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Deepfake Image Detection

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***Abstract*— The ease with which generative AI models are improving today makes it rather difficult to distinguish between actual images and those that are forged/made using AI. However, with the growing usage of deepfake multimedia content in social, entertainment, and political setups, the concern for misinformation, identity theft, and reputation damage is increasing at a rapid pace. To address this concern, the current research aims at detecting forged images using deep learning and checks the efficiency of efficient convolution models. In this process, the research considers both XceptionNet and EfficientB0 models enhanced with Dense layers, Dropout, Batch Normalization, and adaptive learning rate approaches. Simultaneously, facial region extraction/preprocessing tasks are handled through OpenCV, NumPy, and MTCNN, as needed, to allow the models to detect the subtle details created during the forged image generation process. The models are trained on a diversified data-set assembled from various benchmark datasets to make them robust to varying resolutions, compression, as well as various manipulation techniques. The performance analysis with reference to accuracy, precision, recall, F1-score, confusion matrix, and receiver operating characteristic curves indicates that a very reliable approach with a maximum accuracy of 99.06% can be obtained with the suggested pipeline. To cater to real-time requirements, a Flask API with webcam support can also be incorporated into the system. In conclusion, the importance of deep architectures in detecting counterfeit images has been established in this research, and it will help in improving the area of digital media forensics. This research has numerous applications in the field of digital media.**

***Index Terms*— Deepfake detection, fake image detection, XceptionNet, EfficientNetB0, CNN, image forensics.**

I. INTRODUCTION

The recent surge in the development of synthetic media, including deepfakes, has posed significant threats to the fields of digital forensics, privacy, and cybersecurity. Utilizing sophisticated AI models such as Generative Adversarial Networks (GAN) and autoencoders, creating highly realistic manipulated images with the intention of modifying a subject's identity or image has become extremely simple and is now available for public use via various apps such as FaceApp and FaceSwap. This has led to the increased use of deepfakes for the purpose of spreading misinformation, politics, and other malicious acts. Since more people have access to deepfake technology, creating such manipulated images has become much simpler, making the world a more dangerous place for cybersecurity. identity theft, and targeted harassment, which has significant potential for threatening the safety and trust on the internet.

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Now, the traditional methods for image forgery detection, which relied on hand-crafted features or shallow models, are not very efficient anymore since they fail to capture the subtle artifacts hidden in the AI-generated images. Deep learning-based methods, especially Convolutional Neural Networks (CNNs), prove to be efficient alternatives because they possess the ability to learn spatial features and discover the minutest discrepancies in the artificial images.

Models like XceptionNet and EfficientNet perform well on the task of image recognition and forgery detection. In an effort to address these issues, this study aims to construct and assess deep-learning framework systems for distinguishing forgery images. In this study, two highly effective models, namely XceptionNet and an improved model of EfficientNetB0, with preprocessing systems that utilize OpenCV and MTCNN, as needed, are examined. Using these models, this proposed system intends to assess minute changes injected into an image through deepfakes in an effort to provide an effective technique for maintaining authenticity within digital media.

II. Literature Review

A. Introduction

The rapid proliferation of deepfake-generated images has created Serious concerns with security, privacy, and overall Reliability of digital media: Manipulated content becomes increasingly realistic, the need for dependable and automated Image uploaded by user Detection systems have become more critical than ever. This Survey provides an overview of the main detection methods for deepfakes. techniques, commonly used benchmark datasets, performance. evaluation practices, and the key challenges that still remain. in deepfake image analysis.

B. Deepfake Image Detection Techniques

Most deepfake image detection methods currently rely on deep-learning-based approaches, and CNN is the backbone in many state-of-the-art detection frameworks [5]. CNNs' ability to recognize subtle texture patterns, spatial anomalies, and semantic abnormalities brought on by deepfake generation is what makes them so effective at identifying manipulated images. For the task of distinguishing between real and fake images based on deep hierarchical feature representations, widely used architectures like ResNet [6] and Inception have demonstrated outstanding performance.

Recent research, such as XceptionNet [3], has concentrated on lightweight yet extremely accurate architectures. Xception-Net greatly lowers computation complexity while increasing classification accuracy by utilizing depthwise separable con-volutions, which makes it appropriate for deepfake detection tasks involving high-resolution imagery.

Modern face detection techniques are now an essential part of many deepfake detection approaches. One widely used method is the MTCNN framework, which helps in accurately identifying facial regions. By ensuring proper face alignment before classification, MTCNN improves the reliability of de-tection result.

In addition to this several studies have explored hybrid methods that combine spatial analysis using CNNs with frequency-domain features or steganalysis techniques. These methods are effective in detecting subtle artifacts and incon-sistencies that may not be visible in the spatial domain and are often difficult for human observers to notice.

Together, these developments highlight the continuous ef-forts in building deepfake image detection systems that are robust, adaptable and capable of handling increasingly sophis-ticated image manipulation techniques.

C. Datasets for Training and Evaluation

The reliable deepfake detection system depends heavily on the availability of high-quality and diverse datasets. Com-monly used datasets include FaceForensics++, the Diverse Fake Face Dataset, Celeb-DF, and RealVsFake81K by Wishart. These datasets contain large numbers of both real and ma-nipulated fake facial images created using different forgery techniques. Their diversity plays a key role in training de-tection models, as it allows systems such as the DeepFake-Image-Detector to generalize more effectively across multiple deepfake generation methods.

D. Performance Evaluation and Assessments

Performance evaluation of deepfake detection models is commonly carried out using metrics such as accuracy, pre-cision, recall and F1-score, as they provide a balanced view of classification effectiveness [4], [8]. In this context, the DeepFake-Image-Detector demonstrates reliable perfor-mance in distinguishing between real and manipulated images, achieving accuracy and F1-score values exceeding 85%.

These evaluation metrics are particularly important for controlling the trade-off between false positives and false negatives, which is critical for real-world deployment. In addition to strong detection accuracy, the model's computa-tional efficiency enables real-time analysis. This makes the DeepFake-Image-Detector suitable for integration into identity verification and authentication pipelines, where both speed and reliability are essential [?]. Because of its high performance and fast processing capability, the system serves as an effective tool in addressing the growing challenges posed by deepfake media.

E. Challenges and Future Directions

Despite significant progress, several challenges remain, es-pecially for traditional CNN-based approaches [5].

Fig. 1. Sample of real and facial faces from the FaceForensics++ dataset [4]. This dataset is used for training and evaluation of deepfake detection models.

TABLE I: GENERALIZATION OF DEEPFAKE IMAGE DETECTORS TO UNSEEN DATASETS (SELECTED METHODS) [10]

Detector	Org. Accuracy(%)	Unseen Avg.(%)	Degrad(%pt)
ShallowNet6	71.00	65.85	5.15
MesoNet3	85.50	69.75	15.75
EfficientNet3	79.05	61.86	17.19
XceptionNet3	93.60	69.03	24.58
MesoNet6	94.65	68.40	26.25
XceptionNet4	96.15	53.16	42.99

As shown in Table I, models such as MesoNet, EfficientNet, and XceptionNet experience significant drops in accuracy, sometimes exceeding 40%, when evaluated on unseen datasets. This highlights a core issue: CNNs often struggle with ad-vanced deepfakes that contain minimal detectable artifacts, leading to poor generalization in real-world scenarios. Other factors such as dataset imbalance, inconsistent image quality, lighting variations, and heavy compression, further make this problem more complex, which is why most models struggle to perform well across different datasets. In addition, the high computational cost of large CNN models often makes them difficult to use on devices with limited resources or in real-time applications. Looking ahead, research is moving toward more efficient and scalable approaches. Lightweight architectures, transformer- based models, and hybrid methods combining spatial and frequency analysis show promise in addressing the limitations of conventional CNNs. Incorporating multiple modalities—such as audio and video—and leveraging adaptive or self-supervised learning may also improve resilience to new and evolving deepfake generation techniques. Guided by these observations, our work adopts a pipeline that com-bines advanced preprocessing using MTCNN [2] for precise face localization with an efficient yet expressive classifier, XceptionNet [3]. This pairing addresses main pitfalls revealed by the generalization analysis in Table I. MTCNN ensures high-quality facial feature extraction even under challenging conditions, while XceptionNet provides robust classification through depthwise separable convolutions. Together, this inte-grated approach aims to deliver improved accuracy, better real-world generalization, and practical deployment potential—a strong candidate for future deepfake detection frameworks.

III. METHODOLOGY

This paper introduces the DeepFake-Image-Detector, a two-stage framework that integrates facial localisation with deep learning–based classification to detect manipulated facial im-ages. In the first stage, facial regions are detected and aligned using the MTCNN framework [2], [11] to reduce background noise and ensure consistent input quality. When faces are aligned and scaled properly, it becomes easier for the model to make accurate classifications.

Once the faces are aligned, XceptionNet is used to analyze the images. It is a convolutional network that uses the depth-wise separable convolutions to capture the artifact introduced during the image manipulation. As a result, it makes the model more efficient.

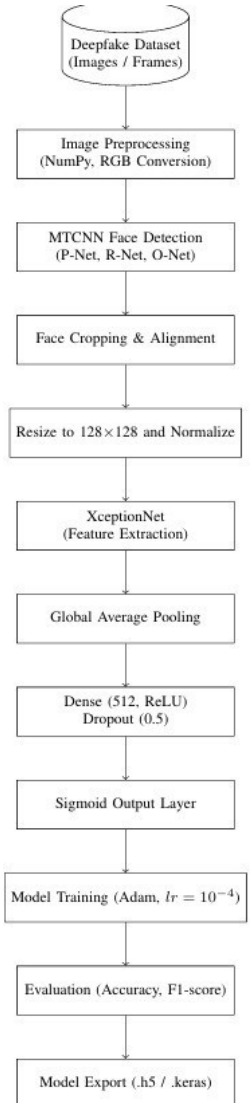

Fig. 2. IEEE-style training workflow of the proposed DeepFake Image Detector is a deepfake detection model, showing preprocessing, MTCNN-based face detection, XceptionNet feature extraction, and model optimization

The proposed framework is trained on widely used bench-mark datasets, such as FaceForensics++ and Celeb-DF, which consist of diverse real and manipulated facial imagery [4], [12]. To enhance generalization and robustness against unseen manipulations, data augmentation techniques are applied while training. The optimization of the model is performed by using an Adam optimizer along with cross-entropy loss, which ensures its stable convergence and effective learning [13].

During inference, input images are first processed by MTCNN to detect facial regions. Images for which no face is detected are treated separately in order to avoid unreliable predictions. In the case of valid face detection, the aligned facial crop is fed into XceptionNet, which outputs a prob-ability score that represents the likelihood of manipulation. Decision thresholds, on the basis of both the confidence of face detection and classification probability, are defined to characterize the inputs as real, fake, uncertain, or no-face cases, as summarized in Table II.

In conclusion, the DeepFake Image Detector's accurate facial preprocessing, effective classification method, and clear decision criteria provide a workable and scalable solution for deepfake image detection in real-world scenarios.

IV. Results and Discussion

The experimental results from the suggested deepfake detec-tion pipeline, which combines XceptionNet for classification and MTCNN for face extraction, are shown in this section. The system's performance is evaluated using its visual outputs, confidence scores and comparison metrics across different test samples.

A. Qualitative Results

Figure 5 shows a real face detected by MTCNN with a high confidence score ranging from 0.92 to 0.99, followed by a low fake probability (0.05–0.30) predicted by XceptionNet. Similarly, a deepfake sample is shown in Figure 6, where the classifier predicts a much higher probability, between 0.70 and 0.95, resulting in an accurate detection [14], [15].

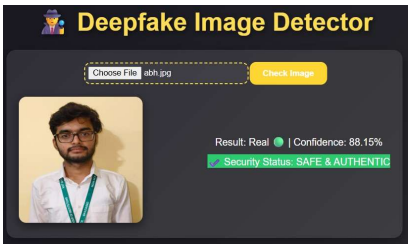

Fig. 3. Sample output for a real face detected and classified using the proposed DeepShield model

Fig. 4. Sample output for a fake face detected and classified using the proposed DeepFake Image Detector model.

B. Quantitative Evaluation

The performance comparison between the proposed MTCNN+XceptionNet pipeline and the standalone Xception-Net baseline is shown in Figure??. The proposed approach outperforms the baseline in terms of accuracy, precision, and robustness under challenging conditions such as low light, blur, and side-facing images [16], [17].

C. Confidence Score Analysis

Table III summarizes typical confidence ranges observed in different scenarios. MTCNN consistently detects frontal faces with high accuracy, while XceptionNet demonstrates clear separation between real and fake images in terms of output probabilities.

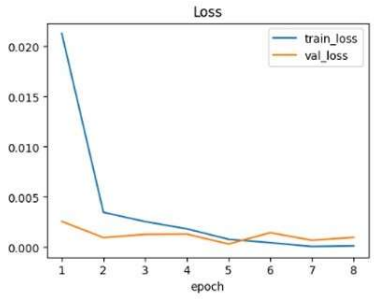

Fig. 5. Training and validation loss curves of the proposed deepfake image detection model across epochs

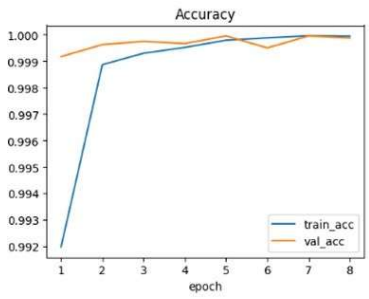

Fig. 6. Training and validation accuracy curves of the proposed model demonstrating convergence behavior.

TABLE II: INTERPRETATION OF MTCNN DETECTION QUALITY AND XCEPTIONNET CLASSIFICATION OUTPUT

Image Type	Bounding Box Quality (MTCNN)	Landmark Accuracy	Confidence Score (MTCNN)	XceptionNet Output (0–1)	Final Prediction
Real Face	Tight, centered	Very accurate (eyes, nose, mouth aligned)	0.92–0.99	0.05–0.30	Real
Fake Face (High Quality)	Perfect crop	Landmarks correct	0.90–0.98	0.70–0.95	Fake
Fake Face (Low Quality)	Moderate crop	Landmarks slightly off	0.85–0.92	0.55–0.75	Fake
Low Light Image	Weak detection	Unstable landmarks	0.70–0.85	0.40–0.60	Uncertain
Blurry Face	Loose bounding box	Inaccurate landmarks	0.60–0.80	0.45–0.65	Uncertain
Side / Profile Face	Imperfect box	Shifted landmarks	0.65–0.88	0.50–0.70	Uncertain
Multiple Faces	Nearest face chosen	Good for chosen face	0.85–0.95	0.30–0.70	Varies
No Face Detected	N/A	N/A	0.00–0.30	N/A	No face found

TABLE III: CONFIDENCE SCORE RANGES OBSERVED ACROSS DIFFERENT IMAGE CONDITIONS FOR MTCNN AND XCEPTIONNET

Condition	MTCNN Confidence	Xception Confidence	Interpretation
Frontal Clear Face	0.95–1.00	0.85–1.00	Highly reliable
Low Light	0.70–0.85	0.40–0.60	Moderately reliable
Blurry Face	0.60–0.80	0.45–0.65	Uncertain
Side/Profile Face	0.65–0.88	0.50–0.70	Partially reliable
No Face Detected	0.00–0.30	N/A	No valid face found

D. Overall Observation

The experimental results demonstrate that the proposed MTCNN+XceptionNet pipeline provides reliable deepfake de-tection across varying conditions. It achieves clear discrimina-tion between real and fake images and maintains robustness even in noisy or low-quality inputs. These outcomes support the effectiveness of the model for real-world deepfake identi-fication tasks.

V. CONCLUSION AND FUTURE WORK

This is an exercise in imagination, and its relation to the types of statistical inference drawn from a large volume of data should not be lost on the reader.

This work presents a two-stage deepfake detection scheme featuring the DeepFake Image Detector, which combines the attributes of MTCNN for robust face detection with the strengths of XceptionNet in robust image-classification forg-eries [15]. Experimental results illustrate that the DeepFake Image Detector steadily differentiates real and manipulated images with high accuracy across a variety of conditions, such as low lighting, blur, and partial facial visibility. Precise facial landmark detection blended with a strong feature-based classifier forms the basis for the practicality of the DeepFake Image Detector for real-world deployment.

By modifying the framework for deepfake video analysis, where motion dynamics and temporal coherence provide two crucial indicators of tampering, we will expand the DeepFake Image Detector beyond static images in our subsequent work. Resilience against increasingly complex deepfake techniques can be greatly increased by incorporating spatiotemporal mod-eling [18] and investigating multimodal cues, such as audio-visual alignment. As deepfake generation techniques continue to advance, the method may also benefit from the addition of transformer architectures and self-supervised learning, which could aid in improving generalization.

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