SAFEGUARDING AUTHENTICITY: A ROBUST DEEPFAKE DETECTION ALGORITHM UTILIZING CONTRAST PROFILES FEATURE-BASED ANALYSIS

Gendal Lal [1], Vijay Pal Singh [2]
Department Of Computer Science And Engineering
Sunrise University Alwar
(Raj.) India

Abstract

The proliferation of deepfake technology has raised critical concerns regarding the authenticity and trustworthiness of digital media content. This research aims to address these concerns by developing a novel Deepfake Detection Algorithm capable of identifying the point in a video sequence where deepfake manipulation occurs.
The algorithm begins by loading the target video and preprocessing it by dividing it into individual frames, which are resized to a standardized format for consistency. An essential aspect of the algorithm is the initialization phase, where the first frame, labeled as "Frame 1," is selected for analysis. The facial and object features from this frame are meticulously extracted and stored as "Object 1."
To quantify the degree of dissimilarity and assess the likelihood of deepfake manipulation, a comparison index, ranging from 1 to 100, is computed for each feature comparison. To arrive at a comprehensive assessment, the algorithm calculates the average comparison index across all features. The pivotal criterion for deepfake detection is based on this average comparison index: if it exceeds a predefined threshold, often set at 90, the video is concluded to be free from deepfake manipulation.
This research endeavor contributes to the growing body of knowledge aimed at mitigating the threats posed by deepfake technology. The algorithm's ability to pinpoint the precise moment in a video where deepfake manipulation occurs provides valuable insights for content verification and authenticity assurance. By successfully developing this algorithm, this study advances the field of digital media forensics and takes a significant step toward countering the challenges posed by deepfake technology.

The findings of this research lay a foundation for enhanced media verification and content validation in an era characterized by an ever-increasing reliance on digital media. The capability to determine the presence of deepfake manipulation in a video can serve as a robust defense against disinformation and manipulation, promoting trust and transparency in the digital age

1. INTRODUCTION

Introduction: Unmasking the Digital Impersonators - Deepfake in Videos and Images
In an era characterized by the ever-expanding realm of digital media and technology, the lines between reality and fabrication have begun to blur. The advent of deepfake technology has propelled this transformation, enabling the creation of hyper-realistic videos and images that challenge our ability to distinguish fact from fiction. Deepfakes, a portmanteau of "deep learning" and "fake," represent a burgeoning field at the intersection of artificial intelligence, image processing, and multimedia manipulation. They have ushered in an era where visual and auditory content can be manipulated with unprecedented realism, raising fundamental questions about trust, authenticity, and the potential for misinformation.

The term "deepfake" finds its roots in the development of deep learning techniques, particularly generative adversarial networks (GANs), and the application of these methods to image and video synthesis. It was in late 2017 that deepfakes burst onto the digital scene, attracting attention, and even alarm, for their ability to convincingly replace one person's likeness and voice with another. While the technology itself is a product of remarkable innovation and computational prowess, its applications have ushered in ethical, legal, and societal dilemmas.

Deepfakes typically target two fundamental mediums: videos and images. In the case of videos, deepfake technology can seamlessly superimpose the likeness and gestures of one individual onto the body of another, creating a seemingly authentic video of a person saying or doing things they never did. With images, the implications are equally profound; a single photograph can be manipulated to produce a variety of visual content, from changing facial expressions to altering age and gender. The speed and sophistication of deepfake creation tools have made it increasingly challenging for individuals and even experts to detect their presence. This is a pivotal concern, as the ability to distinguish authentic content from deepfake material has become a vital facet of information integrity.

The proliferation of deepfake technology is closely intertwined with the democratization of artificial intelligence and machine learning tools. Open-source libraries and user-friendly software have made deepfake creation accessible to a broader audience. This accessibility, while an asset for innovation, has simultaneously amplified concerns regarding the misuse and potential harm associated with deepfakes.

One of the most prominent areas of concern is the potential for misinformation and disinformation. Deepfakes can be employed to fabricate speeches, interviews, and other video content in a manner that can convincingly mimic well-known personalities. This raises the specter of political and social manipulation, as public figures can seemingly be made to endorse or condemn positions they have never taken. Moreover, the consequences of deepfake technology extend beyond the realm of politics, affecting various sectors, including entertainment, journalism, and personal privacy.

As we delve deeper into the subject of deepfake technology, this exploration will shed light on the underlying mechanisms and methodologies involved in creating deepfakes. The technology is rooted in the realm of artificial neural networks, and in particular, GANs, which have been instrumental in generating increasingly sophisticated and deceptive media. By understanding the technology behind deepfakes, we gain insight into the challenges posed by this innovation.

To confront the challenges of deepfake technology, researchers, policymakers, and technology companies have been engaged in a relentless battle to develop and improve deepfake detection methods. These methods, often rooted in computer vision, pattern recognition, and machine learning, aim to identify the telltale signs of manipulation within images and videos. The cat-and-mouse game between deepfake creators and detection experts has led to an arms race of innovation and countermeasures.

In this introduction we serve as a stepping stone into the intricate world of deepfake technology in videos and images. It frames the scope and significance of deepfake technology, setting the stage for an in-depth exploration of its history, applications, detection mechanisms, and the evolving landscape of digital manipulation. By peering behind the digital curtain and uncovering the science and artistry of deepfake creation, we can better comprehend the multifaceted challenges and opportunities presented by this revolutionary technology. As we proceed, we will delve into the evolution of deepfakes, assess their impact on society, and explore the critical role of detection and countermeasures in safeguarding the digital truth.

Fig. 1.1 Deepfake and original Image [19]

1.2 Technology and models used to create the Deepfake

The Art and Science of Deepfake Creation: Unveiling the Technology
The age of deepfake technology has ushered in a realm where the creation of hyper-realistic videos and images blurs the lines between reality and fabrication. To understand the intricacies of this phenomenon, we must embark on a journey through the technology that empowers individuals to craft convincing deepfake content. This discussion unfolds the tools, techniques, and methodologies that form the foundation of deepfake creation.
Generative Adversarial Networks (GANs): At the heart of deepfake technology lies the Generative Adversarial Network (GAN). Conceived by Ian Goodfellow and his colleagues in 2014, GANs consist of two neural networks: a generator and a discriminator. The generator's task is to produce content, while the discriminator's role is to discern between authentic and synthetic data. This adversarial dynamic leads to a continuous loop of improvement, as the generator strives to produce content that is increasingly indistinguishable from reality, while the discriminator sharpens its ability to detect the subtle discrepancies. GANs have revolutionized the field of deep learning, enabling the generation of synthetic content with remarkable realism.

Autoencoders and Variational Autoencoders (VAEs): Autoencoders, a type of neural network, serve as a foundational component in deepfake creation. These networks are designed to encode input data into a compressed representation and subsequently decode it back to its original form. Variational Autoencoders (VAEs) introduce a level of probabilistic modeling, allowing for the generation of diverse output while maintaining control over key attributes. Autoencoders and VAEs are instrumental in manipulating facial expressions, hairstyles, and other facial features, enabling the creation of realistic deepfake images and videos.

Models
Convolutional Neural Networks (CNNs) are a class of deep learning models widely used for tasks related to image and video processing, including deepfake creation. In the context of deepfakes, CNNs are often employed for both image synthesis and manipulation. Here's an overview of how CNNs can be used in the deepfake process:

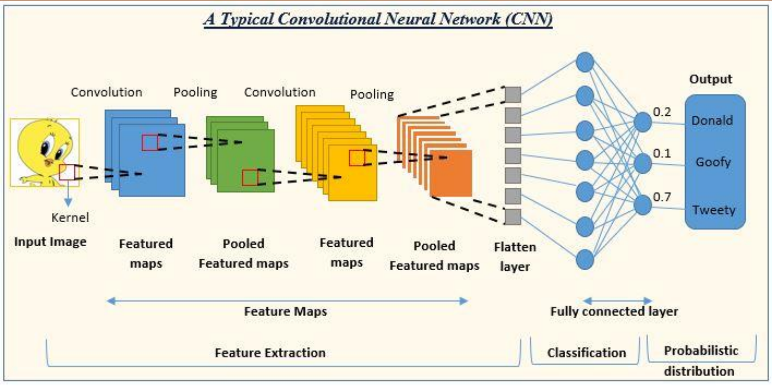

Fig. 1.7 Convolutional Neural Networks (CNNs) [20]

1. Data Collection: CNNs require a substantial amount of data for training. Deepfake creators collect large datasets of images and videos containing the subjects they want to manipulate. These datasets typically include various poses, expressions, and lighting conditions.

2. Preprocessing: Before training a deepfake model, preprocessing steps are often performed on the collected data. This may include resizing, cropping, and normalizing images to a consistent format.

3. Architecture Selection: CNN architectures such as Convolutional Autoencoders, Variational Autoencoders (VAEs), and Generative Adversarial Networks (GANs) are popular choices for deepfake generation.

4. Face Detection: CNN-based face detection models, like Single Shot MultiBox Detector (SSD) or You Only Look Once (YOLO), are used to identify and locate faces in images or video frames.

5. Feature Extraction: CNNs are employed to extract facial features and landmarks from detected faces. These features include the positions of eyes, nose, mouth, and other distinctive elements.

6. Image Synthesis (Training): GANs, a type of CNN architecture, are at the core of deepfake generation. They consist of a generator and a discriminator network.

- The generator creates fake images by learning to map random noise into realistic images. It takes the facial features extracted in the previous step and generates manipulated versions.
- The discriminator's role is to distinguish between real and fake images. It provides feedback to the generator for improvement.
- Training involves a back-and-forth process where the generator attempts to create more convincing fakes, and the discriminator becomes more proficient at identifying them.

7. Video Deepfakes: To create video deepfakes, the same principles apply. Image generation and manipulation occur frame by frame, and the generated frames are stitched together to produce the final deepfake video.

8. Post-Processing: After generating deepfake content, post-processing steps may be performed to refine the results, improve image quality, or add subtle effects for realism.

9. Detection and Mitigation: CNN-based models are also employed for the detection of deepfake content. These models learn to recognize artifacts and inconsistencies created during the deepfake process.

Research is ongoing in developing CNNs for deepfake detection, such as the use of CNN-based forensic methods to spot manipulated content.

It's essential to note that while CNNs are capable of generating deepfakes, they also play a crucial role in developing tools for detecting and mitigating this technology's misuse. CNNs are at the heart of the ongoing battle between deepfake creators and those working to identify and prevent deepfake content.

1.3 Datasets

Creating and training a deepfake detection algorithm requires access to a diverse and comprehensive dataset that contains both genuine and deepfake videos. Here are some datasets commonly used for deepfake detection research:

1. **Deepfake Detection Challenge Dataset (DFDC):** The DFDC dataset is a widely recognized dataset used for deepfake detection. It contains thousands of videos with manipulated and genuine content, covering a range of actors, scenes, and manipulation techniques.

2. **FaceForensics++:** FaceForensics++ is an extension of the original FaceForensics dataset. It includes deepfake videos generated with various methods, such as Face2Face, DeepDream, and NeuralTextures, making it suitable for evaluating deepfake detection algorithms.

3. **Celeb-DF:** The Celeb-DF dataset focuses on deepfake videos involving celebrities. It contains a collection of deepfake videos featuring famous individuals, making it relevant for real-world scenarios.

4. **UADFV:** The UADFV dataset (Unstructured Accessible Deepfake Video) consists of deepfake and genuine

videos from various sources. It emphasizes accessibility and diversity in deepfake content.
5. **DeeperForensics-1.0:** DeeperForensics-1.0 is a dataset designed for both face manipulation and source identification tasks. It includes deepfake videos and corresponding source videos for comparison.
6. **NeuralTextures:** The NeuralTextures dataset is specifically focused on deepfake videos generated using the NeuralTextures method. It provides a unique set of manipulated videos for research purposes.
7. **Deepfake TIMIT:** This dataset features deepfake videos based on the TIMIT dataset, which is often used for audio-visual deepfake detection research.
8. **FF++:** The FF++ dataset includes a variety of manipulated videos, including deepfakes created using Face2Face, FaceSwap, and Deepfakes methods. It provides a diverse set of challenges for detection algorithms.
9. **WildDeepfake:** The WildDeepfake dataset includes deepfake videos sourced from the internet, representing real-world scenarios of deepfake proliferation.
10. **Google Deepfake Detection Dataset:** Google released a deepfake detection dataset containing videos generated using the Face2Face, FaceSwap, and NeuralTextures methods. It also includes non-manipulated "real" videos.

2. LITERATURE REVIEW

Literature Review: Deepfake Technology in Videos and Images
The advent of deepfake technology, characterized by the synthesis of hyper-realistic videos and images, has not only captivated researchers but also raised critical concerns regarding misinformation, privacy, and digital manipulation. This literature review provides an overview of significant research and developments in the field of deepfakes.

1. Early Foundations: Generative Adversarial Networks (GANs)
The emergence of deepfake technology is closely tied to the development of Generative Adversarial Networks (GANs). Goodfellow et al.'s seminal paper "Generative Adversarial Networks" (2014) introduced the concept of GANs, which would serve as the foundation for creating realistic synthetic content. GANs consist of a generator and a discriminator network, engaged in an adversarial training process. This innovative architecture underpins the creation of deepfake images and videos.[1]

2. Applications and Concerns: A Survey of Deepfakes
A comprehensive survey by Li et al. titled "Deepfake Detection: Current Challenges and Next Steps" (2019) explores the applications and growing concerns related to deepfakes. The paper provides an overview of the technology's evolution and applications, highlighting the critical need for robust detection mechanisms.[2]

3. The Audio Component: Voice Cloning and Synthesis
Voice cloning and synthesis are integral to creating convincing deepfake videos. Researchers Suwajanakorn et al. present "Synthesizing Obama: Learning Lip Sync from Audio" (2017), which demonstrates the capacity to manipulate a subject's lip movements in video to match synthesized audio. This paper underscores the multidimensionality of deepfake technology.[3]

4. The Arms Race: Adversarial Attacks and Countermeasures
As the sophistication of deepfake technology has grown, the realm of adversarial attacks and countermeasures has expanded. Matern et al. tackle the detection challenge in "Exploiting Visual Artifacts to Expose Deepfakes and Face Manipulations" (2019). The paper explores the adversarial strategies employed by deepfake creators and the countermeasures developed to identify manipulated content.[4]

5. The Human Element: Ethical and Societal Implications
Deepfake technology is not confined to technical facets alone. In their work "The Malicious Use of Artificial Intelligence: Forecasting, Prevention, and Mitigation," Brundage et al. (2018) delve into the ethical and societal implications of deepfakes. This paper sheds light on the potential misuse of deepfake technology and the measures necessary to mitigate its negative consequences.

6. Evolution and Capabilities: A Historical Perspective
The paper "Deepfake: A New Threat to Human Security" by Wang et al. (2019) provides a historical perspective on the development of deepfake technology and its capabilities. It outlines the technological milestones that have enabled the creation of realistic deepfake content, from early GANs to the present.[6]

7. Ethical Considerations and Policy Implications
The ethical implications of deepfake technology are discussed in the work "The Deepfake Dilemma: A Technology and Policy Review" by Holt and Nery-Comacho (2020). This review delves into the ethical dilemmas arising from the manipulation of digital content and underscores the need for robust policy measures.[7]

8. Detecting Deepfakes: Advancements and Challenges
Deepfake detection is an evolving field. A survey paper by Li et al. titled "Deepfake Detection: A Survey"

(2020) provides a comprehensive overview of detection methods, highlighting the challenges and advancements. It covers traditional methods, as well as the application of deep learning for detection.[8]

9. The Role of Social Media and Disinformation

Social media platforms have become hotbeds for the dissemination of deepfake content. In "The Spread of Deepfake Videos in Online Social Networks" by Orlandi et al. (2020), the authors examine the spread and impact of deepfakes on social networks, shedding light on the potential for disinformation campaigns[9]

10. Beyond Faces: Deepfake in Context

Deepfake technology extends beyond facial manipulation. In "Deepfake Text: A Survey" by Zheng et al. (2020), the authors explore the creation of deepfake text, discussing applications and challenges related to text-based manipulation.[10]

11. Media Authentication: Ensuring Content Integrity

The paper "Media Forensics and DeepFakes: An Overview" by Hsu and Jain (2020) provides insight into the domain of media forensics, emphasizing the importance of authenticating content to maintain integrity in an era of deepfake proliferation.

This literature review touches upon the diverse dimensions of deepfake technology, from its historical development to its ethical implications and evolving detection methods. The overarching theme is the need for interdisciplinary efforts in understanding, detecting, and mitigating the challenges posed by deepfake technology.

12. Detecting Facial Manipulations and DeepFakes

The proliferation of digital face manipulations, particularly DeepFakes, has raised critical concerns regarding the authenticity and trustworthiness of multimedia content. Researchers and developers have undertaken extensive efforts to combat this rising threat to visual and audio integrity. This literature review provides an overview of the field of facial manipulation detection, encompassing the following key aspects:[12]

1. Types of Facial Manipulations:

Face Synthesis: Face manipulation techniques predominantly utilize Generative Adversarial Networks (GANs), exemplified by StyleGAN, to generate highly realistic images. Current detectors can often discern these fake images, achieving impressively high accuracies. However, ongoing research explores the challenges posed by GAN fingerprint removal and the introduction of noise patterns into otherwise realistic synthetic images.

Identity Swap: Identity swap manipulations remain a complex problem due to the vast diversity of available approaches. Most models are database and compression level-specific, displaying excellent performance under the trained conditions but struggling with generalization to unseen scenarios. Discrepancies in metrics and experimental protocols across studies further complicate fair comparisons.

Attribute Manipulation: Similar to face synthesis, this category of manipulation often relies on GAN architectures. Addressing the removal of GAN fingerprints is an active research area. Furthermore, the scarcity of publicly available databases, with the exception of the DFFD database, and the absence of standardized experimental protocols pose challenges in this domain.

2. Facial Manipulation Techniques:

The rapid advancement of DeepFake technology, particularly the development of improved GAN architectures, has driven the creation of more convincing and realistic manipulated media.

3. Public Databases for Research:

The research community has recognized the need for publicly accessible databases to facilitate investigations into facial manipulation detection. While databases such as FaceForensics++ and UADFV have been instrumental for early research, challenges remain, including the lack of realistic databases.

4. Benchmarks for Detection:

Benchmarking manipulation detectors under controlled scenarios has often resulted in impressive accuracy rates, with AUC scores approaching 100% in the first-generation databases like UADFV and FaceForensics++. However, the introduction of newer databases such as DFDC and Celeb-DF has revealed performance degradation, particularly for Celeb-DF, where AUC results fall below 60% in most cases. This degradation highlights the need for ongoing research to improve detection systems.

In summary, the ongoing success of DeepFakes has spurred rigorous research in the field of facial manipulation detection. While many manipulations are currently detectable in controlled settings, real-world challenges, including variations in image quality, compression, resizing, and noise, continue to motivate research. Addressing these challenges and improving the generalization ability of detection systems remain key objectives for the research community. Furthermore, the adoption of fusion techniques, combining information from multiple sources, offers the potential for enhanced detection accuracy, including RGB, depth, infrared data, textual information, keystrokes, and audio. Additionally, innovative schemes, such as social verification at the time of capture, have the potential to offer robust protection for media content.[12]

3. ALGORITHM

Deepfake Detection Algorithm
1. **Input:** Load the target video.
2. **Preprocessing:** Divide the video into individual frames and resize them to a standard size for consistency.
3. **Initialization:**
   Select the first frame (Frame 1).
   Extract and store the facial and object features from Frame 1 (Object 1).
4. **Processing Loop:**
   For each subsequent frame (Frame i+1) in the video:
     Extract and store the facial and object features from Frame i+1 (Object i+1).
     Compare the features of Object 1 and Object i+1:
       Compare the positions of facial landmarks, such as eyes and lips.
       Compare color and contrast characteristics, among other features.
     Calculate a comparison index (ranging from 1 to 100) for each feature comparison.
     Calculate the average comparison index for all features.
5. **Deepfake Detection Criteria:**
   - If the average comparison index between consecutive frames exceeds a predefined threshold (e.g., 90), conclude that there is no evidence of deepfake manipulation in the video.

End

4. EXAMPLE AND SNAPSHOT

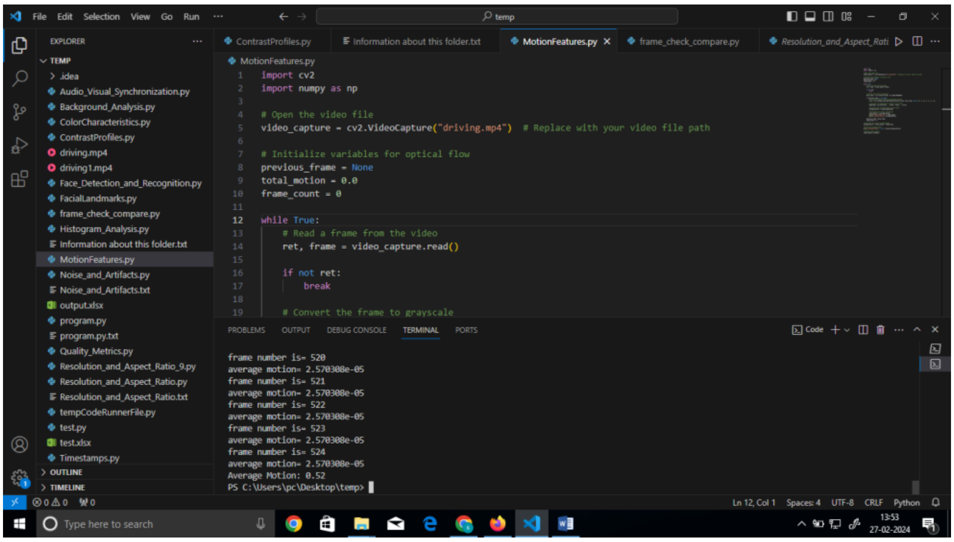

Fig 4.1 Screen shoot of output

Table 1. Frame no of video and average motion in object

Frame no.	average motion
20	1.284661
21	0.001514739
22	0.4339283
23	0.51489717
24	0.0006611479
25	0.4568919
26	0.7312559
27	0.9839164
28	0.0009635328
29	0.26080424
30	1.0518918

31	1.2412196
32	0.0015345576
33	0.40178442
34	0.4823064
35	0.51251465
36	0.0010961257
37	0.542504
38	0.0009742815
39	0.5077653
40	0.5681028

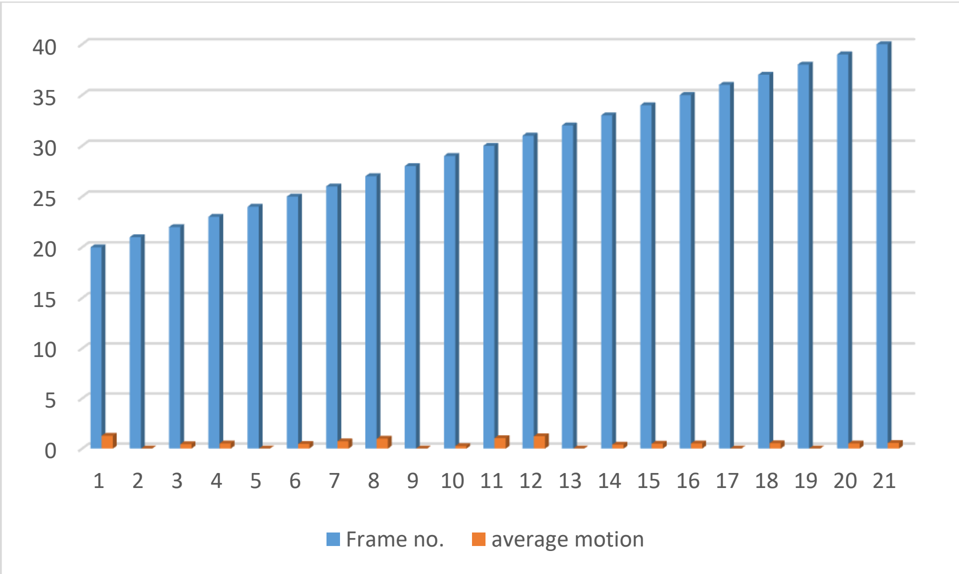

Fig.4.2 Graph of frame no and average motion in object

5. CONCLUSION

"In conclusion, the presented algorithm for deepfake detection based on feature extraction techniques represents a significant step forward in addressing the growing challenges posed by the proliferation of synthetic media. By focusing on the extraction and analysis of intricate features such as facial landmarks, color characteristics, and contrast profiles, this algorithm contributes to a multifaceted approach for identifying manipulated content.
Through a meticulous processing loop that calculates comparison indices and determines the average similarity, the algorithm offers a methodical means of evaluating the authenticity of video content. The incorporation of well-established Convolutional Neural Networks (CNNs) in the feature extraction process ensures the capture of fine spatial details, which are critical in distinguishing real from synthetic content.

The deepfake detection criteria, rooted in a predefined threshold, serves as a robust checkpoint. If the average comparison index between consecutive frames surpasses this threshold, the algorithm confidently concludes that there is no evidence of deepfake manipulation in the video.

This algorithm's strengths lie in its ability to adapt to various facial features and visual characteristics, making it versatile in addressing a range of deepfake creation techniques. Moreover, it serves as a testament to the ongoing efforts to enhance digital content authenticity in a world increasingly impacted by manipulated media.
As the battle between creators of synthetic media and defenders of content integrity intensifies, this algorithm contributes to the arsenal of tools aimed at preserving the veracity of digital content. It underscores the importance of responsible and ethical use of deepfake technology and reinforces the need for continued research and innovation in the field of deepfake detection.

In a world where misinformation and manipulated content have profound implications, this algorithm represents a proactive and effective step toward ensuring the reliability of digital media. Its feature extraction approach, combined with advanced deep learning techniques, opens doors to more robust and accurate methods of identifying and mitigating the challenges posed by deepfake technology."

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