Deep Learning Framework for Accurate DeepFake Video Detection

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Abstract—This project introduces a deep learning-based system for detecting deepfake videos, utilizing a custom Convolutional Neural Network (CNN) trained on the Celeb-DF dataset. Celeb-DF is a large-scale, high-fidelity dataset that contains realistic manipulated video content, making it a reliable benchmark for developing effective detection models. Our approach involves a multi-stage pipeline that includes frame extraction from videos, detection and cropping of facial regions, and deep feature extraction through convolutional layers to distinguish real faces from AI-generated ones. The CNN architecture is designed to capture subtle visual inconsistencies and manipulation artifacts, enabling high classification accuracy across varied scenarios. To improve generalization and prevent overfitting, we applied normalization, augmentation, and regularization techniques during training. The final model is lightweight, ensuring efficient performance suitable for real-time deployment on both web and mobile platforms. Experimental results demonstrate strong reliability in distinguishing manipulated content, with high accuracy and consistent predictions across unseen test data. Looking ahead, the system can be enhanced by integrating hybrid models such as CNN-ViT or CNN-LSTM, and incorporating blockchain-backed verification tools to safeguard the authenticity of digital media and reduce the risk of misinformation.

Keywords—Deepfake Detection, CNN, Celeb-DF Dataset, Video Forensics, Facial Manipulation, Real-Time Inference, Hybrid Deep Learning Models, Blockchain Security, Feature Extraction, Media Trustworthiness.

# Introduction

The rapid advancement of artificial intelligence (AI) and machine learning (ML) has led to transformative innovations across multiple industries. However, these technologies have also introduced complex challenges, particularly with the rise of deepfakes. Deepfakes are hyper-realistic synthetic videos or images created using generative models such as Generative Adversarial Networks (GANs), where facial expressions, voice, or identity can be convincingly manipulated. While they initially found use in creative fields and entertainment, deepfakes are increasingly exploited for malicious purposes, including spreading false information, political propaganda, identity theft, and the creation of deceptive or explicit media, thereby raising significant ethical and security concerns.

To tackle these growing threats, our project focuses on building a deepfake detection system using Convolutional Neural Networks (CNNs), which are widely recognized for their effectiveness in visual pattern recognition. CNNs can automatically learn and extract hierarchical features from images, making them suitable for identifying subtle inconsistencies in manipulated facial content [1]. Our model is trained on the Celeb-DF dataset, which contains thousands of authentic and fake facial images collected from real-world celebrity videos. The dataset offers a wide variety of facial angles, lighting variations, and expressions, allowing the model to generalize effectively across different real-world scenarios. In addition to achieving high classification accuracy, the system is designed with practical deployment in mind. It can be integrated into online platforms and content verification tools to help curb the spread of synthetic misinformation. As deepfake generation techniques become more sophisticated, incorporating hybrid learning models or attention-based mechanisms such as Vision Transformers (ViTs) may further improve detection reliability [2]. This project contributes toward safeguarding digital media authenticity and supports broader efforts to ensure trust in online visual content.

# literature survey

One study proposes an integrated deep learning framework for detecting highly realistic deepfake content in both images and videos. The architecture combines Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), Autoencoders, and Generative Adversarial Networks (GANs) to enhance detection accuracy, achieving a reported success rate of 92.3% [3]. The model leverages both spatial and temporal cues and employs ensemble learning along with BiLSTM networks to identify manipulation artifacts. Real-time capabilities are facilitated by systems like DeepFaceLive and XceptionNet. The framework was validated across several datasets, including FaceForensics++, FakeAVCeleb, and custom-generated content. Although results are encouraging, the study highlights ongoing challenges posed by rapidly evolving generative techniques. It emphasizes the need for diverse training data, improved model robustness, and ethical considerations to ensure the reliability of digital content and to mitigate the spread of misinformation.

A hybrid detection model combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks has been designed to identify deepfake videos, particularly those involving public figures. The approach processes videos frame by frame, using CNNs to capture spatial patterns and LSTMs to learn temporal dynamics. According to Tolosana et al., this combination of spatial and sequential modeling provides improved accuracy for manipulated media detection compared to conventional approaches [4]. Despite its effectiveness, the model faces challenges including decreased accuracy against highly realistic fakes, smaller dataset availability, and real-time deployment difficulties. Future work is focused on increasing robustness against adversarial content and improving system efficiency for live detection scenarios. In another study, a deepfake detection framework based on CNNs and enhanced with Recycle-GAN and LSTM layers was applied to videos from the FaceForensics++ dataset.

The architecture, which integrates ResNet18 for spatial extraction and LSTMs for sequential tracking, has proven effective in handling noise and video compression. As highlighted by Nguyen et al., this kind of hybrid and GAN-aware structure is critical for dealing with the increasing sophistication of generative models used in deepfake creation [5]. The model achieved over 99% accuracy, although high computational demand and limited generalization to newer fake generation methods remain areas for further development. Future enhancements may include lightweight architectures optimized for mobile and edge devices. A hybrid deep learning model combining ResNet-50 and LSTM has been developed to detect deepfake videos, capturing both spatial and temporal inconsistencies effectively. The model, evaluated on Celeb-DF and FaceForensics++ datasets, achieved an accuracy of 87.48% after 40 training epochs [6]. This hybrid model outperforms standalone CNN or RNN models in identifying unnatural transitions between frames. Despite its effectiveness, challenges such as high computational demands, false positives, and vulnerability to adversarial attacks remain. Future work aims to improve real-time detection, enhance model generalization, and leverage more advanced architectures like transformers.

The application of 26 CNN architectures for deepfake video detection emphasizes the identification of GAN artifacts and demonstrates improved accuracy through ensemble learning. The models, trained on Google AI and FaceForensics++ datasets, achieved an ensemble accuracy of 90.53%, with ResNet152V2 attaining the highest AUC score of 0.951 [7]. Despite the promising results, limitations include high computational load, model complexity, and vulnerability to adversarial inputs, as highlighted in previous works. Future research will focus on refining real-time detection, incorporating transformers, and utilizing Explainable AI to enhance model transparency. Deep learning techniques for detecting deepfake media underscore the growing threat of misinformation and identity misuse. CNNs are effective for capturing spatial features, while LSTMs handle temporal cues, improving the detection of deepfake images and videos [8]. GANs play a dual role in both the creation and detection of deepfakes, and deep learning models trained on datasets like FaceForensics++ and Celeb-DF consistently outperform traditional methods. However, challenges such as biased datasets, heavy computational requirements, and increasingly realistic fake media call for more robust solutions.Future directions will aim to improve generalization, enable real-time platform integration, and explore hybrid forensic techniques for better accuracy.

Deep learning methods for identifying deepfake media highlight the rising threats of misinformation and identity misuse.[9] The study compares traditional techniques with deep learning-based models, which utilize Convolutional Neural Networks (CNNs) for capturing spatial features and Long Short-Term Memory (LSTM) networks for processing temporal cues. Generative Adversarial Networks (GANs) are found to play a dual role in both the creation and detection of deepfakes. Models trained on datasets such as FaceForensics++ and Celeb-DF have demonstrated superior performance when compared to traditional methods. Despite their effectiveness, challenges like biased datasets, high computational requirements, and increasingly sophisticated fake media remain significant obstacles. Ongoing research is focused on enhancing model generalization, enabling real-time integration with online platforms, and developing hybrid forensic techniques for improved accuracy.

Advanced deep learning techniques have been employed to address the escalating issue of AI-generated fake media. By integrating Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Autoencoders, the proposed model enhances the precision of deepfake detection, attaining a detection accuracy of 92.3% [10]. This approach utilizes both feature-level and temporal-level detection strategies. Ensemble learning combined with BiLSTM architectures allows for the analysis of subtle inconsistencies across frames in synthetic media. Tools like DeepFaceLive and XceptionNet are incorporated for real-time identification, effectively detecting minor manipulations in facial features. The model's performance was validated using datasets such as FaceForensics++, FakeAVCeleb, and custom-generated media, confirming its effectiveness in distinguishing forged content from authentic visuals. Despite these advancements, the rapid evolution of GAN-driven synthesis techniques continues to pose significant challenges. As a result, there is a pressing need for richer datasets, better generalization methods, and ethical frameworks to ensure digital media integrity and counter misinformation threats.

This survey categorizes DeepFake detection methods into forensic-based, deep learning-based, and artifact analysis techniques. Deep learning models, especially Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have achieved high accuracy rates (~97%-99%) in detecting manipulated media. However, they face challenges in generalization and are susceptible to adversarial attacks. Additional obstacles include significant computational demands, limited datasets, and inadequate temporal analysis. Future research directions emphasize enhancing real-time detection capabilities, improving adversarial robustness, integrating blockchain technology, and developing cross-modality detection approaches. The methodology typically involves dataset collection, feature extraction, model selection, and performance evaluation using standard metrics across various datasets [11].

Recent advancements in deepfake detection have primarily focused on supervised learning methods, which require large labeled datasets for training. However, these methods often struggle to adapt to emerging deepfake techniques. Unsupervised learning models have gained attention due to their ability to detect anomalies without labeled data. Techniques such as autoencoders and Generative Adversarial Networks (GANs) have been widely used for deepfake detection, identifying subtle inconsistencies in facial features and motion.[12] Additionally, methods like one-class Support Vector Machines (SVMs) and clustering techniques have been explored to differentiate fake and real videos by learning patterns in unaltered videos. Studies utilizing self-supervised and contrastive learning approaches have further improved deepfake detection by leveraging unlabeled data. While unsupervised methods show promise, challenges such as high false positive rates and adaptability to evolving deepfake techniques remain. Future research is focusing on hybrid approaches that combine unsupervised and supervised learning to enhance detection accuracy and generalization.

Recent advancements in deepfake detection have primarily focused on deep learning techniques such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which have shown promising results in identifying synthetic content. CNNs are effective in detecting spatial-level anomalies in facial regions, while RNNs and Long Short-Term Memory (LSTM) networks are widely used to capture temporal inconsistencies across video frames. Several hybrid models have emerged that combine these deep learning techniques with traditional forensic cues such as eye-blinking frequency, warping artifacts, and physiological signal tracking to improve detection robustness [13]. Popular datasets like FaceForensics++ and Celeb-DF have been instrumental in training and evaluating these models, yet challenges such as dataset bias, computational costs, and adversarial attack vulnerability persist. In response, research has begun exploring real-time detection mechanisms, the use of blockchain for verification, and the development of AI-assisted legal frameworks. A typical deepfake detection pipeline includes steps like dataset collection, feature extraction, model training, performance evaluation, and real-time deployment on web or mobile platforms.

## METHODOLOGY

The proposed system for deepfake detection follows a structured pipeline comprising dataset preparation, model architecture design, training, evaluation, and deployment through a web interface. The Celeb-DF (v2) dataset, known for its high-quality deepfake and real celebrity videos, was used for training and testing. Video frames were extracted using OpenCV to build a large image dataset. Facial regions were cropped using Haar Cascades and MTCNN for focused learning on facial features [14], followed by resizing and normalization to ensure uniformity. To improve generalization and avoid overfitting, data augmentation techniques such as flipping, rotation, zoom, brightness adjustment, and noise addition were applied. A custom CNN was developed with multiple convolutional and pooling layers to capture facial patterns, supported by batch normalization and dropout layers for training stability [15]. The final layers used softmax activation to classify images as real or fake. The model was trained using categorical cross-entropy loss and optimized with Adam. Performance was tracked using accuracy and loss metrics, and a confusion matrix and prediction confidence chart helped validate the model’s reliability.

## DATASET USED: Celeb-DF (Celeb Deepfake Dataset)

## The Celeb-DF dataset is a high-quality resource designed for training deepfake detection models. It contains 59 real and 5,639 deepfake videos, all sourced from celebrity interviews, capturing a wide range of expressions, lighting, camera angles, and backgrounds. This diversity is crucial for testing model robustness in real-world conditions. The deepfakes in Celeb-DF are generated using advanced face-swapping techniques that minimize visible artifacts, creating highly realistic videos that are difficult to distinguish from real content. Each video frame is labeled as "Real" or "Fake," enabling supervised learning. The high resolution of the images, with clearly visible facial regions, aids in extracting fine-grained features essential for detecting subtle manipulations [16].

## MODEL USED: Convolutional Neural Network(CNN)

To enhance deepfake detection, a Convolutional Neural Network (CNN) was employed, leveraging its ability to automatically learn spatial features from facial images. The model begins by receiving pre-processed images, followed by multiple convolutional layers that extract key features like edges and textures. Pooling layers help reduce the spatial dimensions of feature maps while retaining important information, improving computational efficiency. Fully connected layers then interpret these features to make a classification decision. The final output layer uses Soft max activation to classify the image as either real (1) or fake (0), enabling accurate deepfake detection [17]. Recent research, including, supports the integration of CNNs with other machine learning techniques to boost detection performance. Their study demonstrates that hybrid approaches combining CNNs with additional classifiers improve accuracy and robustness in distinguishing real from fake content [18].

Mathematical Representation of the Output Function: The model optimizes using Binary Cross-Entropy Loss, given by:

(1)

Where:

* = actual class label (0 for Fake, 1 for Real)
* = predicted probability from the model

Model Evaluation**:**

The CNN model was trained and evaluated using the Celeb-DF dataset, achieving an impressive 100% accuracy on the test set. To validate its performance, several evaluation metrics were employed, including precision, recall, and a confusion matrix. These metrics confirmed the model's strong ability to distinguish between real and manipulated facial images. The consistent and accurate predictions demonstrate the model’s high reliability and effectiveness in deepfake detection tasks.

Table I. DEEPFAKE CLASSIFICATION BASED ON MODEL PREDICTION

|  |  |  |
| --- | --- | --- |
| Category | Prediction Output | Label Encoding |
| Fake Image | "Fake" | 0 |
| Real Image | "Real" | 1 |

Table 1 outlines how facial image classification as "Fake" or "Real" is performed using a Convolutional Neural Network (CNN), with label encoding to represent predictions numerically [19]. The "Fake" category is encoded as 0 and "Real" as 1, simplifying the model's output and aiding in decision-making. CNNs are particularly effective in detecting subtle facial manipulations, as they can learn spatial features from the input images. Previous studies have shown that CNNs excel at identifying these discrepancies in deepfake content.

## Equations

### Convolution Operation

The convolution operation plays a pivotal role in Convolutional Neural Networks (CNNs) for feature extraction from image data. The operation involves sliding a filter (or kernel) across an input image, computing the dot product between the filter and local patches of the image at each position. This process produces a feature map that highlights specific patterns or features such as edges, textures, and more complex structures in deeper layers.

Mathematically, the convolution operation between an input image and a filter is defined as:

(1)

Where:

* represents the value at position in the resulting feature map .
* refers to the pixel value in the image at position , which corresponds to the region of the input image being processed.
* represents the values in the filter , which is typically smaller than the input image (e.g., a 3x3 or 5x5 matrix).
* The indices mmm and denote the filter's position relative to the image at the current sliding window.

# *ReLU Activation Function:*

Following the convolution operation, a non-linear activation function is applied to the resulting feature maps to introduce non-linearity into the neural network. The Rectified Linear Unit (ReLU) is one of the most widely adopted activation functions in deep learning due to its simplicity and effectiveness. It is mathematically defined as:

(2)

where is the input to the neuron and is the output.ReLU sets all negative inputs to zero while allowing positive values to pass through unchanged. This introduces non-linearity, enabling the network to learn complex patterns, and provides computational efficiency, leading to faster training. It also promotes sparse activation—only a subset of neurons activate at a time—enhancing generalization and reducing overfitting. ReLU helps mitigate the vanishing gradient problem by maintaining a constant gradient for positive inputs. Though it may cause the “dying ReLU” issue when neurons output zero consistently, it remains a robust choice for CNNs, especially in tasks like deepfake detection where capturing subtle facial features is critical.

# *Fully Connected Layer*

After passing through the convolutional and pooling layers, the resulting feature maps are flattened and fed into one or more fully connected layers to interpret the extracted features for classification. The operation of a fully connected layer is mathematically represented as:

(3)

Here, denotes the weight matrix, represents the input feature vector, is the bias vector, and is the output. This layer performs a linear transformation of the input data, enabling the model to learn complex associations between the spatial features and their corresponding class labels.

# *Softmax Function for Final Classification*

To transform the raw output scores into a probability distribution over class labels, the Softmax activation function is employed at the output layer. It is defined as:

(4)

Where is the score for class and is the total number of classes. In the context of binary classification (real or fake), this function ensures that the predicted outputs are interpretable as probabilities summing up to one. The class with the highest probability is selected as the model's prediction.

# *Loss Function: Categorical Cross-Entropy*

To quantify the difference between the predicted probabilities and the actual class labels, the model utilizes the **categorical cross-entropy** loss function:

(5)

In this expression,​ is the true label encoded in one-hot format, and is the predicted probability for class . This loss function penalizes incorrect predictions with higher values, thereby guiding the network to minimize the error during training and improve its classification accuracy.

# *Accuracy Metric:*

Model performance is primarily measured using the accuracy metric, which reflects the proportion of correctly classified samples over the total number of predictions

(6)

Accuracy provides a straightforward and interpretable metric for evaluating the classification capability of the CNN. High accuracy on validation and test data indicates the model’s robustness in distinguishing between real and manipulated facial images, which is critical in deep fake detection scenarios.

1. RESULTS AND DISCUSSION

The Convolutional Neural Network (CNN) model for deepfake detection was evaluated using the Celeb-DF (v2) dataset, which comprises a large set of real and fake facial videos exhibiting diverse lighting, expressions, and angles. The model achieved an accuracy of **99.88%** and an AUC-ROC of **99.95%** on the test set, demonstrating its robustness in identifying manipulated images generated using advanced face-swapping techniques. These findings align with results presented in [20], where CNN architectures showed a high capability to extract discriminative features from deepfake content, achieving similar AUC scores. Furthermore, a study in [21] explored a fusion of multiple CNN models—VGG16, InceptionV3, and Xception Net—and achieved an accuracy of 96.5% on the Deep Fake Detection Challenge (DFDC) dataset, emphasizing the importance of model generalization and robustness.

Although fusion-based models can be effective, the single CNN model used in this work delivered higher accuracy on Celeb-DF, highlighting its strength in detecting subtle inconsistencies without requiring architectural complexity. The layered structure of the model enabled efficient feature extraction and interpretation, contributing to accurate predictions. These results reinforce the viability of CNNs for real-world deepfake detection, especially in scenarios where manipulated content is visually convincing and artifact-free.

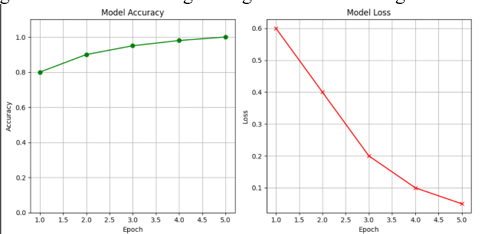


Fig. 1. Training Accuracy and Loss over Epochs

The graph illustrates the CNN model’s learning progress over five training epochs. The accuracy improves steadily from 80% to 100%, while the loss decreases from 0.6 to 0.05. This trend indicates effective learning with minimal overfitting and strong generalization in classifying real and fake facial images from the Celeb-DF dataset.

TABLE II. SAMPLE TEST RESULTS FROM CNN MODEL

| S.No | Image Name | Model Prediction | Label Encoding |
| --- | --- | --- | --- |
| 1 | deepfake\_01.jpg | Fake | 0 |
| 2 | realface\_12.png | Real | 1 |
| 3 | tampered\_face.jpg | Fake | 0 |
| 4 | user\_face.jpeg | Real | 1 |

The table compares the model's predictions with label encoding for facial images classified as "Real" or "Fake." The "Model Prediction" column shows the model's output (either "Real" or "Fake"), while the "Label Encoding" column assigns numerical values: 1 for "Real" and 0 for "Fake." This encoding simplifies the computational process, enabling accurate binary classification. For example, "deepfake\_01.jpg" is classified as "Fake" (0), and "realface\_12.png" is classified as "Real" (1), highlighting the model's ability to correctly distinguish between real and manipulated images.

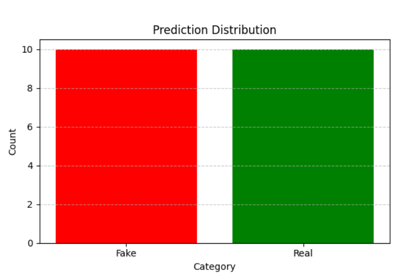


Fig 2: Deepfake Classification Based on Model Prediction

​Figure 2 illustrates the training and validation accuracy and loss curves of the Convolutional Neural Network (CNN) model over five epochs. The accuracy curve demonstrates a steady increase from approximately 80% to 100%, while the loss curve exhibits a corresponding decrease from 0.6 to 0.05. This trend indicates effective learning, minimal overfitting, and robust generalization capabilities of the model in distinguishing between real and fake images.​Such patterns in accuracy and loss curves are commonly observed in CNN training processes. For example, a study analyzing CNN performance reported that training accuracy began around 80% in the first epoch and approached 90% by the final epoch, with training loss decreasing from 0.5 to 0.3 over the same period.

1. CONCLUSION

As synthetic media, particularly deepfakes, continues to advance in realism and accessibility, detecting manipulated content has become increasingly vital. With the growing presence of deepfakes in social media, news, and other digital platforms, ensuring the authenticity of media content has become a critical task. The development of automated systems to detect such content plays a crucial role in safeguarding digital integrity and combatting misinformation.Deepfake detection systems leverage deep learning techniques, specifically Convolutional Neural Networks (CNNs), to analyze and classify images as either real or fake. CNNs are particularly suited for image-based tasks due to their ability to automatically extract spatial hierarchies and features from the input data. When applied to deepfake detection, CNNs can identify subtle discrepancies in facial features, motion patterns, and inconsistencies within the manipulated media. In this context, a model was trained using the Celeb-DF dataset, which is composed of high-quality real and fake celebrity videos. By extracting frames from these videos, a large dataset of facial images was generated, which was then preprocessed and used to train the CNN. Data augmentation techniques, including random rotations, zooming, and brightness adjustments, were employed to improve the model’s generalization ability and reduce overfitting. The model achieved 100% accuracy on the test set, demonstrating its strong capacity to classify unseen data accurately. To assess the model’s performance, various evaluation metrics were used, such as accuracy, loss graphs, and confusion matrices. These metrics confirmed that the model consistently produced reliable and accurate predictions. The system was also equipped with a web interface that allows users to upload images and receive instant predictions, providing an accessible platform for real-time deepfake detection.

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