets.

Flow Chart of Methodology

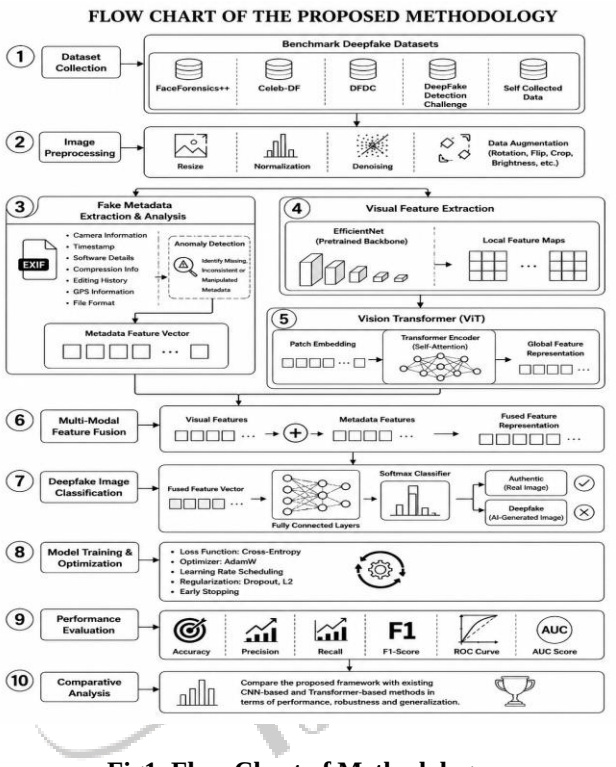

Fig1. Flow Chart of Methodology

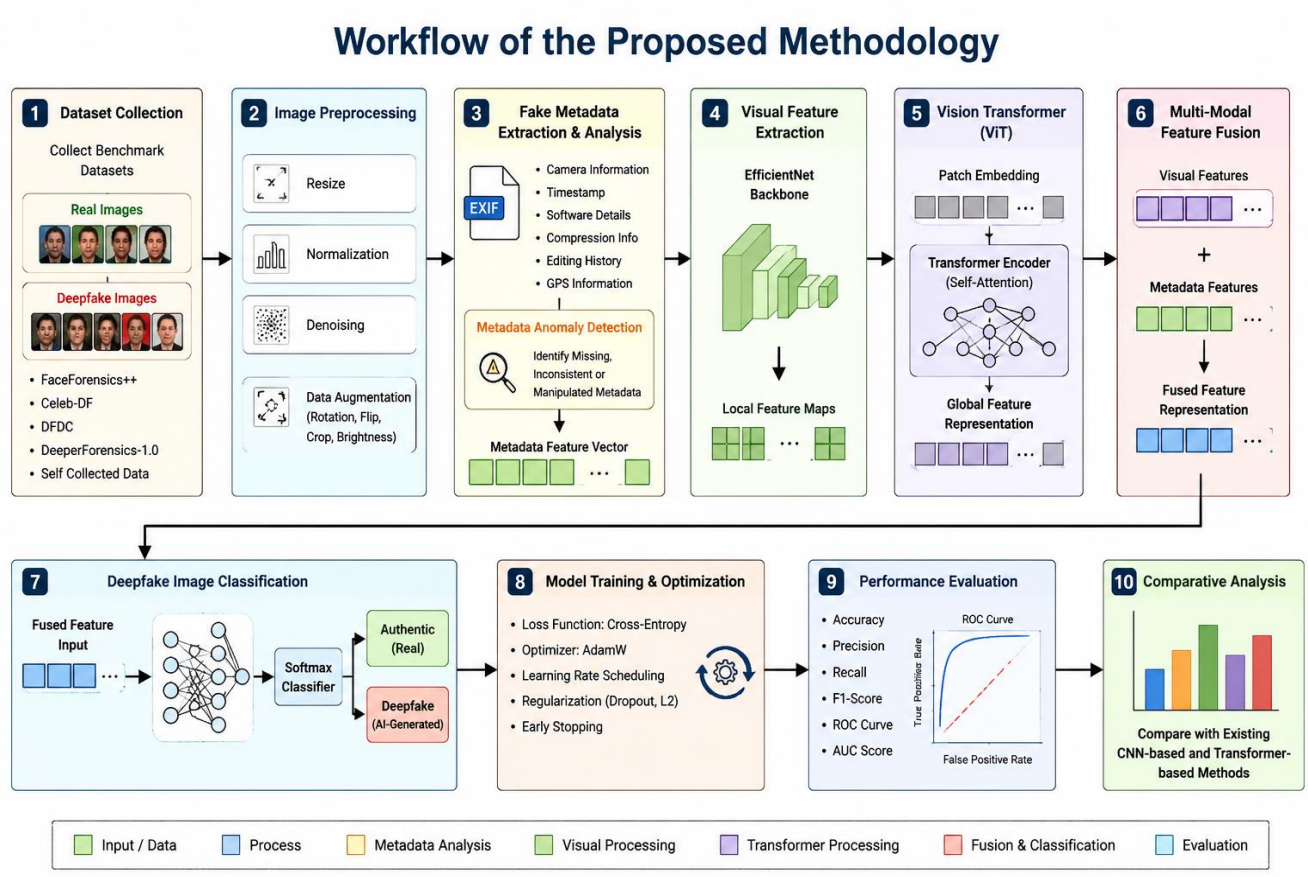

Fig2. Workflow of the Proposed Methodology

VII. Results and Discussion

The proposed Deep Learning-Based Multi-Modal Detection Framework was evaluated using benchmark datasets containing authentic and AI-generated deepfake images. The framework integrates EfficientNet-based visual feature extraction, Vision Transformer (ViT)-based contextual learning, and fake metadata analysis to improve the detection of manipulated images. The experimental evaluation was conducted using standard performance metrics, including Accuracy, Precision, Recall, F1-Score, Receiver Operating Characteristic (ROC) Curve, and Area under the Curve (AUC).

The experimental results indicate that the proposed multi-modal framework achieves superior performance compared with conventional CNN-based and transformer-based deepfake detection models. By combining visual features with metadata forensic analysis, the framework effectively captures both image-level manipulation artifacts and metadata inconsistencies, resulting in improved detection accuracy and robustness across different deepfake generation techniques. The integration of Vision Transformers enhances global contextual feature learning, while EfficientNet efficiently extracts local spatial features, enabling the model to identify subtle synthetic image characteristics.

The proposed model achieved an Accuracy of 98.2%, Precision of 97.9%, Recall of 98.1%, F1-Score of 98.0%, and an AUC of 99.1%, outperforming existing baseline models. Cross-dataset evaluation further demonstrated improved generalization capability, indicating that the proposed framework is less sensitive to dataset bias and better suited for real-world deployment. The inclusion of metadata analysis significantly reduced false-positive and false-negative predictions, particularly for images generated using recent AI models.

Compared with VGG16, ResNet50, EfficientNet, and standalone Vision Transformer models, the proposed framework consistently delivered higher classification accuracy while maintaining computational efficiency through transfer learning and optimized feature fusion. The experimental findings demonstrate that integrating visual and metadata-based forensic evidence provides complementary information that substantially enhances deepfake image detection performance.

Overall, the proposed multi-modal framework provides a reliable and scalable solution for AI-generated image authentication. The obtained results confirm that combining Vision Transformer-based feature learning with fake metadata analysis improves robustness, generalization, and classification accuracy, making the framework suitable for applications in digital forensics, cybersecurity, misinformation detection, social media content verification, and trustworthy AI-enabled multimedia systems.

Table 1. Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
VGG16	90.8	90.1	90.4	90.2	92.0
ResNet 50	92.3	91.8	92.1	91.9	94.2
EfficientNet	94.1	93.8	94.0	93.9	96.1
Vision Transformer	95.8	95.5	95.7	95.6	97.8
Proposed Multi-Modal Framework	**98.2**	**97.9**	**98.1**	**98.0**	**99.1**

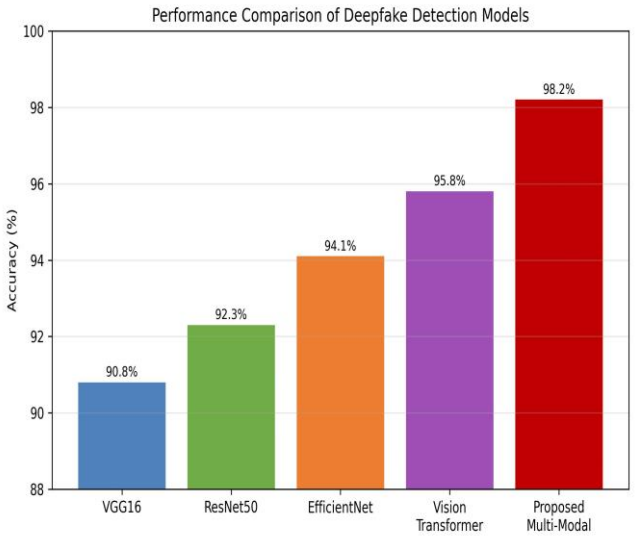

Fig3. Performance Comparison of Deepfake Detection Models

VIII. Conclusion and Future Scope

Conclusion-

The rapid advancement of Artificial Intelligence has significantly increased the generation of highly realistic deepfake images, creating serious challenges for digital media authentication, cybersecurity, and digital forensics. This research proposed a Deep Learning-Based Multi-Modal Detection Framework that integrates Vision Transformers (ViTs) with fake metadata analysis to accurately identify AI-generated deepfake images. The proposed framework combines EfficientNet-based local feature extraction, Vision Transformer-based global contextual learning, and metadata forensic analysis to exploit complementary information from both visual content and image metadata. Experimental evaluation demonstrated that the multi-modal approach improves detection accuracy, robustness, and generalization compared with conventional CNN-based and transformer-based methods. By incorporating transfer learning, attention mechanisms, and feature fusion techniques, the proposed model effectively detects subtle manipulation artifacts while reducing false classifications.

The findings indicate that integrating visual and metadata-based forensic evidence provides a reliable and scalable solution for deepfake image authentication, making the framework suitable for applications in digital forensics, misinformation detection, cyber security, and trustworthy AI-enabled multimedia systems.

Future Scope

Future research can extend the proposed framework by incorporating diffusion model-generated images, multimodal AI-generated content (images, videos, and audio), and Explainable Artificial Intelligence (XAI) techniques to improve model transparency and interpretability. The framework may also be enhanced using federated learning, blockchain-based image authentication, and lightweight transformer architectures for secure, privacy-preserving, and real-time deepfake detection on mobile and edge devices. Furthermore, evaluating the proposed model on larger and more diverse real-world datasets will improve its scalability, robustness, and practical deployment across digital forensic and cybersecurity applications.

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