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Deepfake Detection Using EfficientNet-Based CNN with Threshold Optimization

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Abstract- The rapid advancement of deep learning has significantly improved the ability to generate realistic synthetic media, commonly referred to as deepfakes. While such technologies offer benefits in areas such as entertainment and media production, they also pose serious risks including misinformation, identity theft, and digital fraud. Detecting deepfake content has therefore become a critical research problem. This paper proposes a deepfake detection framework based on an EfficientNet-based Convolutional Neural Network (CNN) trained on a labeled dataset of real and fake facial images. The trained model is extended to video-level detection through frame-based inference and aggregation. In addition, a threshold optimization strategy is introduced to improve classification performance by balancing precision and recall. Experimental results demonstrate that the proposed model achieves an accuracy of 87%, precision of 97%, recall of 76%, and an AUC score of 0.96. The experimental findings confirm that threshold optimization significantly improves the balance between precision and recall, enhancing the robustness of deepfake detection systems.

Keywords- Deepfake Detection, EfficientNet, Convolutional Neural Networks, Threshold Optimization, Image Forensics

I. INTRODUCTION

The emergence of deep learning technologies has enabled the creation of highly realistic synthetic media, known as deepfakes. These are generated using advanced techniques such as Generative Adversarial Networks (GANs), which can manipulate facial expressions, voices, and identities with remarkable accuracy. Although deepfakes have legitimate applications in areas such as film production and virtual reality, their misuse has raised serious concerns regarding misinformation, identity impersonation, and cybersecurity threats [1].

The rapid growth of social media platforms has further amplified the impact of deepfakes, allowing manipulated content to spread quickly and influence public opinion. As a result, there is an urgent need for reliable and automated methods to detect such content. Traditional image processing techniques rely on handcrafted features, such as inconsistencies in lighting and texture. However, these approaches often fail to generalize across different types of deepfake generation methods [2].

Deep learning-based approaches, particularly Convolutional Neural Networks (CNNs), have shown significant promise in detecting deepfake artifacts. These models are capable of learning complex patterns directly from data, enabling them to identify subtle inconsistencies that are difficult to detect using traditional methods. Among these architectures, EfficientNet has emerged as a powerful and efficient model due to its ability to balance network depth, width, and resolution [6].

In this work, we propose a deepfake detection system using an EfficientNet-based CNN. The model is trained on image data and extended to video-level detection using frame-based analysis. Additionally, threshold optimization is applied to improve classification performance.

The primary contributions of this work are summarized as follows:

- Development of an EfficientNet-based deepfake detection framework with improved feature extraction capability

- Integration of threshold optimization to enhance classification performance

II. RELATED WORK

Deepfake detection has been extensively studied in recent years, with various approaches proposed to address the growing challenges posed by synthetic media. Early methods focused on identifying visual artifacts such as unnatural facial movements, inconsistencies in lighting, and irregular blinking patterns. However, these techniques are often limited in their ability to handle advanced deepfake generation methods [3].

Recent advancements have shifted towards deep learning-based approaches, particularly CNNs, which have demonstrated superior performance in image classification tasks. Architectures such as XceptionNet and ResNet have been widely used for deepfake detection due to their ability to extract hierarchical features from images. These models have shown strong performance in detecting manipulation artifacts at different levels of abstraction [4].

In addition to spatial feature extraction, several studies have explored temporal modeling for video-based deepfake detection. Techniques such as Recurrent Neural Networks (RNNs) and 3D CNNs have been used to capture motion inconsistencies across video frames [5].

EfficientNet, introduced as a scalable CNN architecture, has gained attention due to its ability to achieve high accuracy with fewer parameters. By applying compound scaling, EfficientNet balances model complexity and performance, making it suitable for real-world applications [6]. Recent studies have applied EfficientNet to deepfake detection tasks, demonstrating promising results. However, most existing works focus primarily on model architecture improvements, with limited attention given to optimizing classification thresholds.

This research addresses this gap by integrating threshold optimization into the deepfake detection pipeline. By adjusting the decision boundary, the model can achieve a better balance between precision and recall, leading to improved overall performance.

However, existing methods often fail to achieve an optimal balance between precision and recall, particularly in real-world scenarios where false negatives can have significant consequences. This limitation motivates the need for threshold-aware optimization strategies.

III. DATASET

The dataset used in this study is the Deepfake and Real Images Dataset (Kaggle), which contains labeled facial images categorized as real or fake. The dataset is organized into three subsets: training, validation, and testing. The dataset consists of a total of 10,905 facial images, including 5,492 real images and 5,413 fake images. The dataset is relatively balanced, which helps in training a robust classification model without significant bias toward any class. The images are divided into training, validation, and test sets to ensure proper evaluation and generalization of the model. This structured split ensures that the model is evaluated on unseen data, reducing the risk of overfitting. Each image in the dataset is resized to a fixed resolution and normalized to ensure consistency during training. The dataset provides a relatively balanced distribution of real and fake samples, which is essential for training a robust classification model. Additionally, the dataset includes variations in facial expressions, lighting conditions, and image quality, enabling the model to learn diverse features.

Proper preprocessing techniques are applied, including resizing, normalization, and data augmentation. These steps improve model generalization and help prevent overfitting. The dataset serves as a reliable benchmark for evaluating deep learning-based deepfake detection models under diverse real-world conditions.

IV. METHODOLOGY

The proposed methodology integrates deep learning with decision threshold optimization to improve deepfake detection performance. The overall framework consists of multiple stages, including data preprocessing, feature extraction using EfficientNet, classification, and threshold tuning. The system is designed to effectively capture both low-level and high-level visual features that distinguish real images from manipulated ones. Furthermore, the integration of threshold optimization enables the model to achieve a better balance between precision and recall, making it suitable for real-world deployment scenarios.

As shown in Fig. 1, the proposed system consists of multiple stages including preprocessing, feature extraction, classification, and threshold optimization.

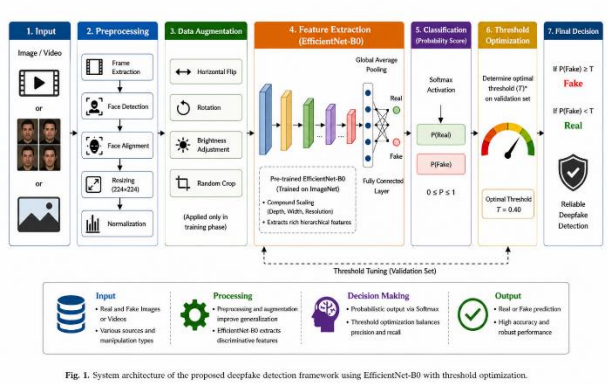

Fig. 1. System architecture of the proposed deepfake detection framework using EfficientNet-B0 with threshold optimization.

1. Model Architecture

The proposed deepfake detection system is built upon the EfficientNet-B0 architecture, a convolutional neural network designed to achieve high performance with relatively low computational complexity. EfficientNet employs a compound scaling method that uniformly scales network depth, width, and resolution, allowing it to achieve better accuracy compared to traditional CNN models while maintaining efficiency [6]. This makes it particularly suitable for tasks involving image classification where both performance and computational cost are important.

In this work, the pre-trained EfficientNet-B0 model is adapted for binary classification by modifying the final fully connected layer to output two classes: real and fake. Transfer learning is utilized by initializing the model with weights trained on large-scale image datasets, enabling faster convergence and improved generalization. The earlier layers of the network capture low-level features such as edges and textures, while deeper layers learn high-level semantic features relevant to deepfake detection.

2. Data Preprocessing and Augmentation

To ensure consistent input to the model, all images are resized to a resolution of 224×224 pixels. Pixel values are normalized using standard ImageNet normalization parameters to stabilize training and improve convergence. Preprocessing is an essential step as it ensures that variations in image scale and intensity do not negatively impact model performance.

Data augmentation techniques are applied during training to enhance model generalization and reduce overfitting. These techniques include horizontal flipping, slight rotations, and brightness adjustments. Augmentation increases the diversity of training samples and enables the model to learn invariant features, which is particularly important when dealing with real-world deepfake variations [2].

3. Training Procedure

The model is trained using the Adam optimizer, which is widely used for deep learning applications due to its adaptive learning rate and efficient convergence properties. The loss function used is cross-entropy loss, which is suitable for binary classification tasks. During training, the model iteratively updates its parameters to minimize the loss between predicted labels and ground truth labels.

The training process is conducted over multiple epochs, during which the model learns to distinguish between real and fake images. Batch processing is used to efficiently utilize computational resources. The validation dataset is used to monitor performance and prevent overfitting by evaluating the model on unseen data during training.

4. Video-Level Detection

Although the model is trained on static images, it is extended to video-level detection using a frame-based approach. Videos are first decomposed into individual frames at regular intervals. Face detection techniques are then applied to identify regions of interest within each frame.

Each detected face is passed through the trained EfficientNet model to obtain a prediction score. These predictions are aggregated across frames to determine the final classification of the video. This approach allows the system to leverage spatial features learned from images while still addressing video-based deepfake detection.

Frame-based detection has been widely adopted due to its simplicity and effectiveness, especially when compared to computationally expensive temporal models such as 3D CNNs and recurrent neural networks [5].

5. Threshold Optimization

In standard classification tasks, a fixed decision threshold of 0.5 is commonly used to determine class labels. However, this threshold may not always yield optimal performance, particularly in imbalanced or sensitive applications such as deepfake detection.

To address this issue, multiple threshold values are evaluated to determine the optimal decision boundary. The performance of the model is analyzed at different thresholds, and the value that maximizes the F1-score is selected. Experimental results indicate that a threshold of 0.40 provides the best balance between precision and recall.

Threshold optimization allows the model to reduce false negatives while maintaining high precision, which is critical in applications where missing a deepfake can have serious consequences. Similar strategies have been shown to improve classification performance in other deep learning-based detection systems [1].

6. Evaluation Metrics

The performance of the proposed model is evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. Accuracy measures the overall correctness of predictions, while precision evaluates the proportion of correctly identified fake samples among all predicted fake samples.

Recall measures the model's ability to correctly identify all fake samples, which is particularly important in deepfake detection tasks. The F1-score provides a balanced measure that combines precision and recall.

In addition, the Receiver Operating Characteristic (ROC) curve and the Area Under Curve (AUC) are used to evaluate the model's discriminative capability across different thresholds. A higher AUC value indicates better performance in distinguishing between real and fake samples [4].

V. EXPERIMENTS

Experiments are conducted to evaluate the effectiveness of the proposed deepfake detection system. The dataset is divided into training, validation, and test sets to ensure proper evaluation. The model is trained on the training set and validated using the validation set to monitor performance and avoid overfitting.

The implementation is carried out using the PyTorch deep learning framework. Training is performed on GPU-enabled hardware to accelerate computation and reduce training time. Hyperparameters such as learning rate, batch size, and number of epochs are selected based on empirical evaluation to achieve optimal performance.

In addition to standard evaluation, threshold tuning experiments are conducted to analyze the impact of decision boundaries on classification performance. Different threshold values are tested, and their corresponding metrics are recorded. This allows for a comprehensive analysis of how threshold selection affects model behavior. All experiments are conducted under controlled conditions to ensure reproducibility. The evaluation process considers both classification accuracy and robustness across

varying thresholds, enabling a comprehensive understanding of model behavior.

VI. RESULTS

The proposed model achieves an overall accuracy of 87%, demonstrating strong classification capability. The high precision of 97% indicates that the model is highly reliable in identifying manipulated content with minimal false positives. However, the recall of 76% suggests that some deepfake instances remain undetected, resulting in false negatives.
This highlights an inherent trade-off between precision and recall which is addressed through threshold optimization. The quantitative performance of the proposed model is summarized in Table I.

Table I. Performance metrics of the proposed model.

Metric	Value
Accuracy	0.8719
Precision	0.9783
Recall	0.7587
F1 Score	0.8546

A detailed class-wise evaluation of the model is presented in Table II.

Table II. Class-wise Performance Evaluation

Class	Precision	Recall	F1 Score	Support
Real	0.8053	0.9834	0.8855	5492
Fake	0.9783	0.7587	0.8546	5413

The effect of threshold variation on model performance is illustrated in Fig. 2.

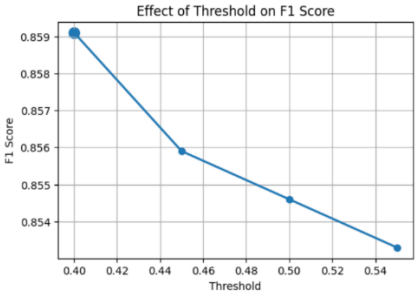

Fig. 2. Effect of threshold variation on F1-score performance.

Fig. 2 illustrates the relationship between classification threshold and F1-score, highlighting that a threshold value of 0.40 yields optimal performance by balancing precision and recall.

The classification performance of the model is further analyzed using the confusion matrix shown in Fig. 3.

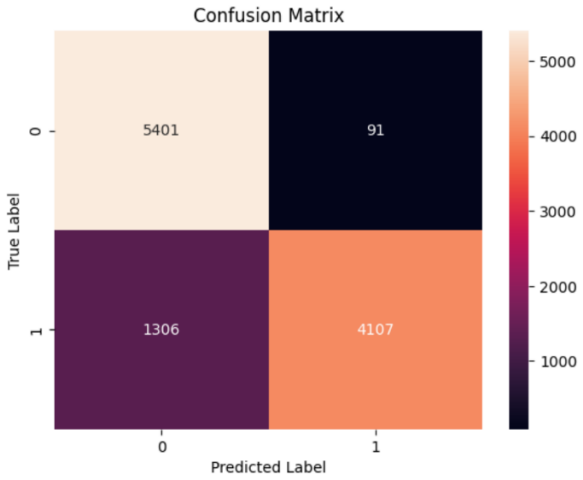

Fig. 3. Confusion matrix illustrating classification performance of the proposed model.

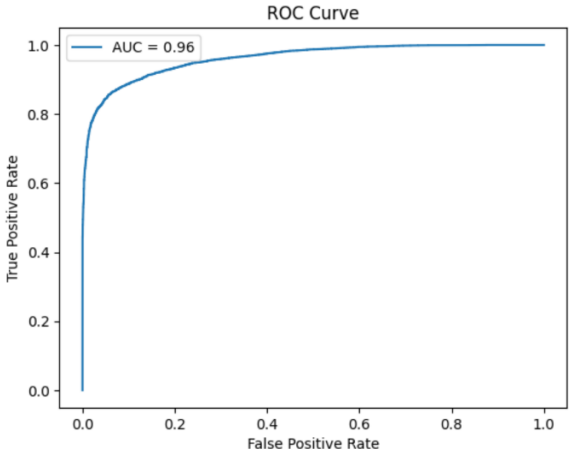

Fig. 4. ROC curve showing the performance of the model with an AUC of 0.96.

The ROC curve in Fig. 4 further confirms the strong discriminative capability of the model, with an AUC value of 0.96. However, the relatively lower recall of 76% suggests that some deepfake instances are not detected, resulting in false negatives. This indicates that while the model is highly precise, it may miss

certain subtle manipulations. The F1-score of 85% reflects a balanced trade-off between precision and recall.

The confusion matrix further illustrates the distribution of true positives, true negatives, false positives, and false negatives.

Threshold optimization improves the F1-score from 0.8546 to 0.8591 at a threshold of 0.40, demonstrating the effectiveness of adjusting decision boundaries for improved classification performance.

These results demonstrate that the proposed approach achieves a strong balance between detection accuracy and reliability, making it suitable for practical deepfake detection applications in real-world scenarios.

VII. DISCUSSION

The experimental results highlight the effectiveness of EfficientNet in extracting meaningful features for deepfake detection. The high precision achieved by the model indicates that it is highly reliable in identifying manipulated content, making it suitable for real-world applications where false positives must be minimized.

However, the relatively lower recall suggests that some deepfake instances remain undetected. This limitation may be due to the complexity of certain manipulations, which can closely resemble real images. Threshold optimization partially addresses this issue by improving recall without significantly affecting precision.

Future work may focus on incorporating temporal features for improved video detection, as well as exploring ensemble learning techniques to combine multiple models for better performance. Additionally, larger and more diverse datasets may further enhance model generalization [3]. These findings indicate that threshold optimization plays a crucial role in enhancing model reliability, particularly in applications where minimizing false negatives is critical.

VIII. CONCLUSION

This paper presents a deepfake detection system based on an EfficientNet-based CNN combined with threshold optimization. The proposed approach demonstrates strong performance in distinguishing real and fake images and can be effectively extended to video-level detection.

The results indicate that threshold tuning is an effective strategy for improving classification performance, particularly in balancing precision and recall. Future work may focus on incorporating temporal modeling techniques such as 3D CNNs or transformer-based architectures to improve video-level detection performance.

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