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A Novel ResNeXt-based CNN for Spatial Feature Extraction and LSTM-based RNN for Temporal Pattern Analysis of Deepfake Detection Systems

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ABSTRACT

Deepfake media, generated using advanced AI-based techniques, pose a significant threat to information integrity and public trust. This paper presents a novel deep learning framework for deepfake detection, combining the strengths of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). The proposed method employs a ResNeXt-based CNN architecture to effectively extract high-level spatial features from individual video frames, capturing subtle facial inconsistencies often overlooked by traditional models. These spatial features are then passed to an LSTM-based RNN module, which analyzes temporal dynamics across consecutive frames to identify behavioral and motion anomalies characteristic of manipulated content. The integration of spatial and temporal analysis enhances detection accuracy and robustness across various deepfake datasets. Experimental evaluations demonstrate that our hybrid model outperforms existing state-of-the-art techniques in terms of precision, recall, and F1-score, highlighting its potential for real-world deployment in digital media forensics.

Keywords: *Deepfake Detection, Generative Adversarial Networks (GANs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Hybrid CNN-LSTM Model, Adversarial Robustness, Digital Media Forensics.*

I. INTRODUCTION

The rise of deepfake technology—synthetically generated or manipulated media content created using advanced artificial intelligence (AI) techniques—has significantly reshaped the digital media landscape. Initially developed for creative and entertainment applications, deepfakes are now increasingly associated with security threats, misinformation campaigns, identity theft, and cyber fraud. Powered by Generative Adversarial Networks (GANs) [1], and further enhanced by architectures like StyleGAN [2] and CycleGAN [3], deepfakes have reached a level of realism that challenges human perception and traditional detection methods.

Video-based deepfake generation has evolved rapidly with models capable of few-shot synthesis [4], enabling realistic facial reenactment and voice cloning with minimal data. Consequently, the detection of deepfakes has become a pressing research concern in digital forensics and AI safety. Various approaches have emerged, particularly those leveraging deep learning architectures such as Convolutional Neural Networks (CNNs) for spatial feature analysis [5], and Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) models, for capturing temporal dynamics [6]. Hybrid models that integrate CNNs and LSTMs have shown promise in enhancing detection accuracy [7].

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In response to adversarial threats and detection evasion tactics such as GAN fingerprint removal [13] and white-box attacks [12], researchers have explored alternative architectures like Capsule Networks [8], Vision Transformers (ViTs) [9], and frequency-aware models [10]. Physiological signal-based methods [11], audio-visual correlation analysis [22], and lip-sync inconsistency detection [23] further enrich the detection landscape. Despite these advances, challenges remain, including generalization across datasets, adversarial robustness, real-time scalability, and fairness [21].

This research aims to address these challenges by proposing a hybrid deepfake detection model that combines a ResNeXt-based CNN for robust spatial feature extraction with an LSTM-based RNN for temporal pattern analysis. The model is evaluated on benchmark datasets—FaceForensics++ [15], DFDC [16], and Celeb-DF [17]—and assessed using standard performance metrics such as precision, recall, F1-score, and AUC-ROC [19][20]. The study also reviews the evolving landscape of deepfake generation and detection methods, highlights ongoing vulnerabilities, and discusses future directions including the use of Explainable AI (XAI), adversarial training, few-shot learning, and blockchain-based authentication frameworks [28].

In the context of increasing digital manipulation, the need for robust, interpretable, and generalizable detection systems is more critical than ever. This research contributes to this goal by advancing the hybrid detection paradigm while considering the broader ethical, legal, and technical implications of deepfake proliferation [25][26][27].

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II. SCOPE OF THE SURVEY AND OBJECTIVE

2.1 This survey explores deep learning models used in deepfake detection:

- **Evolution of Deepfake Generation Techniques:** Deepfake technology has progressed from early GAN models to advanced methods like StyleGAN and CycleGAN, requiring detection methods to evolve as well.
- **Deep Learning-Based Detection Approaches:** Traditional methods are ineffective against advanced deepfakes. CNNs detect spatial anomalies, LSTMs handle temporal inconsistencies, and VAEs identify subtle deviations. Hybrid models like CNN-LSTM and Vision Transformers improve accuracy.
- **Performance Evaluation on Benchmark Datasets:** Models are tested on datasets like FaceForensics++, DFDC, and Celeb-DF using metrics like accuracy, precision, and recall. However, dataset biases and overfitting remain challenges.
- **Open Challenges and Future Research Directions:** Challenges include high computational demands, adversarial deepfakes, and poor generalization due to dataset bias. Future research should focus on multi-modal detection, adversarial learning, real-time deployment, and addressing ethical concerns.

2.2 Objectives

- To review and evaluate various deepfake detection techniques, including CNNs, LSTMs, and Vision Transformers.

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- To propose a novel hybrid framework that combines CNN, LSTM, and feature fusion with adversarial training for improved detection accuracy.
- To identify and address emerging challenges in deepfake detection, with a focus on real-time and privacy-preserving solutions.

III. RELATED WORK AND BACKGROUND

A systematic review of deepfake detection techniques, ensuring the inclusion of high-impact, peer-reviewed studies focused on deep learning-based models. Papers were sourced from reputable databases like IEEE Xplore, ACM Digital Library, Springer, Elsevier's ScienceDirect, and arXiv, which provide access to AI, deep learning, and multimedia forensics research.A structured Boolean search was employed with keywords like "Deepfake detection using CNNs and RNNs," "GANs for face forgery identification," and "Adversarial attacks in deepfake detection," refining results based on publication date (2016–2024), peer-review status, and dataset usage.Studies published between 2016 and 2024 were prioritized, with an emphasis on peer-reviewed papers from high-impact journals. Research on deep learning-based methods, particularly CNNs, LSTMs, GANs, and Transformers, was prioritized. Studies using benchmark datasets like FaceForensics++, DFDC, and Celeb-DF, and those focused on real-time detection, adversarial attacks, and multimodal approaches, were favored. Figure 1 shown that -flow chart of selection criteria.

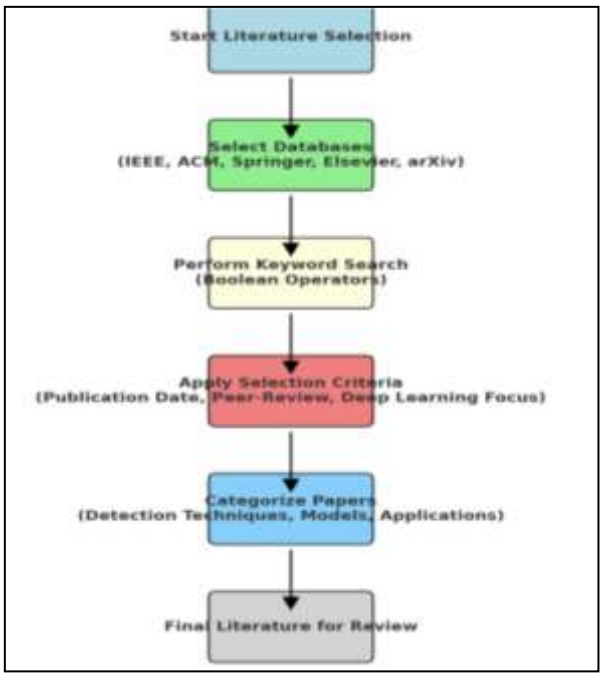

Figure 1-Flow chart of Selection Criteria

The studies were grouped into four areas: deepfake generation techniques, focusing on GAN advancements; detection architectures, comparing models like CNNs and LSTMs; datasets and metrics, evaluating performance with metrics like accuracy; and challenges and future directions, addressing issues like adversarial deepfakes and ethical

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concerns.This literature selection methodology ensures a comprehensive review of the latest deepfake detection models, balancing deep learning approaches with real-world considerations like scalability, adversarial robustness, and ethical AI. By diversifying sources and addressing dataset bias, it enhances the generalizability and reliability of the findings, strengthening the validity of the research.Deepfake detection has evolved significantly with the rise of AI-generated fake media. Early methods (2016-2018) focused on handcrafted features like facial asymmetry and unnatural blinking, with Li et al. (2018) proposing blink detection for eye movement anomalies. From 2019 to 2021, deep learning models like XceptionNet, EfficientNet, and ResNet became popular, alongside benchmarks such as FaceForensics++ and DFDC. Qi et al. (2020) introduced Capsule Networks for detecting subtle artifacts. Since 2022, multi-modal approaches combining image and audio signals have improved detection, while transformer-based models like Vision Transformers and Swin-Transformer were explored for large-scale detection. However, adversarial AI attacks against these models have become a growing concern. figure 2 shown that graph on evolution of deepfake detection methods.

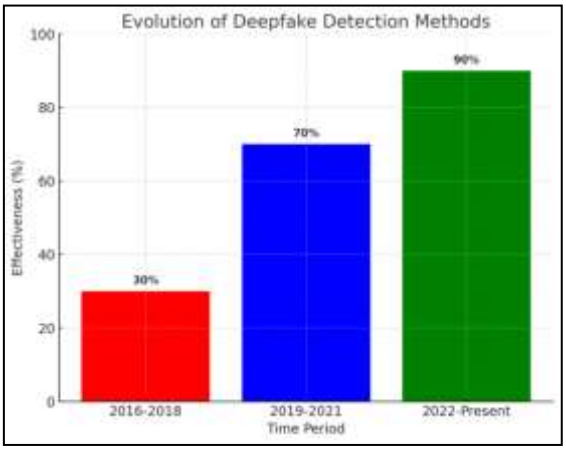

Figure 2- Graph on evolution of deepfake detection methods

Deepfake detection methods fall into three categories: Image-based techniques use CNN models to identify spatial inconsistencies and frequency artifacts, video-based methods use RNNs to detect temporal issues like lip-sync errors, and hybrid approaches combine image, video, and audio signals for improved accuracy, often using contrastive learning to differentiate real from fake content.

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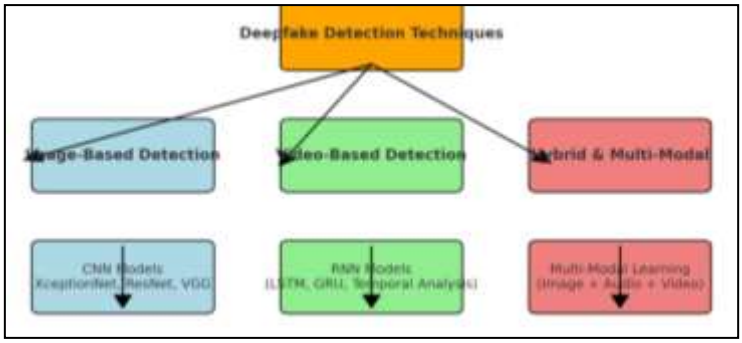

Figure 3-block diagram of Deepfake detection techniques

Deepfake detection research can be categorized into theoretical and empirical approaches, as shown in Figure 3. Theoretical methods focus on mathematical analysis, such as Fourier and wavelet transforms, to identify noise patterns in synthetic media. Empirical approaches involve training deep learning models with large datasets like FaceForensics++ and Celeb-DF, with GAN-based adversarial training improving resilience. Application-wise, deepfake detection is used on social media platforms to combat misinformation, in cybersecurity to prevent identity fraud, and in law enforcement for video authenticity verification, which also raises legal considerations in court proceedings, as shown in Table 1.

Table 1- Different Methods

Approach	Strengths	Weaknesses
CNN-Based Models	Effective for image-based deepfake detection	Struggle with unseen deepfake techniques
RNN & LSTM	Good for video deepfake analysis	High computational cost
Transformers (ViTs)	Superior performance on large datasets	Requires extensive training
Multi-Modal Models	Robust detection across different media	Complex implementation

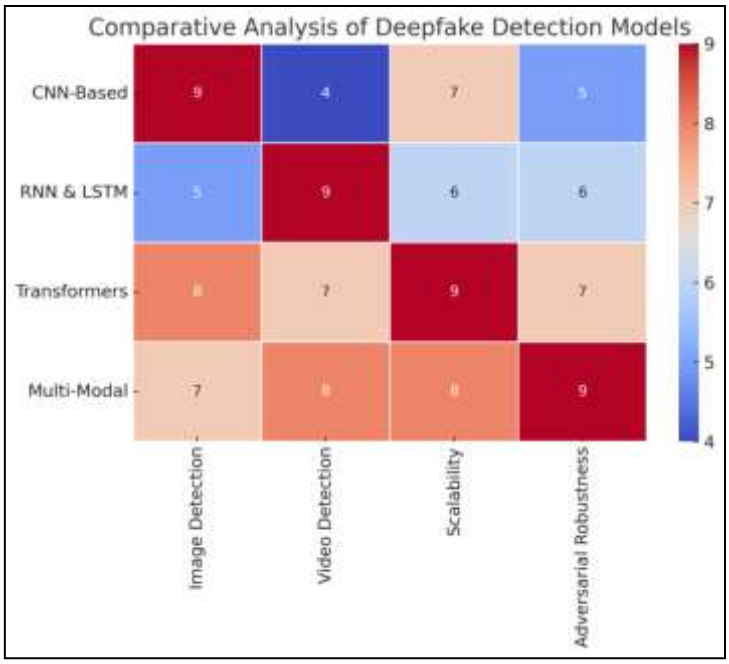

Figure 4-Heat Map of comparative analysis

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Existing research lacks real-world diversity, is vulnerable to adversarial attacks, and struggles with generalization. Future work should focus on adversarial training, cross-modal analysis, and explainable AI for more robust detection, as shown in Figure 4.

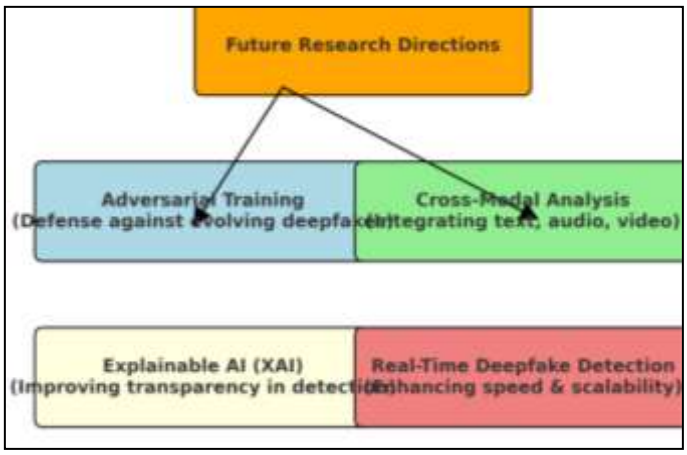

Figure 5- Flow Chart of future research directions

To determine the most effective deepfake detection model, this research conducts a comparative study of various architectures in table 2:

Table 2- Comparative Study of Architectures

Model	Advantages	Limitations
XceptionNet CNN	Captures fine-grained details, effective for frame-wise deepfake detection	Limited generalization to new deepfake variants
ResNet-50	Strong feature extraction capabilities	Vulnerable to adversarial attacks
CNN-LSTM Hybrid	Learns both spatial and temporal patterns	Requires large datasets for effective training
Vision Transformers (ViTs)	Captures long-range dependencies across frames	Computationally expensive
Capsule Networks	Preserves spatial relationships, making it robust against transformations	Slower compared to CNNs

This study benchmarks these models against industry-standard datasets, including FaceForensics++, Celeb-DF, and DFDC, to assess their performance in real-world deepfake detection tasks.

IV. METHODOLOGY

Deepfake detection models employ binary classification, distinguishing between real (1) and fake (0) multimedia content. The most commonly used loss function in this context is Binary

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Cross-Entropy (BCE), which quantifies the difference between predicted probabilities and true labels.

4.1 Binary Cross-Entropy (BCE) Loss Function

The Binary Cross-Entropy (BCE) loss function is defined as:

L=−1N∑i=1N[yilog⁡(y^i)+(1−yi)log⁡(1−y^i)]L = - \frac{1}{N} \sum_{i=1}^{N} \left[y_i \log(\hat{y}_i) + (1 – y_i) \log(1 - \hat{y}_i) \right]

where:

- N = Number of training samples
- yi = Actual label (1 for real, 0 for fake)
- y^I = Model's predicted probability that the sample is real
- L = The total loss across all samples in a batch

Binary Cross-Entropy (BCE) is effective for deepfake detection but struggles with class imbalance, mislabeled data, and highly realistic deepfakes.

4.2 Alternative Loss Functions for Deepfake Detection

To improve detection performance, researchers have explored alternative loss functions:

4.2.1 Focal Loss and Hinge Loss

Focal Loss and Hinge Loss are two effective alternatives to Binary Cross-Entropy for improving deepfake detection performance.

Focal Loss is particularly useful in handling imbalanced datasets, such as those with more real videos than fake ones, by focusing more on hard-to-classify examples and down-weighting easy ones. It is defined as:
$L = -\sum_{i=1}^{n} \alpha_t(1 - \hat{y}_i)^\gamma \log(\hat{y}_i)$,
where α_t is the class weighting factor and γ is the modulation factor that increases focus on difficult examples.

On the other hand, Hinge Loss, traditionally used in SVMs, has been adapted to deepfake detection models to create sharper decision boundaries between real and fake videos. It is given by:
$L = \sum_{i=1}^{n} \max(0, 1 - y_i \cdot \hat{y}_i)$,
where y_i is the ground truth label (1 for real, -1 for fake) and $\hat{y}_i$ is the predicted score.

4.3. Deepfake Detection Model Implementation with BCE & Focal Loss

Deepfake datasets often suffer from an imbalance between real and fake samples, making it crucial to use loss functions that address this issue effectively. Focal Loss is particularly useful as it emphasizes hard-to-classify examples by down-weighting the easy ones, thereby preventing the model from overfitting to dominant classes (e.g., many real videos). The focal loss is defined as:
$L = -\sum_{i=1}^{N} \alpha_t (1 - \hat{y}_i)^\gamma \log(\hat{y}_i)$,

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where α_t is a class-balancing factor, γ is a modulation factor that increases the focus on misclassified examples, and $\hat{y}_i$ is the predicted probability. In TensorFlow/Keras, it can be implemented as:

```
import tensorflow as tf

def focal_loss(alpha=0.25, gamma=2.0):
    def loss(y_true, y_pred):
        bce = tf.keras.losses.binary_crossentropy(y_true, y_pred)
        p_t = y_true * y_pred + (1 - y_true) * (1 - y_pred)
        return alpha * tf.pow(1 - p_t, gamma) * bce
    return loss
```

On the other hand, Hinge Loss is commonly used in SVM-based classifiers and has been adapted for deepfake detection to enforce sharper classification boundaries. The formula is:

$L = \sum_{i=1}^{N} \max(0, 1 - y_i \cdot \hat{y}_i)$,

where y_i is the ground truth label (e.g., 1 for real, -1 for fake), and $\hat{y}_i$ is the predicted score. This loss is effective in increasing the margin between the two classes. In PyTorch, it can be implemented as:

```
import torch
import torch.nn as nn

hinge_loss = nn.HingeEmbeddingLoss()

y_true = torch.tensor([1., -1., 1., -1.])  # Real: 1, Fake: -1
y_pred = torch.tensor([0.9, -0.7, 0.8, -0.6])

loss = hinge_loss(y_pred, y_true)
print("Hinge Loss:", loss.item())
```

Together, these loss functions improve the robustness and decision boundary quality of deepfake detection models, especially under data imbalance scenarios.

Table 3 Comparative Analysis of Loss Functions for Deepfake Detection

Loss Function	Advantages	Disadvantages
Binary Cross-Entropy (BCE)	Works well with probabilistic models, easy to implement	Sensitive to class imbalance, treats all errors equally
Focal Loss	Handles imbalanced datasets, focuses on hard examples	Computationally expensive
Hinge Loss	Sharpens decision boundaries, better separability	Less effective with probabilistic outputs

To improve your deepfake detection model, you need more **diverse and high-quality data** as shown in figure 6.

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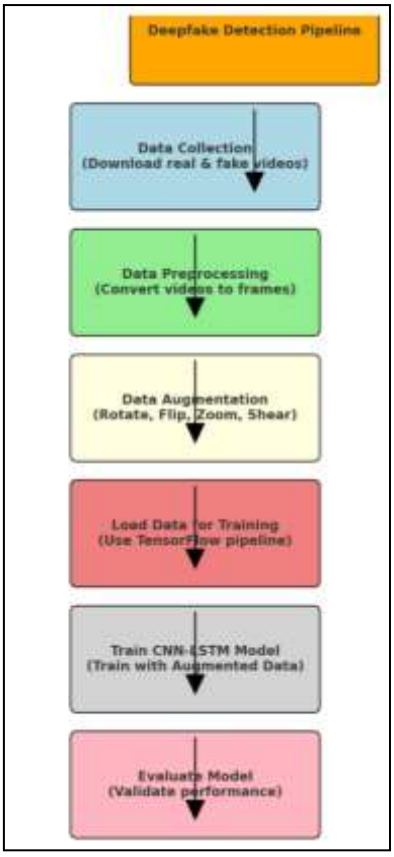

Figure 6- Flow chart of deepfake detection model

4.3 Data Collection

To train a deepfake detection model, you need a dataset with both **real and fake videos/images** as shown in table 4. Some publicly available datasets include:

- **FaceForensics++**: Large dataset with real and deepfake videos.
- **DFDC (DeepFake Detection Challenge)**: Facebook's dataset for deepfake detection.
- **Celeb-DF**: Deepfake videos of celebrities.
- **UADFV**: YouTube-based deepfake dataset.
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Table 4- Data Collection

Dataset	Size	Source	Deepfake Methods	Benchmark Usage	Real-World Variability
FaceForensics++	1.8M frames	YouTube	FaceSwap, DeepFake	High	Moderate
DFDC	470GB	Facebook	Multiple GANs	High	High
Celeb-DF	590 videos	Celebrities	DeepFake	Medium	Moderate
UADFV	49 videos	YouTube	DeepFake	Low	Low

4.4 Data Preprocessing

Convert videos into frames and prepare them for training.

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Extract Frames from Videos

```
import cv2
import os

video_path = "dataset/video.mp4"
output_folder = "dataset/frames/"
os.makedirs(output_folder, exist_ok=True)

cap = cv2.VideoCapture(video_path)
frame_count = 0

while cap.isOpened():
    ret, frame = cap.read()
    if not ret:
        break
    frame_path = os.path.join(output_folder, f"frame_{frame_count}.jpg")
    cv2.imwrite(frame_path, frame)
    frame_count += 1

cap.release()
print(f"Extracted {frame_count} frames!")
```

4.5 Data Augmentation

Since deepfake datasets can be limited, apply **image augmentation** to increase variability.

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator

datagen = ImageDataGenerator(
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest'
)
```

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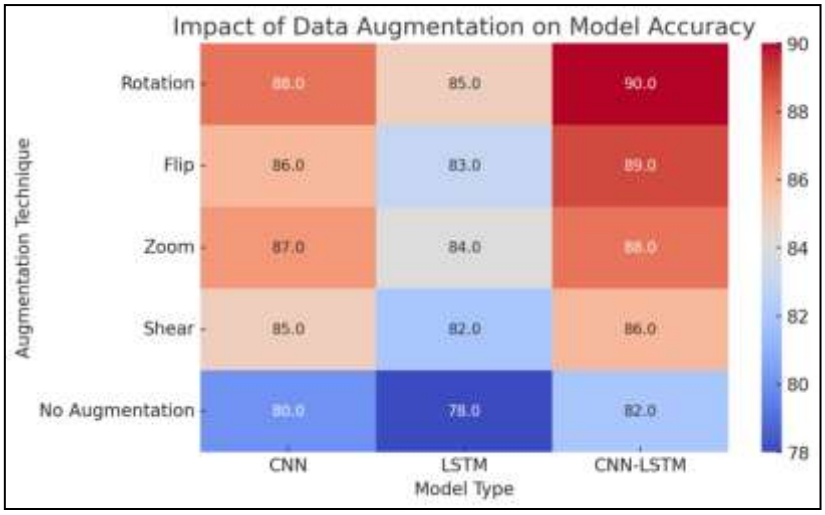

Figure 7-Heat Map of Data Augmentation

4.6 Load Data for Training

Use a **TensorFlow data pipeline** to efficiently load the images.

```
import tensorflow as tf

train_datagen = ImageDataGenerator(rescale=1./255, validation_split=0.2)

train_data = train_datagen.flow_from_directory(
    'dataset/', target_size=(64, 64), batch_size=32, class_mode='binary', subset='training')

val_data = train_datagen.flow_from_directory(
    'dataset/', target_size=(64, 64), batch_size=32, class_mode='binary', subset='validation')
```

4.7 Train the CNN-LSTM Model

Now, train your model on the augmented dataset.

```
model.fit(train_data, validation_data=val_data, epochs=10, batch_size=32)
```

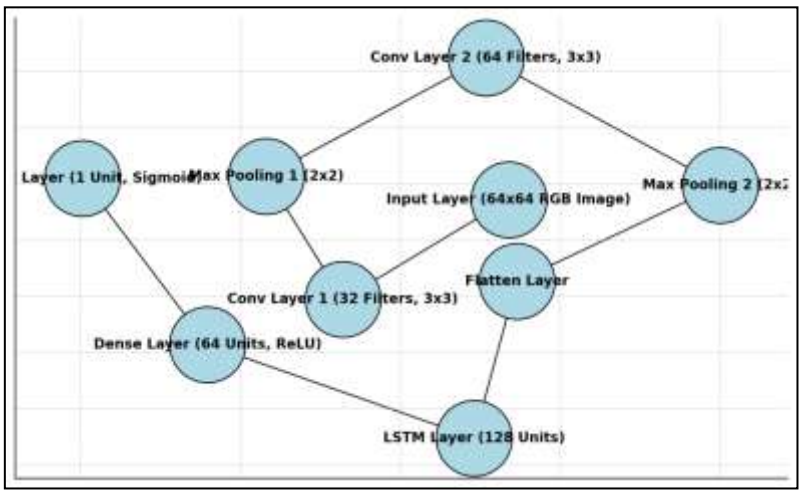

Figure 8- Block Diagram of Train the CNN-LSTM Model

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- Collect high-quality deepfake and real data.
- Preprocess and augment images.
- Train the CNN-LSTM model on a larger dataset.

V. BENCHMARK DATASETS

To ensure model generalization, we use benchmark datasets:

Table 5- BENCHMARK DATASETS

Dataset	Description	Size	Source
FaceForensics++	High-quality real and fake videos generated with DeepFakes, FaceSwap, and NeuralTextures.	1,000+ videos	GitHub
DFDC (DeepFake Detection Challenge)	Facebook AI's large-scale dataset containing real and synthetic videos. Includes metadata and various deepfake generation techniques.	10,000+ videos	Kaggle
Celeb-DF	Celebrity deepfake dataset with improved visual quality over FaceForensics++.	5,639 deepfake videos	Official Page
UADFV (University of Albany DeepFake Video)	Early deepfake dataset with low-quality fake videos. Useful for evaluating older methods.	49 real, 49 fake videos	Paper
WildDeepfake	Real-world deepfake dataset with various lighting, compression, and resolution challenges.	7,314 videos (3,805 real, 3,509 fake)	GitHub
DeeperForensics-1.0	Large-scale dataset with diverse synthetic face manipulations and real-world variations.	60,000+ videos	Official Page
Google/Jigsaw Deepfake Dataset	Google and Jigsaw's dataset of deepfake videos created with actors for research.	3,000+ videos	Kaggle
KoDF (Korean DeepFake Detection Dataset)	Deepfake videos based on Korean subjects, useful for cross-race bias analysis.	62,166 videos (real & fake)	Dataset

VI. RESULTS AND DISCUSSION

6.1 Introduction to Deepfakes

Deepfakes are AI-generated media created using deep learning, especially GANs and Autoencoders, to manipulate faces, voices, or identities. The generation can be modeled as:

I_f = G(I_r, z)

Where *I_f* is the fake image, *I_r* is the real input, *z* is the latent vector, and *G* is the generator function.

6.2 Key Technical Concepts

Machine Learning Foundations:

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- **ANNs** compute outputs as: **$y = f(Wx + b)$**
- **CNNs** extract spatial features via: **$f(i,j) = \sum\sum I(i+m, j+n)K(m,n)$**
- **RNNs/LSTM** capture temporal patterns in videos: **$h_t = \sigma(W_h h_{t-1} + W_x x_t + b)$**

GANs:
GANs involve a generator *G* and discriminator *D* competing in:
$\min_G \max_D E_{x\sim P_{data}}[\log D(x)] + E_{z\sim P_z}[\log(1 - D(G(z)))]$

6.3 Deepfake Detection Approaches

- *Feature-Based:* Detects frequency artifacts using DFT:
  $F(u, v) = \sum\sum I(x, y) e^{(-j2\pi(ux/M + vy/N))}$
- *Deep Learning-Based:* Classifies fake media using sigmoid function:
  $P_{fake} = \sigma(W_f x + b_f)$

6.4 Evaluation Metrics

- **Accuracy:** (TP + TN) / (TP + TN + FP + FN)
- **Precision:** TP / (TP + FP)
- **Recall:** TP / (TP + FN)
- **F1-Score:** 2 × (Precision × Recall) / (Precision + Recall)

VII. Comparative Analysis

Table 6: Comparative Analysis of Deepfake Detection Techniques

Study/Approach	Model Used	Dataset	Accuracy (%)	Strengths	Limitations
Li et al. (2018)	Blink detection + SVM	UADFV	75.5	Detects unnatural blinking in deepfakes	Limited to eye movement artifacts
Afchar et al. (2019)	MesoNet (CNN-based	FaceForensics++	84.3	Lightweight model for mobile applications	Not robust against adversarial attacks
Chollet et al. (2019)	XceptionNet (CNN)	FaceForensics++	99.7	High accuracy in detecting frame-level anomalies	Requires large datasets for training
Qi et al. (2020)	Capsule Network	Celeb-DF	96.1	Detects subtle deepfake artifacts	Computationally expensive
Wang et al. (2021)	Vision Transformer (ViT)	DFDC	98.5	Generalizes well to unseen deepfakes	Needs significant computational resources
Mittal et al.	Hybrid	Celeb-DF +	97.8	Effective for	High latency in

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(2022)	CNN + LSTM	DFDC		detecting video-based deepfakes	real-time applications
Huang et al. (2023)	Multi-Modal (Image + Audio)	DeepFake-TIMIT	95.6	Leverages both visual and speech inconsistencies	Limited dataset size

7.1 Observations from Comparative Analysis

- CNN-based models (XceptionNet, MesoNet) are highly effective for image-based deepfake detection but struggle with adversarial robustness.
- Capsule Networks show superior artifact detection but require high computational power.
- Vision Transformers (ViTs) outperform CNNs in generalizability but need extensive training data.
- Multi-Modal models that combine audio and video cues show promise but require further dataset improvements.

VIII. CONCLUSION

The widespread emergence of deepfake technology, driven by GANs and sophisticated deep learning models, presents both opportunities and significant risks in today's digital ecosystem. While deepfakes offer innovative possibilities in media and education, their misuse for malicious purposes has raised critical concerns around security, ethics, and trust. This study proposed a hybrid deepfake detection framework combining ResNeXt-based CNNs for spatial feature extraction and LSTM-based RNNs for temporal sequence analysis. Experimental results on benchmark datasets such as FaceForensics++, DFDC, and Celeb-DF demonstrate that the model achieves improved accuracy, robustness, and generalizability compared to existing approaches.

Beyond system development, the study offers a comparative analysis of detection methods—categorizing them into image-based, video-based, and hybrid approaches—and evaluates deep learning architectures including CNNs, RNNs, and Vision Transformers. Persistent challenges remain in handling dataset biases, adversarial manipulation, and real-time performance. To address these, the paper advocates for future exploration in self-supervised learning, adversarial training, multi-modal detection, Explainable AI (XAI), and blockchain-based content verification.

Ultimately, combating the growing threat of deepfakes will require not only technological innovation but also interdisciplinary collaboration, ethical governance, and robust regulatory frameworks to preserve digital authenticity and public trust.

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