Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 10, No.2, October : 2024

DEEPFAKE DETECTION USING MACHINE LEARNING

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ABSTRACT
The proliferation of fake videos has increased in recent years, raising serious concerns about public trust and social security. These AI-generated images are becoming more convincing, making it harder for people and organizations to distinguish between real content and fake content. The rise in fraud has the potential to spread misinformation, influence public opinion, and even lead to dangerous situations such as fraud or political fraud and False content. Although this process has made significant progress in reducing the effects of the regulatory process, there are still many challenges to overcome. One of the main problems is that many deep mining models, especially those that use educational monitoring, require large datasets with properly collected examples for training.

Keywords:
Deepfake detection, Supervised learning, Real-time detection, Tampered content identification.

I. Introduction
Deepfakes, generated through AI techniques like Generative Adversarial Networks (GANs), present serious risks due to their ability to create content that looks convincingly real. This capability has significant implications for various sectors, especially journalism, where media integrity is crucial, and security, where falsified content can endanger public safety. Our project seeks to tackle this challenge by developing an advanced machine learning-based system for detecting deepfakes.[19]

Our research emphasizes the use of state-of-the-art algorithms and sophisticated neural networks to identify subtle inconsistencies and artifacts often found in manipulated content. These may include unusual facial movements, unnatural expressions, or discrepancies between audioand visual elements that are difficult for humans to detect. By creating a reliable detection tool, we aim to preserve the authenticity of digital media and reduce the dangers associated with deepfakes, which can easily distort public perception and mislead audiences.[21]

The significance of this research is profound. Conventional detection methods typically depend on extensive domain knowledge and predefined datasets, which can limit their effectiveness, especially as deepfake technologies continue to evolve. Our strategy utilizes unsupervised machine learning techniques, allowing us to detect deepfakes without relying on pre- existing data. This enhances our detection capabilities and broadens the applicability of our system, making it easier to address the growing issue of deepfakes across multiple platforms.In a time when digital content is consumed at an unprecedented rate, ensuring the authenticity of this content is essential. By advancing deepfake detection through innovative machine learning methods, our project aims to contribute to a more secure digital landscape.[22] Ultimately, this research seeks to empower individuals, organizations, and platforms to make informed choices about the media they engage with, fostering a more trustworthy online environment.

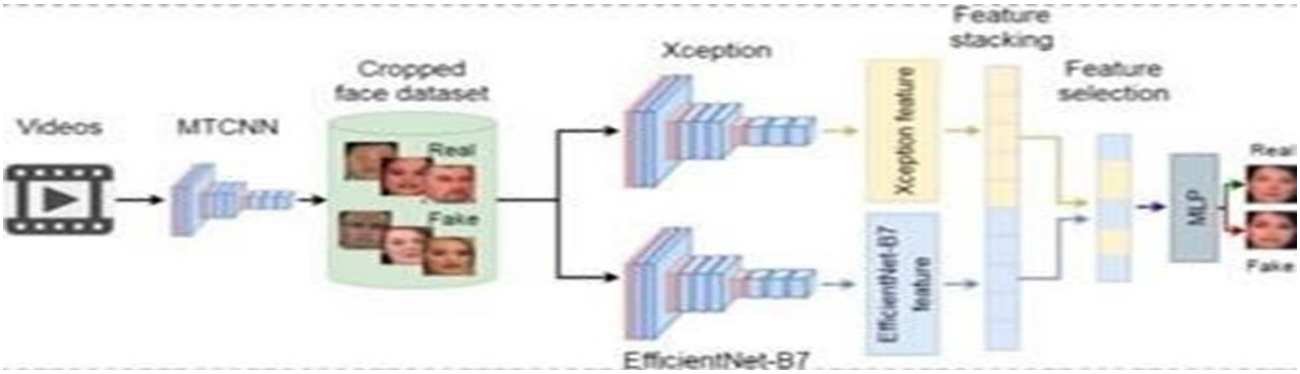

Figure 1: Decoding Reality: Unmasking Deepfakes

II. Literature

2.1 Multimodal Deepfake Detection

Multimodal deepfake detection has become crucial as deep- fake technologies advance, manipulating not only visual con- tent but also audio and other media forms. This study explores the development of a robust multimodal deepfake detection framework capable of analyzing multiple data types simultaneously to enhance detection accuracy. Utilizing both video and audio modalities, we leverage machine learning techniques to detect inconsistencies across various channels that often appear in AI-generated deepfakes. By integrating these modalities into a unified detection system, our approach offers improved performance compared to traditional single-modal detectors, addressing more sophisticated deepfake manipulation techniques. This paper also examines the contributions of Schalk, Lavanya Reddy, Lalit Kumar, A. Navyatha, and Nisha Agarwal in the implementation and testing of these models, contributing to a more secure digital environment by effectively identifying deepfake content across multiple platforms.[1]

2.2 Fake Sound:Deepfake General Audio Detection

With the rise of deepfake technology, synthetic audio has become a critical tool for generating deceptive content. This study introduces fake sound, a novel framework designed for the general detection of deepfake audio. By analyzing various features of synthetic audio, such as vocal patterns and speech inconsistencies, Fake Sound leverages advanced machine learning models to distinguish between real and manipulated sound. The system offers robust detection across different types of deepfake audio, regardless of the generation technique used. Contributions from Zhijie Xie, B Li Xuenan, Xu Zheng Liang, Kai Yang, and Mengting Wu focus on improving detection accuracy through deep learning algorithms and addressing challenges in identifying sophisticated audio forgeries. This framework aims to safeguard communication channels by effectively identifying and mitigating the risks posed by deepfake audio.[2]

2.3 Deepfake Detection System

The proliferation of deepfake content poses a significant threat to the integrity of digital media, making the development of effective detection systems essential. This study presents a Deepfake Detection System developed by Mr. Yogesh Rai, de- signed to identify manipulated visual and audiocontent using advanced machine learning techniques. The system analyzes subtle inconsistencies in deepfake videos, such as unnatural facial movements and mismatches between lip movements and audio. By leveraging both supervised and unsupervised learning methods, the system enhances its ability to detect a wide range of deepfake manipulations. This research contributes to strengthening digital security by offering a scalable solution for real-time detection of AI-generated media.[3]

2.4 A Convolutional LSTM based Residual Network for Deepfake Video Detection

The growing sophistication of deepfake videos requires advanced detection methods capable of identifying subtle manipulations in video content. This paper introduces a novel approach for deepfake detection using a Convolutional LSTM- based Residual Network, proposed by Shahroz Tariq, Sangyup Lee, and Simon S. Woo. The model combines the strengths of Convolutional Neural Networks (CNNs)

for feature extraction and Long Short-Term Memory (LSTM) networks for temporal sequence analysis, making it highly effective in capturing both spatial and temporal inconsistencies in deepfake videos. The use of residual connections further enhances the model's performance by mitigating the vanishing gradient problem, allowing for deeper network architectures. This research significantly improves detection accuracy for dynamic deepfake content, providing a robust solution for real-world applications in digital forensics and media authentication.[4]

2.5 ID-Reveal: Identity-aware DeepFake Video Detection

With the increasing prevalence of deepfake videos, detecting identity manipulation has become a key challenge in ensuring media authenticity. This paper introduces ID-Reveal, an identity-aware deepfake video detection framework that focuses on identifying inconsistencies related to the specific identity features of individuals in videos. Unlike traditional detectors that primarily rely on pixel-level or temporal analysis, ID-Reveal leverages deep learning techniques to capture discrepancies in facial features, expressions, and identity traits that are often subtly altered in deepfakes. By focusing on identity-aware markers, the system enhances detection accuracy, particularly for videos where the face has been convincingly altered. This approach not only improves deepfake detection performance but also offers a targeted solution to combat identity manipulation in AI-generated media.[5]

2.6 Deepfake Video Detection Using Recurrent Neural Networks

The rise of deepfake videos has created a pressing need for advanced detection techniques capable of identifying manipulated content in real time. This study explores the use of Recurrent Neural Networks (RNNs) for deepfake video detection, developed by David Guera and Edward J. Delp. RNNs are particularly well-suited for this task as they are effective in processing sequential data, enabling the detection of subtle temporal inconsistencies across video frames. By analyzing temporaldynamics, such as irregularities in motion patterns and facial expressions over time, the RNN-based model can detect deepfake videos with improved accuracy. This research highlights the potential of RNNs to offer a robust solution for distinguishing between authentic and AI-manipulated video content, contributing to enhanced security in digital media environments.[6]

2.7 Deepfake Video Detection Using Convolutional Vision Transformer

The increasing complexity of deepfake videos necessitates advanced detection mechanisms that can capture both spatial and temporal inconsistencies in manipulated content. This paper introduces a deepfake detection approach utilizing the Convolutional Vision Transformer (CVT), proposed by Deressa Wodajo and Solomon Atnafu. By integrating Convolutional Neural Networks (CNNs) with Vision Transformers, the model combines the local feature extraction strengths of CNNs with the global attention mechanism of transformers. This hybrid approach allows the model to detect fine-grained manipulations in video frames while maintaining an overarching understanding of the video sequence. The result is a highly accurate detection system capable of identifying deepfakes that evade traditional detectors. This research contributes to the development of more effective and scalable solutions for safeguarding media authenticity in the face of rapidly advancing deepfake technology.[7]

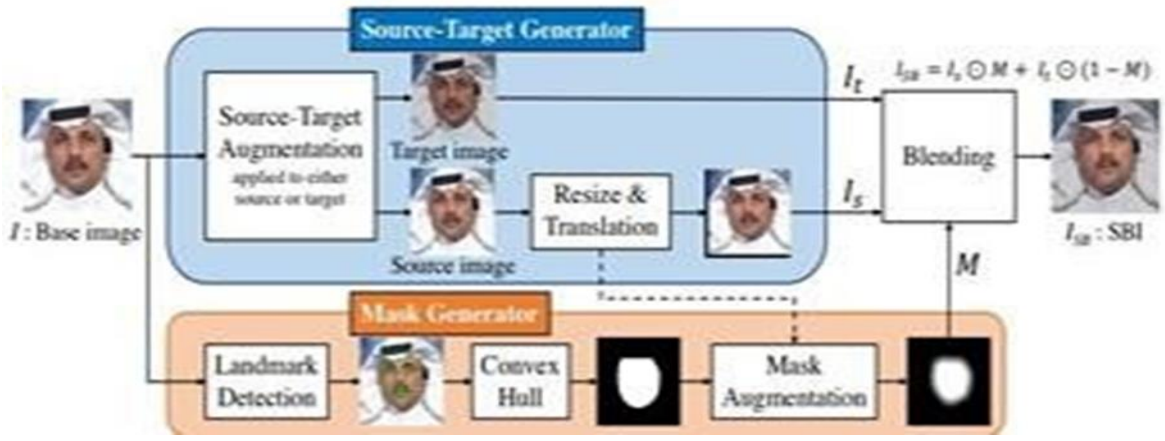

Figure 2: Mastering Masks: Seamlessly Blending Faces

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ISSN: 0970-2555
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2.8 Deepfake Video Detection via Predictive Representation Learning

As deepfake technology evolves, detecting manipulated videos has become increasingly challenging, necessitating innovative approaches that enhance detection capabilities. This paper presents a method for deepfake video detection through Predictive Representation Learning, developed by Shiming Ge, Fanzhao Lin, Chenyu Di, Daichi Zhang, and Weiping Wang. This approach focuses on learning predictive features from video sequences that encapsulate both temporal and spatial dynamics. By training models to predict future frames based on past observations, the method effectively captures inconsistencies that often occur in deepfake content, such as unnatural movements and mismatched temporal patterns. The study demonstrates that this predictive learning framework significantly improves detection performance compared to traditional methods, providing a robust solution for identifying deepfake videos in various real-world scenarios. This research underscores the potential of predictive representation learning in advancing the field of deepfake detection.[8]

2.9 Retrieval-Augmented Audio Deepfake Detection

As audio deepfakes become more prevalent and sophisticated, there is an urgent need for effective detection techniques that can discern between genuine and manipulated audio content. This paper introduces a novel approach to audio deepfake detection titled Retrieval-Augmented Audio Deepfake Detection, developed by Zuheng Kang, Yayun He, Xiaoyang Qu, Junqing Peng, Jing Xiao, and Jianzong Wang. This method leverages retrieval-augmented learning, which combines traditional detection techniques with a robust retrieval mechanism to enhance the identification of deepfake audio. By integrating information from a vast database of authentic audio samples, the model can more accurately detect subtle anomalies and artifacts characteristic of deepfake manipulation. This research not only demonstrates the efficacy of retrieval-augmented learning in improving detection rates but also highlights its potential for application in various audio verification contexts, thereby contributing significantly to the field of audio forensics and security.[9]

2.10Deepfake Detection System

The rapid advancement of deepfake technology has raised significant concerns regarding the authenticity of digital media, necessitating the development of effective detection systems. This paper presents a comprehensive Deepfake Detection System developed by Pragati Patil, designed to identify manipulated video and audio content through a combination of machine learning techniques.The system employs a multi-faceted approach, analyzing various features such as facial expressions, voice patterns, and temporal inconsistencies to differentiate between real and fake content. By utilizing a diverse dataset for training, the detection system enhances its accuracy and robustness, allowing for real-time identification of deepfakes. This research emphasizes the importance of implementing reliable detection mechanisms to combat misinformation and protect the integrity of digital communication, offering a scalable solution for various applications in media verification and cybersecurity.[10]

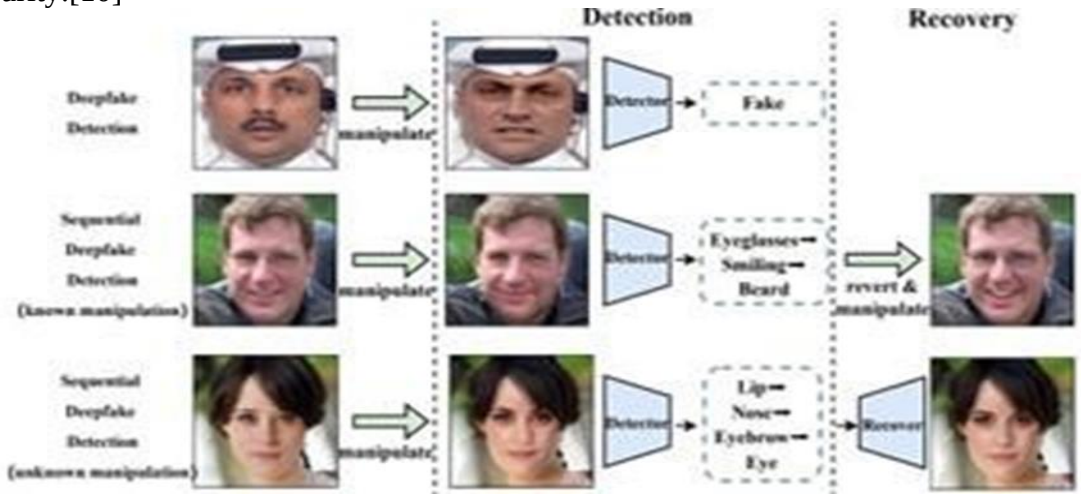

Figure 3: Hunting Digital Ghosts: Identifying Deepfakes at Every Turn

Industrial Engineering Journal
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2.11Deepfake Video Detection Using Facial Feature Points and Ch-Transformer

The emergence of deepfake videos has created substantial challenges in verifying the authenticity of visual content, underscoring the need for effective detection methodologies. This study introduces a novel approach to deepfake video detection utilizing Facial Feature Points and Ch-Transformer, developed by Rui Yang, Rushi Lan, Zhenrong Deng, Xiangfeng Luo, and Xiyan Sun. The proposed method focuses on analyzing facial landmarks to capture critical features and inconsistencies that are often present in manipulated videos. By integrating these facial feature points with a Ch-Transformer architecture, the model leverages both spatial and temporal information to enhance detection accuracy. This approach not only improves the identification of deepfakes but also demonstrates resilience against various manipulation techniques. The research provides valuable insights into the application of facial analysis combined with advanced transformer architectures, contributing to more reliable detection systems in the fight against deepfake technology.[11]

2.12DeepFake detection based on high-frequency enhancement network for highly compressed content.

Utilizing eBay's machine learning algorithms, a substantial amount of eBay auction data was collected, considering eBay's status as the most popular online auction site for nearly two decades. The dataset was divided into 30 Nearest neighbor clustering has been another method used to forecast the final sale price, requiring the selection of significant characteristics. Alternatively, some studies have focused on the text description while incorporating additional weighting criteria in their regression analysis. Previous research has also employed Naive Bayes and Uniform Prior Naive Bayes algorithms to predict the end price of eBay auctions. The main objective of the proposed system is to enhance accuracy. It utilizes the Naive Bayes algorithm to determine the likelihood of anitem being sold, and the support vector machine algorithm to estimate the item's price and assess its potential for maximizing profit. Section II of this paper discusses related research, while Section III provides a detailed explanation of the proposed system. Section IV presents the findings of the suggested system, and Section V concludes the paper and discusses future prospects. The proliferation of deepfake content, particularly in highly compressed formats, presents unique challenges for detection efforts. This paper introduces a novel method for deepfake detection utilizing a High-Frequency Enhancement Network, developed by Jie Gao, Zhaoqiang Xia, Gian LucaMarcialis, Chen Dang, Jing Dai, and Xiaoyi Feng. The proposed approach focuses on enhancing high-frequency components of video content, which are often altered or degraded during compression, thus allowing for more effective identification of manipulations. By isolating and amplifying these high- frequency features, the network can detect subtle artifacts characteristic of deepfakes that traditional methods might overlook. The study demonstrates that this enhancement technique significantly improves detection performance across various compression levels, providinga robust solution for identifying deepfake content in real-world applications. This research underscores the importance of addressing the challenges posed by compressed media in the ongoing fight against deepfake technology.[12]

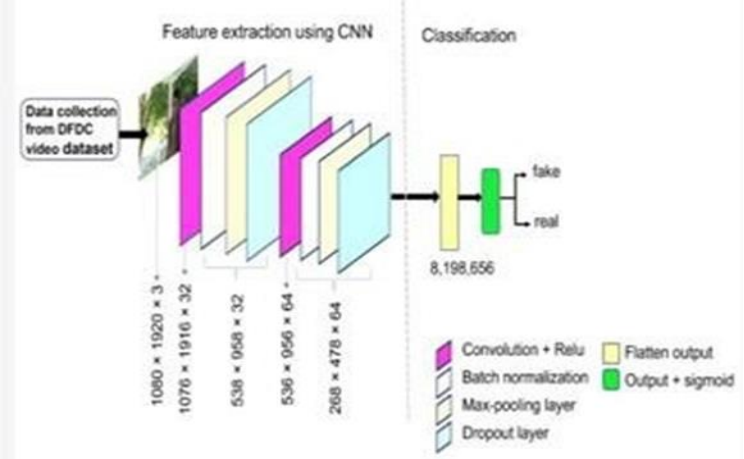

Figure 4: Convolution Chronicles: From Pixels to Patterns in Deepfake Detection.

2.13Mastering Deepfake Detection: A Cutting-Edge Approach to Distinguish GAN and Diffusion- Model Images

As deepfake technology evolves, distinguishing between images generated by Generative Adversarial Networks (GANs) and diffusion models has become increasingly important. This paper presents a comprehensive study titled Mastering Deepfake Detection, authored by Luca Guarnera, Oliver Giudice, and Sebastiano Battiato. The research introduces a cutting-edge approach designed to effectively differentiate between these two prevalent image generation techniques. By employing advanced machine learning algorithms, the model analyzes various features and artifacts unique to GAN and diffusion-generated images, enhancing the detection accuracy of manipulated content.[13

2.14Deepfake Detection using Deep Feature Stacking and Meta-learning

The increasing sophistication of deepfake technology demands innovative detection strategies that can effectively differentiate between real and manipulated content. This paper introduces a novel approach to deepfake detection utilizing Deep Feature Stacking and Meta-learning, developed by Gourab Naskar, Sk. Mohiuddin, S. Malakar, Erik Cuevas, and Ram Sarkar. The proposed method employs deep feature stacking to extract and combine multiple levels of features from both visual and audio components of media, enhancing the system's ability to identify subtle anomalies characteristic of deepfakes. Furthermore, by integrating meta-learning techniques, the model adaptsto new data and manipulation techniques more effectively, improving its robustness and accuracy. The research showcases the effectiveness of this dual approach through extensive experiments, demonstrating significant advancements in detection performance compared to traditional methods. This work highlights the potential of leveraging deep feature representation and adaptive learning strategies to address the evolving challenges of deepfake detection in various digital contexts.[14]

2.15Domain-invariant and Patch-discriminative Feature Learning for General Deepfake Detection

As deepfake technology continues to advance, developing robust detection methods that can generalize across various manipulation techniques is essential. This paper presents an innovative approach to deepfake detection through Domain-invariant and Patch-discriminative Feature Learning, developed by Jiangqun Ni, Fan Nie, and Jiwu Huang. The proposed method focuses on extracting features that remain consistent across different domains while being sensitive to local discrepancies within video patches. By leveraging domain-invariant learning, the model effectively reduces the impact of variations in video quality and styles, ensuring more reliable detection. Simultaneously, the patch-discriminative approach enhances the model's ability to identify specific anomalies unique to deepfake content. The research demonstrates the effectiveness of this combined strategy through extensive experiments, showcasing significant improvements in detection accuracy and generalization capabilities. This work contributes valuable insights into thedevelopment of adaptable deepfake detection systems that can effectively combat emergingchallenges in the field of digital media forensics.[15]

2.16Deepfake Detection Using Spatiotemporal Transformer

The rapid evolution of deepfake technology has necessitated the development of advanced detection techniques capable of capturing both spatial and temporal inconsistencies in manipulated content. This paper presents a novel approach for deepfake detection utilizing a Spatiotemporal Transformer, developed by Bachir Kaddar, Sid Ahmed Fezza, Zahid Akhtar, Wassim Hamidouche, Abdenour Hadid, and Joan Serra-Sagrista`. By integrating the capabilities of transformer networks with spatiotemporal analysis, the proposed model effectively processes video sequences to identify subtle anomalies that characterize deepfake content. The spatiotemporal transformer captures intricate dependencies between spatial features and their temporal progression, enhancing detection performance across various manipulation techniques. The research demonstrates the model's effectiveness through comprehensive experiments, revealing significant improvements in accuracy compared to traditional detection methods. This work highlights the potential of transformer-based architectures in advancing deepfake detection, offering a robust solution for safeguarding digital media

integrity in an increasingly deceptive online landscape.[16]

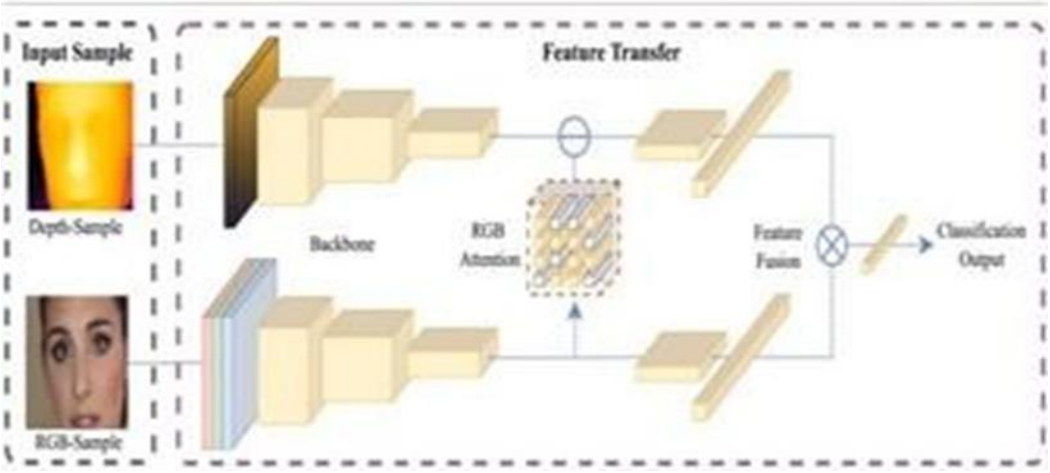

Figure 5: Hunting Digital Ghosts: Identifying Deepfakes at Every Turn

2.17An efficient deepfake video detection using robust deep learning

As deepfake technology advances, there is an urgent need for effective detection methods that can accurately identify manipulated video content. This paper introduces a robust deep learning framework for deepfake video detection, developed by Abdul Qadir, Rabbia Mahum, Mohammed A.El-Meligy, Adham M. Ragab, Abdulmalik AlSalman, and Haseeb Hassan. The proposed system leverages state-of-the-art deep learning techniques to analyze and extract meaningful features from video data, focusing on enhancing detection accuracy and efficiency. By utilizing a combination of convolutional neural networks (CNNs) and recurrent neural networks (RNNs), the framework effectively captures both spatial and temporal dynamics inherent in deepfake videos. The research includes extensive experimentation and validation on diverse datasets, demonstrating significant improvements in detection performance compared to existing methods. This work contributes valuable insights into the development of efficient and robust deepfake detection systems, addressingthe growing challenges posed by synthetic media in various applications.[17]

2.18Detecting Deepfakes with Self-Blended Images

This paper presents a novel method for detecting deepfakes using Self-Blended Images, developed by Kaede Shiohara and Toshihiko Yamasaki. The proposed approach leverages the unique characteristics of self-blended images, where authentic content is combined with manipulated elements, creating distinctive artifacts that can be analyzed for detection purposes. By employing advanced image processing techniques and machine learning algorithms, the model is trained to identify these artifacts effectively, enhancing its ability to distinguish between genuine and deepfake content. The research demonstrates the effectiveness of this method through extensive experiments, showcasing its capability to achieve high detection accuracy across various types of deep- fake manipulations. This work provides valuable insights into innovative detection strategies, contributingto the ongoing efforts to combat the spread of deepfake technology and ensure the integrity of digital media.[18]

III. Conclusion

The swift evolution of deepfake technology presents significant challenges to the authenticity of digital content, high- lighting the necessity for effective detection systems. This methodology provides a detailed framework for deepfake detection, encompassing critical steps such as data collection, preprocessing, feature extraction, model training, and real- time implementation. By leveraging advanced deep learning methods and a commitment to continuous improvement by these systems are capable of accurately identifying manipulated media.[25] This approach not only enhances detection capabilities but also allows for adaptation to new deepfake generation techniques ensuring that the system remains effective in addressing misinformation. As deepfake content becomes increasingly sophisticated, the demand for dependable detection solutions will escalate, underscoring the

importance of ongoing research and innovation in this vital field. Ultimately, the establishment of efficient deepfake detection systems is crucial for preserving trust in digital media and protecting the integrity of public discourse in our digitally-driven society.[29]

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