iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: IX Month of publication: September 2025

DOI: https://doi.org/10.22214/ijraset.2025.74208

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

A Survey on an Integrated Neural Framework for Real-Time Deepfake Detection across Multimedia to Mitigate Misleading Content

Shwetha A B[1], Sushmitha R N[2], S Sahana[3], Vyshnavi N[4], Thrisha M[5]
[1]*Assistant Professor, Dept. of CSE, Sapthagiri College of Engineering*
[2, 3, 4, 5]*Dept. of CSE, Sapthagiri College of Engineering*

Abstract: with the rapid proliferation of information across digital media, the assessment of information reliability has become increasingly critical for individuals and societies. Although the concept of deepfakes is not entirely novel, their widespread prevalence has emerged as pressing concern. The influence of deepfakes and disinformation extends from provoking individuals to shaping public opinion, misleading communities, and potentially impacting national stability. A variety of online techniques exits for both the detection and generation of deepfakes. This study, through a systematic literature review, examines automated detection and generation approaches, encompassing methods, frameworks, algorithms, and tools across multiple modalities (Audio, image and video). Furthermore, it explores the applicability of these approaches in diverse contexts to effectively counter the dissemination of deepfakes and propagation of disinformation. In this paper, a system is created that uses a Convolutional Neural Network (CNN) with EfficientNet and LSTM designs to pull out details from each frame. The Multi-Task Cascaded Convolutional Neural Network (MTCNN) algorithm is used for face detection and alignment in images. It utilizes a series of cascaded convolutional neural networks to efficiently locate faces and facial landmarks. Experimental analysis is performed using the DFDC deepfake detection challenge on Kaggle. These deep learning-based methods are optimized to increase accuracy and decrease training time by using this dataset for training and testing. This study concludes with policy recommendations derived from an analysis of advanced artificial intelligence (AI) methods for deepfake detection and generation in digital media. The review consolidates recent progress in detection and generation frameworks, providing a comprehensive overview of current capabilities. Furthermore, it highlights the potential of AI-driven approaches to improve detection accuracy and support regulatory measures aimed at mitigating the societal risks of deepfakes.
Keywords: Deep learning, Deepfakes, Detection and generation, Artificial Intelligence (AI), Policy recommendations, Literature review and Audio-Video analysis.

I. INTRODUCTION

Deepfakes are AI-generated media—including video, audio, and images—produced using deep learning algorithms to create realistic but falsified content [1]. Since their emergence in late 2019, their proliferation has accelerated, particularly during the COVID-19 pandemic [2]. Deepfake generation relies on large video and image datasets, making public figures frequent targets. Such content can be used to synthesize or replace faces in offensive media, inciting political and religious tensions, deceiving the public, influencing elections [3], [4], destabilizing financial markets through fabricated news, and even manipulating satellite imagery to mislead military operations [5].

A. Deep Learning for Deepfake Detection

Deep learning (DL), a subfield of machine learning, focuses on learning data representations through artificial neural networks with multiple layers. The fundamental unit of a neural network is the neuron, which processes inputs via weighted connections and activation functions to generate outputs. DL architectures include feedforward networks, recurrent neural networks (RNNs), convolutional neural networks (CNNs), among others. Owing to their ability to model complex data such as images and videos, DL methods are widely applied in deepfake detection [6]. Common approaches include the following.

1) Convolutional Neural Networks (CNNs)

CNNs are specialized neural networks designed to automatically extract features from input data by optimizing convolutional filters, reducing the need for manual feature engineering. As shown in Fig. 1, CNNs employ convolution and pooling layers to capture spatial hierarchies in data, leveraging linear algebra operations such as matrix multiplication. Due to their effectiveness in pattern recognition, CNNs are extensively applied in tasks such as fake image detection and object recognition.

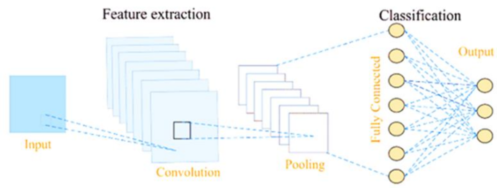


Figure 1. CNN Architecture

The basic framework of a CNN model comprises three types of layers: convolutional, pooling, and fully connected. Figure 1 show the basic structure of a CNN model, where the convolution layer is responsible for feature extraction. During the convolutional operation, a set of numbers (kernel) is applied to the input (tensor) to generate the feature map. The process of creating a feature map involves an element-wise multiplication between the kernel and the input tensor, with the resulting values summed to produce each element of the feature map. The kernel moves across all elements of the input tensor to generate the elements of the features map for that kernel. Using different kernels in the convolution operation can generate multiple feature maps.

2) Recurrent Neural Networks (RNNs)

RNNs are employed to handle sequential data and can analyze temporal patterns across video frames, assisting in the detection of irregularities or inconsistencies in the frame sequence that could indicate manipulation.

B. Dataset

The dataset used for training the model is DFDC (Deepfake Detection Challenge Dataset) **[7]** which is publicly accessible on kaggle. The DFDC dataset consists of 100000 videos, each approximately 10 seconds long, with images extracted from a randomly chosen subset of these videos. Because there were more fake videos than real ones, the dataset was balanced by randomly removing the excess fake images after frames were extracted at 1 fps.

C. MTCNN (Multi-task CNN)

The MTCNN network, known for its high detection accuracy, lightweight design, and real-time performance, is used for face recognition our face recognition process is therefore divided into two main steps: face detection and face recognition. Initially, MTCNN is used for face detection to determine accurate face coordinates. The processing flow of MTCNN begins with repeatedly resizing the test image to generate an image pyramid. Next, the image pyramid is input into P-Net to generate numerous candidate faces. The candidates identified by P-Net are then refined by R-Net. Once R-Net eliminates many candidates, the images are passed to O-Net, which then outputs the accurate box coordinates. Unlike deepfake, FaceNet keeps face alignment, skips the feature extraction steps, and uses CNNs for end-to-end training directly after the face alignment. The “Real and Fake Face-Detection” dataset was used to train the three models, with a learning rate of 0.001 and training period of 10 epochs. As a result, the accuracy on the test set was determined by evaluating the testing dataset. To increase the dataset size, all original images were flipped both vertically and horizontally, tripling the amount of data.

D. Research Motivation and Key Contributions

In response to the risks posed by deepfakes, numerous studies have explored detection and generation methods using deep learning. Tolosana et al. [8] reviewed face manipulation and detection techniques, while Weerawardana and Fernando [9] focused on visual detection without addressing generation or societal impacts. Nguyen et al. [10] and Seow et al. [11] considered both detection and generation but only briefly, excluding audio-visual aspects and policy implications. Toshpulatov et al. [12] examined GAN-based 3D face generation, and Almutairi and Elgibreen [13] surveyed audio deepfake detection but not generation. More recent works by Masood et al. [14] and Dagar and Vishwakarma [15] provided detailed insights into facial manipulation and audio-visual synthesis, yet omitted policy recommendations and trend analysis. Prior surveys have either lacked systematic analysis or addressed deepfake detection and generation separately, without emphasizing AI-based frameworks. Moreover, they have not examined policy recommendations, emerging trends, or recent advances in face manipulation, reenactment, face-swapping, attribute manipulation, identity swapping, facial synthesis, and audio-visual manipulation. To the best of the authors’ knowledge, this work presents the first comprehensive review of both deepfake generation and detection methods, while also outlining modern frameworks, tools, and policy recommendations to mitigate online disinformation.

The primary objective of this systematic literature review is to address gaps in existing research by examining deepfake detection and generation techniques to mitigate the spread of disinformation. This study provides clear insights into the application of emerging AI and deep learning methods for both generating and detecting deepfakes. Furthermore, it identifies modern trends, policies, tools, limitations, and challenges relevant to combating disinformation on social platforms, while offering guidance for future research directions. The key contributions of this review are as follows:

- Provide a systematic analysis of deepfake detection and generation methods across audio, image, and video domains.
- Identify research gaps through a comparative assessment of existing surveys and review studies.
- Consolidate current frameworks, algorithms, and tools for deepfake identification.
- Assess the practical applications of these frameworks and tools in mitigating disinformation.
- Highlight key challenges in deepfake detection and generation, informing realistic policy development.
- Examine the limitations of current approaches to guide future research efforts.
- Present policy recommendations and outline future trends based on emerging AI-driven frameworks.

To achieve the research objectives, this study addresses the following questions: *What AI-based methods exist for deepfake detection and generation? How can deepfakes be detected and generated online using AI? Which AI tools are available for these tasks? What policy recommendations and future trends can counter deepfakes?* A systematic analysis protocol was employed to answer these questions. The remainder of this paper is organized as follows: Section II outlines the research methodology, Section III presents the results of the systematic review, and Section IV provides the conclusions.

II. BACKGROUND

Fake news detection techniques In recent years, researchers have explored various techniques to improve fake news detection. Alghamdi et al. [15] introduce a multilingual fake news detection model to handle low-resource languages. By using a hybrid summarization approach that reduces text length while preserving key content, their system processes multilingual inputs directly, achieving better accuracy. Similarly, Hashmi et al. [16] propose a hybrid model combining CNN with LSTM, achieving 99% accuracy on the WELFake dataset and incorporating XAI techniques like Local Interpretable Model-Agnostic Explanations for greater transparency. Both papers emphasize using hybrid neural networks for more robust fake news detection. Hashmi et al. [17] optimize transformer models like BERT and RoBERTa for multilingual detection, highlighting the need for tuning models for better performance across datasets. They also addressed issues of model transparency and resource demands, and hence incorporate XAI to mitigate trust concerns.

Malanowska et al. [18] provide a review of digital watermarking techniques for fake news detection, originally designed for intellectual property protection but now applied to tamper detection and content authentication. Their DISSIMILAR project focuses on developing watermarking solutions for social media platforms, though the paper lacks detailed comparisons of techniques. Rosales et al. [19] further explore watermarking combined with machine learning to detect digital image modifications, emphasizing user trust through transparent system design. Both papers showcase the expanding role of watermarking in ensuring content authenticity. Bhardwaj et al.'s [20] HostileNet targets hostile post detection in Hindi, using multi-label classification and neural network architectures, though it faces challenges like overfitting and the need for high computational resources. Despite its scale, it faces labeling biases and generalization challenges. Dadkhah et al. [21] introduce TruthSeeker, a large ground-truth dataset for real and fake content across platforms. The authors suggest using a multi-layered review process and propose an emotion-aware multitask model for fake news detection, though the model’s complexity and reliance on high-quality datasets are obstacles.

III. LITERATURE SURVEY

1) *Heidari, A., Jafari Navimipour, N., Dag, H., & Unal, M. (2023). Deepfake detection using deep learning methods: A systematic and comprehensive review. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, e1520. [22]*

METHODOLOGY: a new image forgery detection system was proposed that utilized neural networks, with a particular emphasis on the Convolutional Neural Network (CNN) architecture. The method utilized variations in image compression by applying the differences between original and recompressed images to train the model. This approach successfully identified prevalent types of image forgeries, including splicing and copy-move manipulations.

LIMITATION: The authors identify a major gap in existing CNN-based forgery detection methods, which generally specialize in identifying a single type of forgery. The proposed system aims to address this limitation by efficiently detecting a wider range of novel forgeries within images.

The primary innovation is in leveraging the differences between an image's original and recompressed versions as signals for detecting forgeries. This indicates that the model is intended to identify artifacts and irregularities introduced during the recompression process, which can be indicative of manipulations. The authors stress the lightweight design of the proposed model, emphasizing its focus on computational efficiency and real-time processing. This is important for practical applications, especially in cases where rapid and efficient forgery detection is necessary. The experiments produced very promising result, revealing an impressive overall validation accuracy of 92.23% within the iteration limits.

2) *Li, L., Bao, J., Zhang, T., Yang, H., Chen, D., Wen, F., & Guo, B. (2020). Face x-ray for more general face forgery detection. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 5001-5010). [23]*

METHODOLOGY: Employed the FF-LBPH DBN (Fisherface Linear Binary Pattern Histogram with DBN Classifier) technique for deepfake image detection, highlighting its impressive speed and its effectiveness in distinguishing between real and fake images.
The proposed approach adopts a hybrid methodology, starting with the use of Fisherface with Local Binary Pattern Histogram (FF – LBPH) for face recognition, focusing on reducing dimensionality in the face space. Following this, a Deep Belief Network (DBN) using Restricted Boltzmann Machines (RBM) is utilized for detecting deep fakes.
LIMITATION: This approach aim to boost the accuracy and efficiency of the detection process, offering potential to prevent underserved defamation from manipulated images. The authors point out that inaccuracies and lengthy processing times are major issues in existing deepfake detection techniques. The FF-LBPH model attained remarkable accuracy rates, achieving 98.82% on the CASIA-WebFace dataset and 97.82% on the DFFD dataset. The research concluded by emphasizing the exceptional performance of FF-LBPH in detecting and analyzing deepfake face images.

3) *Yogesh & Tanwar, Sudeep & Bhattacharya, Pronaya & Gupta, Rajesh & Alsuwian, Turki & Davidson, Inno & Mazibuko, ThokoZile. (2023). An Improved Dense CNN Architecture for Deepfake Image Detection. IEEE Access. PP. 1109/ACCESS.2023.3251417. [24]*

METHODOLOGY: carried out a study on deepfake image detection employing a dense CNN architecture. The dataset utilized in the study is sourced from the deepfake images detection and reconstruction challenge, including real images from CelebA and FFHQ, as well as deepfake images from GDWCT, AttGAN, STARGAN, StyleGAN, and StyleGAN2. They introduced a D-CNN model for binary classification to identify deepfake images. The augmented CNN model is integrated with the D-CNN model to extract deep features from input images using convolutional layers. Once convolution operations are performed on the images, they can be used to classify the input images as either fake or real. The proposed model attained 97.2% accuracy on the test dataset. The models performance declines when applied to other existing models, such as MesoNet and MesoInception networks, on the CelebDF dataset.

Limitation:

- Modality Restriction – The architecture may be optimized only for *images* and may not generalize well to *video, audio, or multimodal deepfakes*.
- Dataset Dependence – Performance might rely heavily on specific training datasets (e.g., FaceForensics++, Celeb-DF), limiting real-world applicability where deepfakes differ in style or quality.
- Generalization Challenge – The model may struggle with unseen or novel deepfake generation techniques, especially if trained on limited types of manipulations.
- High Computational Cost – Dense CNN architectures usually require large computational resources for both training and inference, making real-time deployment difficult on edge devices.
- Overfitting Risk – Due to dense connectivity and complex layers, the model may overfit on training data if not regularized properly.
- Adversarial Vulnerability – Deep learning models can be fooled by adversarial attacks, where subtle perturbations in images bypass detection.
- Explainability Issues – Dense CNNs act as black boxes, making it hard to interpret why a sample is flagged as fake, which is critical for trust in forensic applications.
- Scalability Problems – The architecture may not scale efficiently when applied to large-scale social media streams in real time.

4) *El-Gayar MM, Abouhawwash M, Askar SS, Sweidan S. A novel approach for detecting deep fake videos using graph neural network. Journal of Big Data. 2024 Feb 1. [25]*

METHODOLOGY: Introduce a new method for deepfake detection using Graph Neural Network (GNNs). GNNs are adept at modeling relationships between data points. When applied to deepfakes, this capability translates into capturing the complex interactions between facial features in videos. By examining these relationships, GNNs can detect inconsistencies that suggest manipulation, such as unnatural connections between facial landmarks (e.g., eyes and nose). The paper also investigates combining GNNs with other models, like CNNs, through fusion strategies, which could further improve deepfake detection performance.

LIMITATION: The effectiveness of the method also depends heavily on the way graphs are constructed, as suboptimal node and edge representations can significantly degrade detection accuracy. Moreover, the approach may struggle to generalize across datasets or adapt to novel deepfake generation techniques not seen during training, thereby limiting robustness in real-world applications. Another challenge lies in modeling fine-grained temporal inconsistencies across video frames, as conventional GNN frameworks are not inherently designed for long-sequence temporal analysis. In addition, constructing labeled graph-based datasets for training is complex and costly, which may restrict scalability. Finally, like most deep learning models, GNNs are vulnerable to adversarial attacks and suffer from interpretability issues, raising concerns regarding their transparency and reliability in forensic or legal contexts.

5) *Hanqing, Zhao & Wei, Tianyi & Zhou, Wenbo & Zhang, Weiming & Chen, Dongdong & Yu, Nenghai. (2021). Multi-attentional Deepfake Detection. 2185-2194. 10.1109/CVPR46437.2021.00222. [26]*

METHODOLOGY: has redefined deepfake detection as a fine grained classification problem, offering a novel approach to the field. They further introduced an innovative multi-attention network architecture crafted to capture local discriminative feature from various face-focused regions. The datasets employed are FaceForensics ++, CelebDF, and DFDC. The proposed architecture splits the single attention-based structural networks into multiple regions, improving efficiency in capturing local features. They utilized local attention pooling to capture textual patterns. The implementation of the multi-attention framework leads to significant improvement across various datasets using comprehensive metrics.

LIMITATION: The performance is also highly dependent on the diversity and quality of training datasets, which may reduce generalizability to unseen deepfake generation techniques or cross-dataset scenarios. Moreover, multi-attentional models can be prone to overfitting, as they may overemphasize dataset-specific artifacts rather than learning robust forgery patterns. Another limitation lies in their interpretability; while attention maps provide some visualization, they do not fully explain the model's decision-making process, which is critical for forensic and legal adoption. Finally, these models, like other deep learning-based approaches, remain vulnerable to adversarial attacks and may struggle when deepfakes are compressed, noisy, or of low resolution, thereby limiting their applicability in real-world social media environment.

Table 1. Survey table

Study	Year	Network Type	Success Metrics	Key Aspects
Gaze-Guided Spatial in-consistency Learning [27]	2023	GazeForensies (Gaze Guided Learning)	GazeForensies employs gaze-guided spatial inconsistency learning to detect deep fakes by focusing on the eye movements in vedios.	Difficulty in detecting deepfakes with minimal eye movements; dependency on high quality eye tracking data.
Analysis of Deepfake Detection vs imagesQuality Metrics [28]	2024	Image Quality Metric Correlation Anlaysis	Examined the correlation between detection performance and image quality, high lighting metrics that influence detection accuracy.	Lack of robustness against types of deepfakes; difficulty in balancing image quality and detection performance.
Ali.S.et.al(2022) [29]	2022	CNN	Effective in detecting image forgeries	Lightweight model, leverages differences between original and Recompressed images for training

Suganthiet.al. (2022) [30]	2022	FF-LBPH with DBN	Impressive accuracy rates	Hybrid methodology, utilizes FF-LBPH for face recognition and DBN for deepfake detection
Lakshmanan Nataraj et.al. (2019) [31]	2019	CNN with Co- occurrence Matrices	Effective integration of matrices	Hybrid approach, combines co- occurrence matrices with CNN
Luca Guarnera et.al. (2020) [32]	2020	EM Algorithm	Distinguishing deep fake architectures	Leveraging EM algorithm for feature extraction in deepfake creation
Ambica Ghai et.al. (2021) [33]	2021	CNN	Addressing image forgery detection	Image transformation technique For relevant feature isolation
Zhao et.al.(2020) [34]	2020	Multi-Attentional CNN	State-of-the-art deep fake detection	Fine-grained classification, multiple spatial attention heads, and textural feature enhancement
Hsu et.al.(2020) [35]	2020	Modified DenseNet	Effective discrimination in fake/real	Two-streamed network, pair wise learning, and classification layer
Nawaz et.al.(2023) [36]	2023	ResNet-Swish-Dense54	Robust deepfake detection	TailoredResNet-Swish-Dense54 framework, evaluation on
				Challenging datasets, adversarial attack testing
Yang et.al.(2021) [37]	2021	ResNet18 with Image Saliency	Precise detection of genuine and manipulated facial images	Utilizes image saliency to uncover texture distinctions, improved guided filter for preprocessing
Gandhi et.al.(2020) [38]	2020	VGG, ResNet	Fortifying detection against adversarial attacks	Adversarial perturbations, Lipschitz regularization, Deep Image Prior (DIP), VGG and ResNet architectures
Nguyen et.al.(2019) [39]	2019	Capsule Network	Comparable performance to CNNs	Capsule-Forensics method, detection of various attacks, dynamic routing for agreement
Nguyen et.al.(2019) (Comprehensive) [40]	2019	Capsule Network	Versatility in various domains	Comprehensive investigation, random noise utilization during training
Marra et.al.(2018) [41]	2018	XceptionNet	Detecting modified images on social media	Identifying photos modified using GAN-based image-to-Image translation methods

IV. METHODOLOGY

This section details the proposed technique for detecting real and fake images. The method used to identify real and fake images. It employs a deep CNN and its different variants (CNN, EfficientNet, and MTCNN), leveraging transfer learning to enhance image classification. Data augmentation generates additional and diverse examples for the training datasets, improving the models performance and outcomes.

A. Dataset

The standardized dataset introduced in the DeepFake Detection Challenge, publicly available on Kaggle, was employed for training and evaluation. DFDC comprises approximately 100,000 ten-second videos, each containing at least one subject, with manipulated faces across the collection. Frames were extracted at 1 fps, and class imbalance was addressed by randomly removing excess fake samples. The dataset was developed through collaboration between the Partnership on AI's Media Integrity Steering Committee, AWS, Facebook, Microsoft, and academic partners, and is frequently utilized for both the training and validation of CNN-driven deepfake detection models.

©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |

B. Preprocessing

The dataset goes through a preprocessing stage, where the video is broken down into individual frames and then find and crops out the faces in those frames. For everything to be consistent the average of the video dataset is calculated and the processed face-cropped dataset has the same number of frames as that of the average. In our implementation model, we considered face recognition library for face detection. The face recognition module detects the faces in a frame, locates the facial features and cropped that region in 224×224 size. After resize image is comprise then it will create a noise so to reduce that noise we make reshape the image. Since processing 10-second videos at 30 frames per second can be quite demanding, it is suggested to focus on the first 100 frames for training purposes in our experiment. This way, the model can work with a smaller set and still get meaningful results.

C. Extract Frames from Video

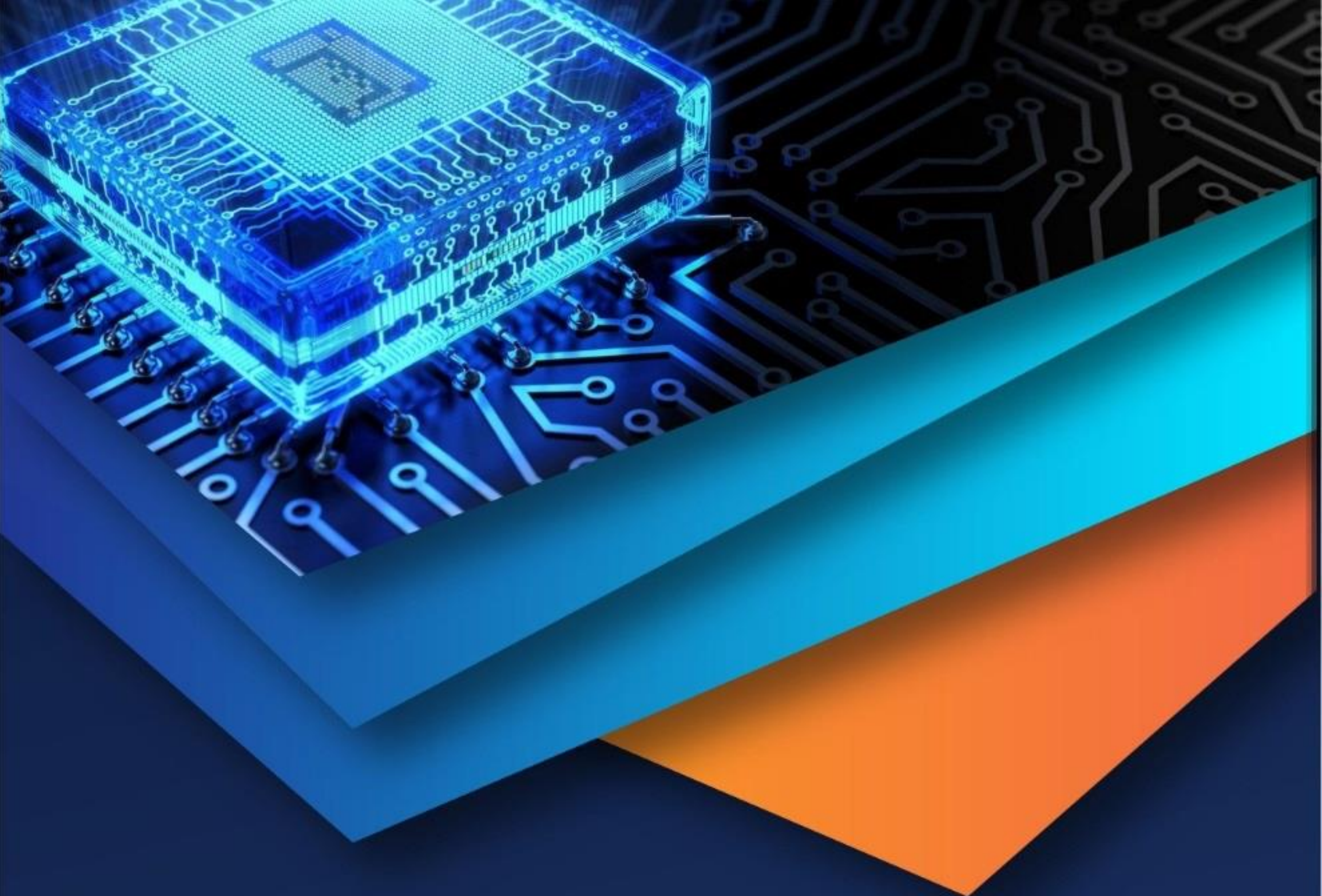
A series of frames make up a video. A video has a frame rate of 10 or 20 frames per second. The image and the period of exposure to the view together make up the frame. An animation is created by extracting many frames in a row. The frame's intended use in this situation is to show the pixel-based image on the screen. The video frame extraction process initially scans and analyses a video before extracting it based on a specified interval. The OpenCV is an effective tool for frame extraction in a video. It is the process of drawing out important images or videos. Videos may be subjected to a variety of processes using the OpenCV library. Extract each frame from a video input, samples of which are displayed. And then the frames are sent to our deep learning model.

D. Face Detection and Cropping

Face detection and cropping from video frame constitute the initial phase. The important elements of the Frame of deep fake manipulated videos are face region. Therefore, we are just concerned with the facial area. A Face detector is used to identify and separate the facial images from the rest of the frame. In our implementation Model, we considered face recognition library for face detection. The face recognition module detects the faces In a frame, locate the facial features and cropped that region in 224×224. Moreover, in order to reduce processing cost, we only considered 10-20 frames from each video rather than all of them.

V. CONCLUSION AND FUTURE WORK

This paper presents a neural network based method for distinguishing between Deep Fake and real videos. With the output showing high prediction confidence it can be concluded that the project was successfully completed. Following an in depth analysis of previously proposed algorithm, the project design was developed. The theoretical background of all the resources and technologies used was extensively explained to provide a clear understanding of their application and rationale Facial manipulation in videos is becoming an increasingly widespread issue. This study carefully reviews relevant literature to gain a deeper understanding of the problem and proposes a network architecture that effectively detects such manipulations using five convolutional neural networks, all while ensuring low computational cost. The paper introduces an innovative approach for detecting Deep Fakes. In this method, a CNN face detector is used to extract facial regions from video frames. The distinct spatial features of these faces are captures using ReLU with CNN, aiding in the detection of visual artifacts in the video frames. Under typical internet conditions, the proposed technology achieves an average detection rate of 98% for Deep Fake videos and 95% for Face2Face video, according to the study's results. The study has demonstrated that CNN performance can be enhanced by adding more convolutional layers and other specific parameters. It also takes into account the compression factors, which presents significant challenges for many Deep Fake detection systems. Future algorithms are expected to concentrate on these issues while utilizing updated datasets. Although this research focused in identifying Deep Fake in still images and videos, we believe that this method identifying Deep Fake in still images and videos, we believe that this method could be applied to detect Deep Fake in audio and text, aiding in the fight against misinformation in the digital age. These areas will be explored in feature investigations.



10.22214/IJRASET

INDEX COPERNICUS

45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)