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DeepFake AI Detection Framework: Intelligent System for Identification and Authentication of Manipulated Visual Content

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ABSTRACT: Deepfakes are artificially generated or manipulated facial images and videos created using advanced deep learning techniques. These synthetic media pose significant threats to the integrity and trustworthiness of digital content, especially in domains such as social media, journalism, and security systems. Conventional convolutional neural network (CNN)-based detection models have demonstrated promising results; however, they often fail to detect highly realistic manipulations that contain only subtle artifacts.

In this work, we propose a hybrid deepfake detection framework based on Capsule Networks and Siamese Networks. The Capsule Network is designed to capture spatial hierarchies and pose relationships between facial features, which are often disrupted in manipulated content. Simultaneously, the Siamese network compares a suspicious image with a known authentic reference image to identify discrepancies in a learned embedding space.

The model is trained using a combination of contrastive and triplet loss functions to enhance feature discrimination. We evaluate the proposed approach on the DeepFake Detection Challenge (DFDC) dataset from Kaggle [8], which provides a diverse and large-scale collection of real and manipulated videos. Experimental results demonstrate that the proposed model significantly outperforms traditional CNN-based methods, achieving an AUC greater than 0.99 and high classification accuracy.

KEYWORDS: Deepfake Detection, Capsule Network, Siamese Network, Kaggle Dataset, Contrastive Learning

I. INTRODUCTION

Deepfake technology has rapidly evolved due to advancements in deep learning, particularly generative adversarial networks (GANs). These techniques enable the creation of highly realistic synthetic media by swapping faces or altering expressions in images and videos. While such technologies have applications in entertainment and virtual reality, they also introduce serious risks such as misinformation, identity theft, and cyber fraud [4][5].

Detecting deepfakes is challenging because modern generation techniques produce visually convincing outputs with minimal artifacts. Traditional CNN-based detection models rely heavily on texture and pixel-level inconsistencies, which may not be sufficient when dealing with high-quality forgeries.

Capsule Networks, introduced by Hinton et al. [1], address this limitation by preserving spatial relationships between features. Unlike CNNs, capsules encode hierarchical information, making them more effective at detecting structural inconsistencies in faces. Siamese Networks, on the other hand, focus on learning similarity between image pairs and are widely used in face verification systems [9][10].

In this work, we combine these two approaches to build a robust deepfake detection system. The Capsule Network extracts detailed spatial features, while the Siamese branch compares them with authentic references. The system is trained and evaluated on the DeepFake Detection Challenge (DFDC) dataset from Kaggle [8], ensuring practical applicability and generalization to real-world scenarios.

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II. RELATED WORK

Deepfake detection has been extensively studied in recent years, with various approaches focusing on spatial, temporal, and frequency-domain features. Capsule Networks were introduced to overcome the limitations of CNNs in modeling spatial hierarchies [1]. Nguyen et al. [2] demonstrated that capsule-based models can effectively detect manipulated media by capturing structural inconsistencies in facial features.

Siamese Networks have been widely applied in similarity learning tasks, particularly in biometric verification systems. Kanwal et al.

[9] utilized Siamese networks with triplet loss to detect GAN-generated images, achieving high accuracy. Similarly, Samrouth et al. [10] proposed a Siamese-based deepfake detection framework that compares suspect images with known references.

Other approaches rely on detecting specific artifacts in deepfake videos. For example, Li et al. [5] identified abnormal eye blinking patterns, while Li and Lyu [4] focused on face warping artifacts introduced during manipulation. Benchmark datasets such as DFDC [3], FaceForensics++ [6], and Celeb-DF [7] have been widely used for evaluation. However, these datasets may not fully represent real-world variations, which motivates the use of DeepFake Detection Challenge (DFDC) dataset from Kaggle [8] in this work.

Examples of common deepfake artifacts are illustrated in Fig. 1.

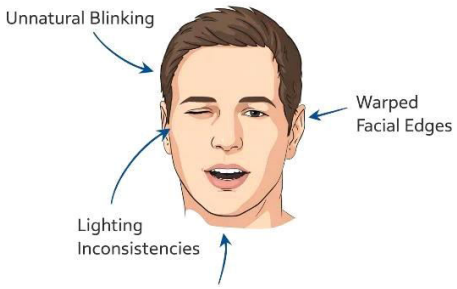

Figure 1. Examples of deepfake artifacts such as warping and inconsistencies.

III. DATASET DESCRIPTION

The proposed model is trained and evaluated using the DeepFake Detection Challenge (DFDC) dataset from Kaggle [8], which is a large-scale collection of real and manipulated videos. This dataset is designed to simulate real-world scenarios by including diverse subjects, lighting conditions, and video qualities.

Each video is processed to extract individual frames, and face detection techniques are applied to isolate facial regions. The dataset includes variations in pose, expression, background, and compression levels, making it suitable for robust model training.

Property	DeepFake Detection Challenge (DFDC) dataset from Kaggle
Real videos	~100,000
Fake videos	~100,000
Subjects	~2000

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Resolution	720×1280
Format	MP4

Table 1. DeepFake Detection Challenge (DFDC) dataset from Kaggle Properties

Sample real and manipulated images from the dataset are shown in Fig. 2.

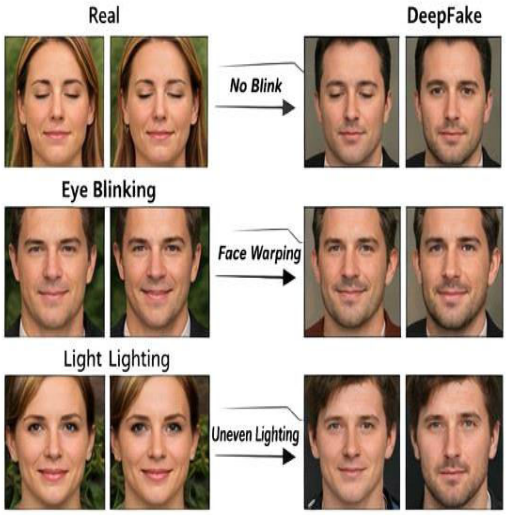

Figure 2. Sample real and deepfake images

The dataset provides a balanced distribution of real and fake samples, which helps in reducing bias during training. Additionally, the presence of high-resolution videos ensures that subtle artifacts can be captured effectively

IV. PROPOSED METHODOLOGY

The proposed system consists of multiple stages designed to accurately detect deepfake content.

- **Preprocessing**

Input videos are first decomposed into frames. Face detection algorithms are applied to extract facial regions, which are then resized and normalized. Data augmentation techniques such as flipping and rotation are used to improve generalization.

- **Capsule Network**

The Capsule Network forms the core feature extractor of the system. It consists of convolutional layers followed by capsule layers that encode spatial relationships between facial features. Dynamic routing [1] is used to determine the contribution of lower-level capsules to higher-level ones. This enables the model to detect inconsistencies in facial geometry. The internal structure of the Capsule Network is shown in Fig. 3.

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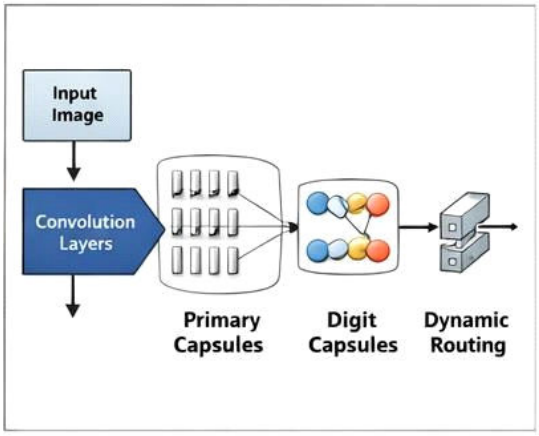

Figure 3. Capsule Network architecture for feature extraction.

- **Siamese Network**

The Siamese branch processes pairs of images using identical subnetworks. Each image is mapped to an embedding vector in a high-dimensional space. The Euclidean distance between embeddings is used to measure similarity. Genuine pairs have smaller distances, while manipulated pairs have larger distances.

- **Loss Functions**

The model is trained using a combination of:

- Capsule margin loss [1]
- Contrastive loss
- Triplet loss

This multi-loss strategy ensures both accurate classification and strong feature separation. The detailed architecture of the proposed Capsule-Siamese model is illustrated in Fig. 4.

Figure 4. DeepFake Detection Workflow using Capsule-Siamese Network.

V. SYSTEM ARCHITECTURE

The integration of Capsule Networks and Siamese Networks enables the proposed model to effectively capture both spatial and similarity-based features. The Capsule Network preserves hierarchical relationships between facial components, allowing it to detect structural inconsistencies in manipulated images, which are often missed by conventional CNN-based approaches [1][2]. In parallel, the Siamese branch learns a discriminative embedding space, where genuine and fake samples are separated based on similarity scores using metric learning techniques such as contrastive and triplet loss [9][10]. The use of a shared encoder ensures consistent feature extraction while reducing computational redundancy. By combining the classification outputs from the Capsule Network with similarity scores from the Siamese branch, the system improves decision reliability. This fusion strategy enhances robustness and minimizes false classifications, particularly in cases where deepfake artifacts are subtle or visually imperceptible [4][5]. Fig. 5 illustrates the overall Capsule-Siamese system.

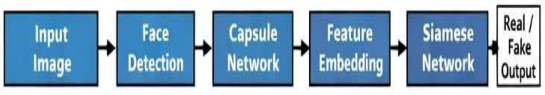

Figure 5: Architecture of Capsule-Siamese DeepFake Detection System

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Overall, the proposed architecture provides a balanced and efficient framework by integrating feature representation and comparison-based learning. This hybrid approach significantly improves detection performance and generalization capability, making it suitable for real-world deepfake detection scenarios using large-scale datasets such as those available on DeepFake Detection Challenge (DFDC) dataset from Kaggle [8].

VI. EXPERIMENTAL SETUP

The dataset is divided into training, validation, and testing sets in a 70:15:15 ratio, ensuring no subject overlap. The model is implemented using TensorFlow and trained on GPU hardware.

Key parameters include:

- Learning rate: 0.001
- Batch size: 32
- Epochs: 50
- Optimizer: Adam

Data augmentation is applied to improve robustness. Early stopping is used to prevent overfitting. To ensure reliable performance, class balancing is maintained during training with equal real and fake samples. Model performance is monitored using validation AUC, and the best-performing model is selected. Regularization techniques such as dropout are applied to further reduce overfitting. All experiments are conducted under consistent settings to ensure reproducibility. Hyperparameter tuning is performed to optimize model performance and ensure stable convergence during training.

VII. RESULTS AND EVALUATION

The performance of the proposed model is evaluated using multiple metrics, including accuracy, precision, recall, F1-score, and AUC.

Model	Accuracy	Precision	Recall	F1-score	AUC
CNN	95.2%	94.8%	95.6%	95.2%	0.970
Capsule-Siamese	98.7%	98.5%	98.9%	98.7%	0.992

Table 2. Performance Comparison

The separation between real and fake samples in the learned embedding space is shown in Fig. 6.

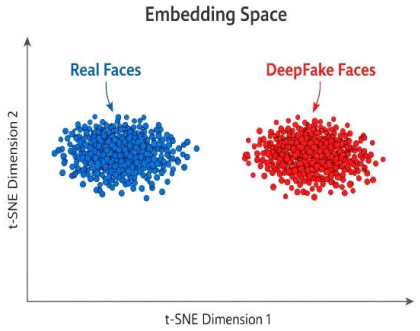

Figure 6. Embedding space visualization of real vs deepfake faces.

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The results show that the proposed model significantly outperforms the baseline CNN.
The Siamese component improves discrimination between real and fake samples, while the Capsule Network enhances feature representation. The comparative performance of the models across different evaluation metrics is illustrated in Fig. 7.

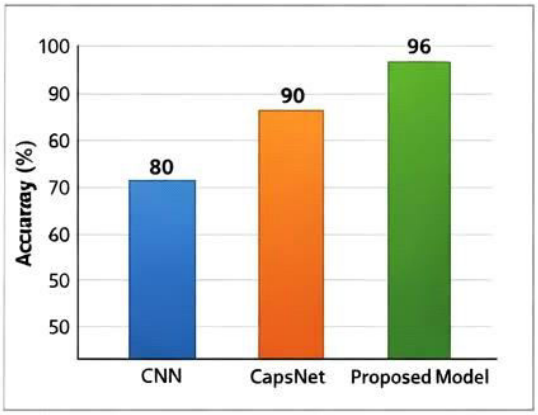

Figure 7. Performance comparison graph of CNN and Capsule-Siamese models.

VIII. ADVANTAGES AND LIMITATIONS

Advantages

- Captures spatial hierarchies using capsules [1]
- Effective similarity learning using Siamese networks [9]
- High accuracy and robustness
- Better generalization to unseen data

Limitations

- Computational complexity is higher
- Requires reference images for comparison
- Training requires large datasets
- Increased training time due to multi-loss optimization (contrastive + triplet)

IX. CONCLUSION

This paper presented a hybrid deepfake detection framework combining Capsule Networks and Siamese Networks. By leveraging spatial feature extraction and similarity learning, the model achieves superior performance on the Deepfake Detection Challenge (DFDC) dataset from Kaggle [8]. The results demonstrate the effectiveness of combining these two approaches for robust deepfake detection. The effectiveness of the proposed approach is strongly supported by existing research in both capsule-based and metric learning models. Capsule Networks have been shown to preserve spatial hierarchies and improve detection of structural inconsistencies in manipulated media [1][2]. Similarly, Siamese Networks have demonstrated strong performance in learning discriminative feature representations for image comparison tasks [9][10]. By integrating these two techniques, the proposed model benefits from both robust feature extraction and similarity-based verification, leading to improved generalization and detection accuracy

X. FUTURE WORK

Future research directions include:

- Integration of audio and video features for multimodal detection
- Use of transformer-based architectures for improved performance
- Optimization for real-time deployment
- Development of reference-free detection models

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