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Deepfake Image Detection Using Convolutional Neural Networks:A Web-Based Approach

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Abstract: Deepfake technology, driven by artificial intelligence, has developed rapidly over the past few years, raising issues of misinformation, privacy violations, and online security threats. This project is centered around creating a robust Deepfake Detection System based on machine learning methods to distinguish real media from the manipulated one. The system has a user authentication module for secure access via a login system. In addition, it incorporates an advanced deepfake detection algorithm that can scan images and videos to verify whether they are authentic. The detection model generates a fake accuracy percentage, reflecting how much media are likely manipulated. This measure adds transparency and gives users quantifiable feedback into possible deepfake risks. The system utilizes convolutional neural networks (CNNs) and deep learning to make high-precision identification of synthetic content. The technology can be applied to real-world scenarios such as media authentication, law enforcement, and social media surveillance, helping in the mitigation against misinformation. To make it scalable and efficient, the platform will be developed with an easy-to-use interface where individuals and organizations can upload and examine media easily.Through the creation of a correct and accessible detection system, we are moving closer to maintaining trust in digital content and preventing the risks involved in synthetic media manipulation.

Keywords: Deepfake Detection, Convolutional Neural Networks (CNNs), deep learning techniques, AI-driven cybersecurity

I. INTRODUCTION

With the advent of deep learning, AI- generated images have grown sophisticated, and it is challenging to differentiate between authentic and artificial media. Deepfake technology, which uses AI for image and video manipulation, has threatened misinformation, identity theft, and digital security threats [1]. As generative models become better, it is important to devise precise and effective means for spotting AI- generated images to ensure digital genuineness.

The existing methods of detecting deepfakes apply deep learning approaches to verify inconsistencies in spoofed images.

Convolutional Neural Networks (CNNs) have gained massive usage because of their spatial features' capability of identifying genuine versus artificial images [2]. Spurred by the same, the present project builds a deepfake detection system upon a CNN model that has been trained on both genuine and artificial image data sets. The model takes image inputs and makes predictions as to whether an image is real or forged.

In an effort to boost detection accuracy, the model receives extensive training utilizing augmented datasets that improve its strength against different deepfake generation methodologies. Pre-processing operations like resizing images, normalizing, and feature extraction fine-tune the performance. The system is prepared to offer an easy-to-use interface where pictures can be submitted for real-time analysis. Automated deepfake

detection in this deployment helps in digital forensics by offering an easy and efficient way of distinguishing manipulated images.

This paper presents the deepfake detection system implementation, which includes the dataset, CNN model architecture, and preprocessing methods employed to improve detection accuracy. The system proposed makes a contribution to digital forensics research by presenting a credible method for detecting deepfake images with high confidence.

II.RELATED WORK

Deepfake image detection has emerged as an important field of research as a result of the tremendous growth in generative adversarial networks (GANs), which have the capability to generate very realistic fake images. Several methods have been tried for detecting tampered images, with Convolutional Neural Networks (CNNs) proving to be one of the most efficient methods because they can learn to detect subtle spatial patterns and anomalies that are hard to detect for the human eye.

1. CNN-Based Framework for Deepfake Detection (2023): Sharma et al.[10] introduced a CNN-based framework aimed at detecting deepfake videos and images generated through Generative Adversarial Networks (GANs). Their approach utilized pre-trained models, specifically MTCNN and ResNext-V1, to automate deepfake identification across various artificially generated datasets. This method demonstrated significant improvements in detection accuracy, underscoring the efficacy of leveraging pre-trained CNN architectures for deepfake detection.

2. Improved Dense CNN Architecture for Deepfake Image Detection (2023): Patel et al. [11]proposed an improved dense CNN architecture tailored for deepfake image detection. Their study focused on enhancing the depth and connectivity of CNN models to better capture subtle artifacts present in manipulated images. The proposed architecture achieved higher accuracy rates compared to traditional CNN models, highlighting the importance of architectural advancements in deepfake detection.

3. Deepfake Image Detection Using CNN and ResNet50 Architecture (2023): In another study, researchers explored the application of deep learning techniques, specifically CNNs and the ResNet50 architecture, for identifying image-based deepfakes. Their findings indicated that integrating ResNet50's deep residual learning capabilities with CNNs significantly improved the detection of manipulated visual content, addressing the urgent need for reliable detection methods[12] amid the rise of deepfake technology.

4. Ensemble Learning for Deepfake Image Classification: Guarnera et al.[9] (2022) examined ensemble learning approaches, combining multiple CNN models to improve deepfake detection performance. Their study concluded that an ensemble of different CNN architectures provided better generalization against adversarial deepfake attacks.

5. Transfer Learning for Deepfake Image Classification: Wang et al. [6](2022) investigated transfer learning approaches for deepfake detection, where pre-trained CNN architectures such as VGG16, ResNet, and EfficientNet were fine- tuned on deepfake datasets. Their results indicated that transfer learning significantly reduced training time while maintaining high accuracy .

6. Deep Learning-Based Fake Image Detection: Nguyen et al. [4](2020) explored different deep learning architectures for deepfake detection and found that CNN-based models performed significantly better than traditional handcrafted feature-based methods. Their research emphasized the need for dataset diversity to improve model robustness against unseen deepfake techniques .

7. Detecting GAN-Generated Images Using CNNs: Li et al. [8](2020) proposed a CNN-based method for detecting GAN-generated images by analyzing texture inconsistencies. Their study found that CNNs could identify artificial textures that differed from natural image patterns, which helped improve deepfake detection accuracy .

8. FaceForensics++ Dataset and Deepfake Detection: Rossler et al. [3](2019) introduced the FaceForensics++ dataset, one of the most widely used datasets for deepfake detection. Their study demonstrated that CNN-based models trained on large datasets could effectively distinguish real from fake images by identifying subtle artifacts introduced by generative models [1]. The dataset has since been a benchmark for testing various deepfake detection techniques.

9. MesoNet for Deepfake Image Detection Afcharet al.[5] (2018) proposed MesoNet, a lightweight CNN architecture designed for detecting manipulated facial images. Their study showed that even shallow CNNs could effectively detect deepfakes, making them suitable for real-time applications with lower computational costs .

10. XceptionNet for Deepfake Detection Chollet[7] (2017) introduced XceptionNet, a deep CNN architecture that later proved to be highly effective in deepfake detection. Multiple studies, including FaceForensics++ [3], have shown that XceptionNet outperforms traditional CNN models in identifying manipulated images by focusing on depthwise separable convolutions .

III. METHODOLOGY

This section describes the dataset used, preprocessing done, the Convolutional Neural Network (CNN) model architecture used, the training procedure, and the metrics used to evaluate model performance.

3.1 Dataset

The data consists of two main classes: real images and deepfake images. Real images are actual photos, and the deepfake images have been generated synthetically with the help of deep learning-based face editing techniques. The dataset is categorized into two different folders: 'Real' and 'Deepfake'. Both the folders hold a significant number of images to have an evenly distributed set of both classes. The data can be easily loaded and pre-processed with ease during training by having such organization.

3.2 Data Preprocessing

To maintain consistency across the dataset and improve the model's accuracy, several preprocessing techniques were applied to all images. Initially, each image was resized to 224×224 pixels, ensuring uniform input dimensions—a common approach in CNN- based image classification [13]. Following this, pixel values were normalized by scaling them within the range (0,1) by dividing each value by 255. This step enhances numerical stability, speeds up training, and facilitates quicker convergence [14]. Additionally, data augmentation methods, including horizontal flipping, random rotations, and zooming, were used to artificially expand the dataset. These variations help prevent overfitting and enhance the model's ability to generalize to new images [15]

3.3 Model Architecture

The deepfake detection model utilizes a Convolutional Neural Network (CNN) architecture, particularly suited to detecting slight patterns that distinguish real images from deepfakes. The architecture consists of several layers, with each of them contributing to feature extraction and classification.

The model begins with an input layer that scans images of dimensions 224×224×3 to provide consistency in all the inputs.It proceeds through three convolutional layers of growing filter sizes, namely 32, 64, and 128. Each of the convolutional layers is followed by a Rectified Linear Unit (ReLU) activation function, which adds non-linearity so that the network can learn sophisticated visual features well [16].To down sample the feature maps and preserve important information, a Max Pooling layer using a 2×2 filter follows every convolutional layer. The process increases computational efficiency and avoids overfitting by maintaining important features.

The features are then flattened into a 1D vector and used as input to the fully connected layers. The first dense layer has 512 neurons to enable sophisticated feature learning. The output layer has one neuron with a sigmoid activation function that outputs a probability score showing whether an image is a deepfake [17].

This organized CNN architecture guarantees the model efficiently detects the important patterns and provides proper deepfake detection predictions.

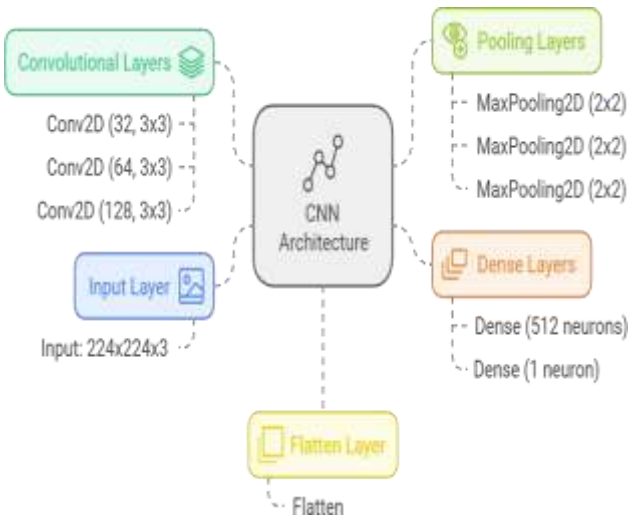

Fig 3.3 CNN Architecture

3.4 Training Process

The model was learned with a controlled methodology to optimize performance and limit the potential of overfitting. The process of training was directed by various important parameters:

For the loss function, Binary Cross-Entropy was chosen since it efficiently calculates the difference between predicted and true labels in binary classification problems [18]. For optimizing learning, the Adam optimizer was employed because of its adaptive learning rate and effectiveness in coping with sparse gradients, making it very effective for deep learning models [19].The batch size was set to 32 to balance computational speed and memory efficiency. The model was trained for 10 epochs, with sufficient learning without excess computation. Early stopping was also implemented through validation loss monitoring, where training[21] was halted once no improvement was observed. This method prevented overfitting and allowed the model to generalize well to new data.

3.5 Workflow

The deepfake detection system follows a structured pipeline to process and classify images efficiently. This section details the sequential steps involved in the detection process, from image input to final classification and result display.

3.5.1 Image Upload

The detection process begins when a user uploads an image[22] through the web-based interface, which is designed using HTML, CSS, and JavaScript. The uploaded image may either be an authentic real image or a deepfake. The interface ensures a user- friendly experience and seamless interaction with the model.

3.5.2 Preprocessing

Before feeding the image into the Convolutional Neural Network (CNN) model, several preprocessing steps are applied to standardize input dimensions [23] and optimize model performance:

1. Resizing – Each image is resized to 224 × 224 pixels to match the input dimensions required by the CNN model.
2. Normalization – Pixel values are normalized to the range (0,1) by dividing by 255, ensuring numerical stability and faster convergence.
3. Data Augmentation – Techniques such as horizontal flipping, rotation, and zooming are applied to introduce variability and improve model generalization.

These preprocessing steps help in reducing variability among images, ensuring uniformity in input data, and enhancing predictive performance.

3.5.3 Model Prediction

After preprocessing, the image is passed into the trained CNN model, which extracts key features and determines whether the image is real or deepfake[24]. The architecture consists of:

- Three convolutional layers with increasing filter sizes (32, 64, and 128) to capture hierarchical features.
- Rectified Linear Unit (ReLU) activation function to introduce non- linearity and improve feature learning.
- Max Pooling layers with a 2 × 2 filter to reduce spatial dimensions while preserving critical information.
- Flattening layer to convert the extracted feature maps into a one- dimensional feature vector.
- Fully connected dense layer with 512 neurons, followed by an output layer with a sigmoid activation function for probability estimation.

The model outputs a probability score between 0 and 1, indicating the likelihood of an image being a deepfake.

3.5.4 Classification Output

The model classifies images based on the probability score it generates:

- If the probability is 0.5 or higher, the image is identified as a deepfake.
- If the probability is below 0.5, the image is classified as real.

This classification approach provides a clear and reliable distinction[25] between genuine and manipulated images.

3.5.5 Result Display

The classification outcome is displayed on the web interface, offering instant feedback to the user. The front-end, built with HTML, CSS, and JavaScript, fetches the result from the backend and presents it in a user-friendly manner. The output clearly states whether the image is real or a deepfake, helping users evaluate its[26] authenticity.

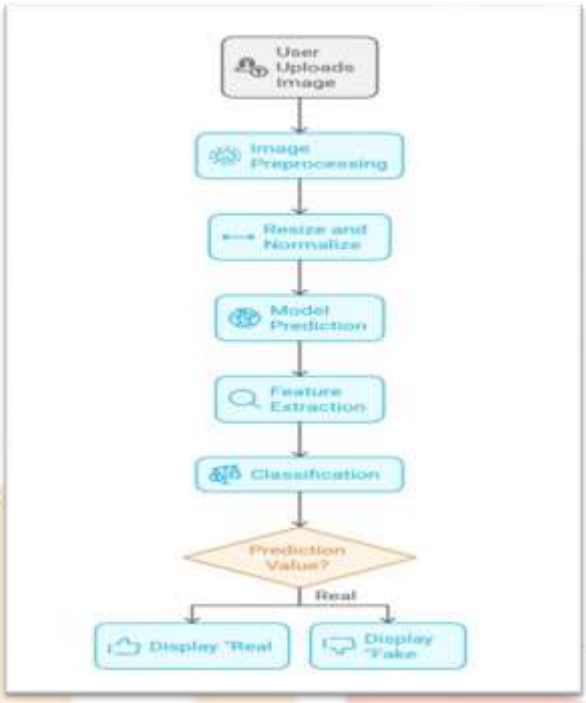

Fig 3.5 Workflow of Deepfake detection System

IV. RESULTS

4.1 Model Prediction and Interpretation

The model outputs a probability score between 0 and 1, indicating the likelihood of an image being a deepfake[27]. The classification decision follows a threshold-based approach:

- Probability close to 0 (e.g., 0.05, 0.12) → The image is predicted as real.
- Probability close to 1 (e.g., 0.87, 0.95) → The image is predicted as fake.
- Thresholding Mechanism → A threshold of 0.5 is applied, where images with a probability ≥ 0.5 are classified as deepfake, while those <0.5 are classified as real.

This probability-based approach provides a confidence level for the model's predictions, assisting in cases where classification is uncertain or ambiguous.

4.2 Model Behavior and Observations

The model's performance varied depending on image quality and facial features:
When processing clear, high-resolution images with well-defined facial features, the model made confident[28] and accurate predictions. However, some images received probability scores close to 0.5, indicating uncertainty in classification. These borderline cases were often associated with low-quality images or partially manipulated deepfakes, where key distinguishing features were less prominent, making it difficult for the model to differentiate between real and fake images.

Additionally, a few misclassifications were observed. Some false positives occurred, where real images were mistakenly labeled as deepfakes, while false negatives involved deepfake images being incorrectly classified as real. These cases suggest potential areas for improvement, such as enhancing preprocessing techniques and expanding the dataset to improve the model's ability to generalize across diverse image conditions.

4.3 Sample Predictions and Website Interface

To illustrate the model's performance and user experience, this section presents sample classification results alongside the web interface layout. A correctly classified real image is showcased to demonstrate the model's ability to accurately detect authentic images. Similarly, an example of a correctly classified deepfake image is provided to highlight the system's effectiveness in identifying manipulated content[29].Additionally, website interface screenshots are included to offer a visual representation of key system components:

1. Image Upload Section – The web interface where users submit images for analysis.
2. Result Display – The classification output presented clearly as either *Real* or *Fake*, ensuring ease of interpretation. These visual elements enhance the understanding of the system's usability, reinforcing the model's reliability in real-world application.

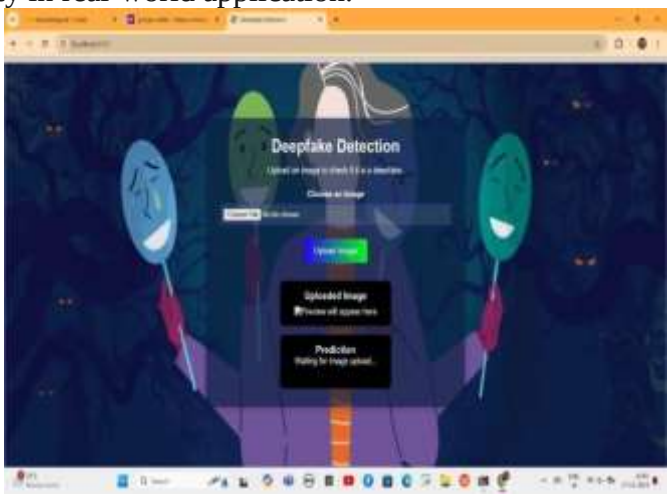

Fig 4.3.1 Deepfake Detection Dashboard

Fig 4.3.2 Output-Real image detected

Fig 4.3.3 Output-Fake image detected

4.4 Model Performance Metrics

To evaluate how well the deepfake detection model performs, several important metrics were considered, including accuracy, precision, recall, and F1-score. Additionally, visual tools like the confusion matrix, ROC curve, and training graphs for accuracy and loss were used to get a better understanding of the model's predictions and overall learning pattern.

1. **F1-score:** The F1-score[30] is a metric that balances both precision and recall, giving a better sense of overall performance, especially in cases with class imbalance. Our model reached an F1-score of 0.9695, showing it performs very well in correctly identifying both real and fake images.

```
F1-Score: 0.9695
```

Fig 4.4.1 F1-score of the model

2. **Classification Report:** To evaluate our deepfake detection model, we relied on standard classification metrics[31]—accuracy, precision, recall, and F1-score. These indicators offer a comprehensive understanding of how well the model distinguishes between real and fake content.

```
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.98      0.98       896
           1       0.97      0.97      0.97       525

    accuracy                           0.98      1421
   macro avg       0.98      0.98      0.98      1421
weighted avg       0.98      0.98      0.98      1421

Accuracy: 0.9775
Precision: 0.9713
Recall: 0.9676
```

Fig 4.4.2 Classification of the model

3. **Accuracy and Loss Trends:** To evaluate the learning behaviour of our deepfake detection model[32], we tracked its performance across epochs using accuracy and loss graphs for both training and validation data. The accuracy curve shows a steady improvement in training accuracy, reaching close to 100%. Validation accuracy also remained consistently high, hovering around 98%, which suggests that the model was able to generalize well to unseen data. The loss curve reveals a sharp drop in both training and validation loss during the initial epochs, indicating rapid learning early on. While the training loss continued to decline smoothly, the validation loss showed slight fluctuations later in training—hinting at mild overfitting. However, the difference between the two remained minimal, reflecting strong overall stability. These curves highlight the model's ability to learn effectively while maintaining high performance on new inputs.

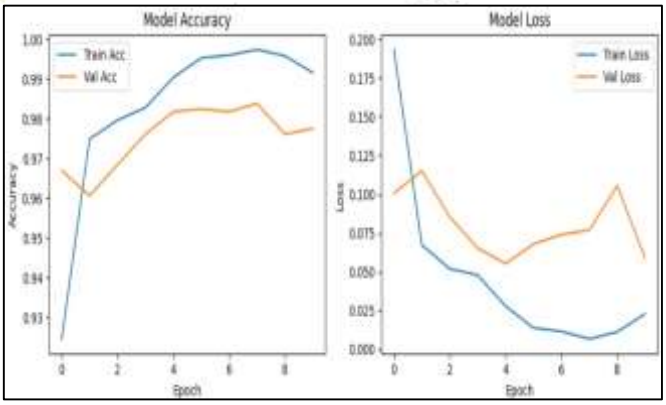

Fig 4.4.3 Accuracy and Loss Graph

4. **Confusion Matrix:** The confusion matrix in the below figure gives a clear view[33] of how well the model classified real (label 0) and fake (label 1) images. It successfully predicted 881 real images and 508 fake ones, with only a small number of errors—15 real images were marked as fake, and 17 fake images were marked as real. These minimal misclassifications highlight the model's strong performance and accuracy in handling both classes. The balanced results also align well with the high F1-score of 0.9695, further demonstrating the model's reliability in detecting deepfakes.

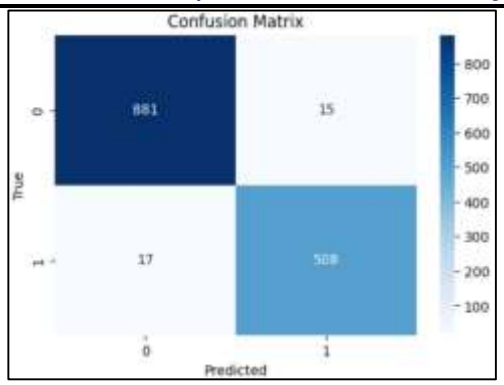

Fig 4.4.4 Confusion Matrix

5. **ROC Curve:** The ROC curve[34] shown in illustrates how well the model differentiates between real and fake images across different classification thresholds. The curve closely follows the top-left boundary, indicating excellent predictive performance. With an AUC score of 1.00, the model demonstrates a near-perfect ability to separate the two classes. A perfect AUC value suggests that the model is highly effective at minimizing classification errors, making it suitable for practical deepfake detection scenarios where accuracy is critical.

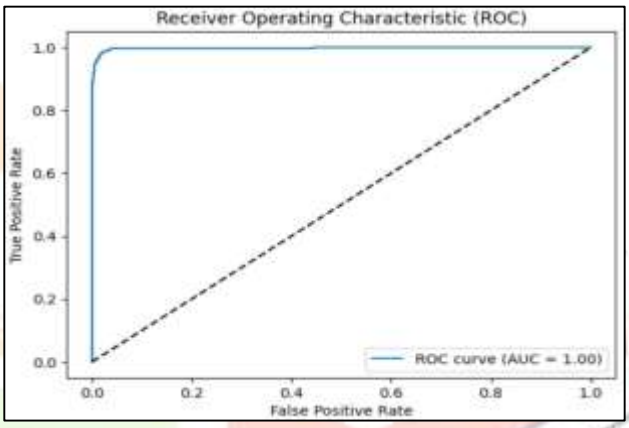

Fig 4.4.5 ROC Curve of model performance

V. CONCLUSION

This study presents a deepfake image detection system built on a Convolutional Neural Network (CNN) to differentiate between authentic and manipulated images. The model was trained on a dataset containing both real and deepfake images, incorporating preprocessing steps such as resizing, normalization, and data augmentation to improve generalization. By utilizing multiple convolutional layers, the system extracts intricate spatial features that aid in distinguishing deepfakes from genuine images. Experimental evaluations indicate that the model effectively identifies deepfake images, offering a viable solution for media authenticity verification. The system is deployed as a web-based platform, allowing users to upload images for instant analysis. This accessibility makes it particularly useful for professionals in fields such as journalism and law enforcement, where verifying media authenticity is crucial. While the system demonstrates promising results, it has certain limitations. The model's accuracy depends on the quality and diversity of the training dataset, which can impact its ability to detect highly sophisticated deepfakes generated with advanced AI techniques. Additionally, the current implementation focuses solely on static images, making it less suitable for detecting manipulations in video content.

5.1 Future Scope

To further improve deepfake detection, future research can explore the following areas:

- Expanding to Video Analysis: Extending the system to process video frames, allowing detection of temporal inconsistencies in manipulated footage.
- Enhancing Model Robustness: Incorporating adversarial training and utilizing larger, more diverse datasets to strengthen resistance against evolving deepfake techniques.
- Exploring Advanced Architectures: Investigating hybrid models, such as combining CNNs with transformers or recurrent neural networks (RNNs), to boost classification accuracy.
- Improving User Experience: Developing an interactive dashboard that provides in-depth

explanations of detection results, increasing transparency and user confidence in the system.

This research addresses the growing demand for deepfake detection by offering a scalable and user-friendly solution. As deepfake generation methods advance, continuous research will be crucial in safeguarding the authenticity and reliability of digital media.

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