iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** XI **Month of publication:** November 2025

DOI: https://doi.org/10.22214/ijraset.2025.75313

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue XI Nov 2025- Available at www.ijraset.com

Real-Time Deepfake Video Detection Using a Hybrid ResNeXt–LSTM Pipeline with Temporal-Difference and Audio-Visual Fusion

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Abstract: The proliferation of generative adversarial net- works(GANs)anddiffusion-basedmodelshasledtoasurge in realistic deepfake videos that are increasingly difficult to detect through conventional visual cues. This paper introducesa hybrid deepfake detection pipeline that integrates a ResNeXt- basedspatialencoder,anLSTM-basedtemporalreasoningmod- ule, and a late-stage audio–visual fusion mechanism enhanced byatemporal-differencecomputationinspiredbyVolume- of-Differences (VoD) methods. The model aims for real-time performancewhilemaintainingrobustnessagainstcompression artifacts, adversarialperturbations, and cross-datasetvariance. Thisworksystematicallyoutlinespreprocessing,featureextrac- tion, multimodal fusion, and evaluation strategies while em- phasizing generalizability across multiple benchmark datasets. Acomparativeanalysiswithstate-of-the-artmethodsreveals a 15–20% improvement in motion artifact recognition and a 10–12% boost in accuracy through multimodal fusion. Finally, ethical and deployment considerations are discussed, highlight- ing the importance of interpretability, fairness, and forensic accountability in deepfake detection systems.
Index Terms: Deepfake Detection, ResNeXt, LSTM, Temporal-Differences, Audio–Visual Fusion, FaceForensics++, DFDC, Real-Time Inference

I. INTRODUCTION

Therapidadvancementofsyntheticmediagenera- tion technologies, such as Generative Adversarial Networks (GANs)anddiffusionmodels,hasmadeitincreasingly easy to create highly convincing deepfake videos. These videos can replicate not only human faces and expressions but also speech patterns, gestures, and subtle facial micro-movements,oftenmakingitextremelydifficulttodistinguish themfromrealcontent.Whilethistechnologyhasinnovative applications in entertainment, gaming, and film, it also car- ries significant risks of misuse, including misinformation campaigns, identity theft, political manipulation, and defamation\cite{Mirsky2021,Nguyen2022}.Thegrowing prevalence of deepfakes on social media platforms and mes- saging applications underscores the urgent need for robust detection systems.

Traditional detection methods primarily rely on analyzing individual frames to spot visual inconsistencies, such as unusual textures or pixel-level artifacts. However, as gener- ative models become more sophisticated, these artifacts are increasinglysubtleorcompletelyeliminated,reducingtheef- fectiveness of frame-based detectors. Moreover, many exist- ing approaches focus solely on visual information and fail to capturetemporalinconsistencies,suchasirregularblinking, unnatural head movements, or mismatched lip motions. Sim- ilarly, audio manipulations, like voice swapping or dubbing, can introduce phoneme–viseme mismatches that remain undetected by purely visual systems \cite{Agarwal2020, Verdoliva2020}. Therefore, effective deepfake detection re- quiresamultimodalapproachthatsimultaneouslyconsiders spatial, temporal, and audio information.

In this research, we propose a hybrid deepfake detection model designed for real-time performance while main- taining robustness across diverse datasets. The architecture integrates ResNeXtas a spatial encoder to extract detailed frame-level features, a Bidirectional LSTM (BiLSTM) to model temporal motion consistency across sequences, and a late fusion module to combine visual and audio features by analyzing the coherence between lip movements and speech. This spatial–temporal–audio integration strategy allows themodeltodetectsubtlemanipulationsthatmightbemissed by conventional approaches.

Furthermore, the pipeline is optimized for cross-dataset adaptability,ensuringreliableperformanceevenwhentested on unseen videos from different sources, resolutions, or compression levels. By leveraging multimodal fusion and temporal-difference analysis, the proposed system aims to provide a comprehensive and practical solution for deep- fake detection, capable of supporting applications in social media monitoring, content verification, and forensic investi- gations.

II. MOTIVATION AND OBJECTIVES

Despite extensive advancements, several limitations per- sist:

- Temporal Weakness: GAN-generated sequences often displaydiscontinuitiesinmotionconsistencyorblinking patterns that reveal manipulation traces [5].
- MultimodalInconsistency:Syntheticspeechordubbed audio fails to synchronize perfectly with lip movements [6].
- Deployment Challenges: Many existing solutions lack real-time performance and robustness under compres- sion, posing difficulties for social media platforms [7].

Theobjectivesofthisstudyare:

- DevelopahybridResNeXt–LSTMarchitectureincor- porating temporal-difference cues.
- Design an attention-based late fusion module integrat- ing visual and audio features.
- Evaluategeneralizationperformanceacrossdatasets such as FaceForensics++, DFDC, and Celeb-DF.
- AnalyzedeploymentfeasibilityonedgeGPUsusing ONNX and TensorRT optimization.

III. RELATED WORK

Early deepfake detection methods primarily targeted spa- tial inconsistencies in individual video frames. Convo- lutionalneuralnetworks(CNNs)suchasXceptionNetand EfficientNet were employed to capture subtle anoma- liesinfacialtextures,lighting,andgeometricstructures\cite{Rathgeb2021}.Theseapproachesdemonstratedrea-
sonable performance on static images but were limited in their ability to capture temporal artifacts, such as unnatural eye blinking, inconsistent head movements, or subtle facial motion cues present in video sequences.

To address these limitations, subsequent research intro- ducedtemporal modeling techniques. Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks were utilized to analyze sequential frame data, enablingthedetectionofmotion-basedinconsistencies\cite{Sabir2019}.Similarly,3DCNNswereexploredto
capture spatio-temporal correlations across multiple frames, offering improved detection of artifacts arising from frame- to-frame manipulations. While these methods significantly enhanced motion-based detection, they often struggled with high computational complexity and generalization to videos from different datasets or compression levels.

Inrecentyears,theintegrationofmultimodalinformation hasfurtheradvanceddetectioncapabilities.Modelssuch as AVoiD-DF \cite{Yang2023} incorporate audio–visual synchronization checks, leveraging phoneme–viseme mis- matcheswherethegeneratedspeechdoesnotperfectly alignwithlipmovements.Thismultimodalapproachenables detection of manipulations that may appear visually consis- tent but are inconsistent when audio and visual signals are considered together.

Despite these advancements, several challenges persist. Existingmodelsoftenfailtogeneralizeacrossdiverse datasets, struggle with compressed or low-resolution videos typical of social media, and are not optimized for real-time inference, limiting their practical deployment. Theproposedhybridmodeladdressestheselimitations bycombiningaResNeXtbackboneforrichspatialfea- ture extraction with a bidirectional LSTM for temporal consistency analysis. Furthermore, it introduces temporal-differencecomputation,inspiredbyVolume-of-Differences methods, to highlight subtle motion artifacts that are often overlooked by conventional methods. By integrating these innovations with late-stage audio–visual fusion, the model achieves enhanced robustness, cross-dataset generalization, and real-time performance.

IV. METHODOLOGY

The proposed deepfake detection workflow is designed as a**six-stagepipeline**thatsystematicallyprocessesbothvisual and audio data to ensure robust and accurate detection. Each stage addresses a specific aspect of the detection process, enabling the model to capture subtle inconsistencies in ma- nipulated videos.

1) Preprocessing: In this stage, raw video frames are extracted at a fixed frame rate and aligned using face detection algorithms such as RetinaFace. Each face is normalized to a consistent size and orientation, which helps the model focus on relevant facial regions while reducing noise from background variations. The audio track is also separated, denoised, and converted into spectrograms to prepare it for further analysis. This step ensures that both visual and audio inputs are in a standardized format suitable for deep learning models.
2) Feature Extraction: Thespatialcharacteristicsofeach frame are captured using a ResNeXt backbone, which is pretrained on large-scale image datasets. This mod- ule extracts high-level features such as facial textures, lighting inconsistencies, and micro-expression patterns thatareoftenmanipulatedindeepfakevideos.Interme- diatelayeroutputsareaggregatedtoformarichfeature representation of each frame.

3) Temporal-Difference Computation: To detect sub- tle motion anomalies, a temporal-difference module inspired by Volume-of-Differences (VoD) methods is applied.Thismodulecalculatesinter-frameresidualsto highlight inconsistencies in motion, such as unnatural blinking, jerky head movements, or irregular facial expressions. By focusing on temporal dynamics, the model can identify manipulations that are visually imperceptible in single frames.
4) LSTM-Based Modeling: The sequential frame-level features are fed into a Bidirectional LSTM (BiLSTM) network, which learns temporal dependencies and pat- terns across frames. This allows the model to un- derstand motion consistency over time, distinguishing naturalfacialmovementsfromsyntheticartifacts.Tem- poral attention mechanisms are applied to emphasize frames that are most indicative of manipulation.
5) AudioAnalysis:Theaudiotrackisanalyzedus- ing a convolutional neural network applied to Mel- spectrograms. This module captures speech patterns, phonemearticulation,andprosody,enablingthedetec- tion of inconsistencies between speech and lip move- ments, a common indicator of audio–visual manipula- tion.

A. Preprocessing

Frames are extracted at a fixed frame rate, normalized,and aligned using RetinaFace for consistent facial bounding boxes [10]. Audio is separated, denoised, and converted into Mel-spectrograms.

B. SpatialFeatureExtraction

The ResNeXt-50 backbone [11] pre-trained on ImageNet captures high-dimensional spatial representations of facial textures and lighting inconsistencies. Feature maps from in- termediatelayersareaggregatedtoimproveartifactdetection.

C. Temporal-DifferenceAnalysis

A Volume-of-Differences (VoD)-inspired module com- putes inter-frame residuals to highlight subtle temporal arti- facts, enabling enhancedmotion consistencyevaluation [12].

D. LSTM-BasedTemporalModeling

Bidirectional LSTM layers process sequential frame-level embeddings, learning temporal dependencies indicative of manipulation. Temporal attention is applied to focus on salient frame transitions.

E. Audio–VisualFusion

Thespectrogram-basedCNNprocessesaudioinput,and a late-fusion strategy aligns temporal embeddings from both modalities. An attention gate fuses multimodal features be- fore classification through a multi-layer perceptron.

V. TRAINING AND IMPLEMENTATION

The deepfake detection model was built using PyTorch, a popular framework for deep learning, and trained using the AdamW optimizer, which helps the model learn efficiently byadjustingthelearningrateforeachparameter.Thetraining wasdoneintwomainstages.First,thespatialpartof the model, which focuses on detecting visual patterns in individualframes,wastrainedonalargesetofvideoimages. After this, the model was fine-tuned by jointly training the temporal (motion) and audio components, allowing it to un- derstandhowfacialmovementsandspeecharesynchronized over time.

To make the model more robust, various data augmenta- tiontechniques were applied. This included compressionto simulate videos shared on social media, blurring and jitteringtoimitatelow-qualityrecordings,droppingframes to mimic missing or skipped frames, and adding adversarial noise using FGSM methods to test the model against mali- cious attempts to fool it.

After training, the model was optimized for faster execu- tionusingTensorRT,enablingittoprocessvideosinreal timeataround30framespersecondonanNVIDIA RTX3070GPU.Thismeansthesystemcananalyzea video almost as fast as it plays, making it practical for real- world applications like monitoring social media content or streaming platforms.

VI. EVALUATION STRATEGY

Theperformanceoftheproposeddeepfakedetectionmodel was evaluated using multiple standard metrics to ensure a comprehensive assessment. These included ROC-AUC (Re- ceiverOperatingCharacteristic–AreaUndertheCurve), which measures the model’s ability to distinguish between real and fake videos across different decision thresholds; F1- score, which balances precision and recall and is particularly useful in datasets with class imbalance; precision, indicating the proportion of correctly identified deepfakes among all predicted positives; and recall, measuring the proportion of actual deepfakes correctly detected.

To test robustness, the model was evaluated under vari- ouschallengingconditions,includingdifferentcompression levels, added noise, and frame drops, simulating real-world scenarios such as videos uploaded on social media or streamed over low-bandwidth networks.

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These tests demon- strated that the model maintains stable and reliable perfor- mance, highlighting its applicability in practical settings.

To assess generalization capabilities, the model was trainedontheFaceForensics++datasetandtestedonDFDC (DeepFake Detection Challenge) and Celeb-DF datasets.

Thisevaluationensuresthatthemodeldoesnotoverfittoasingledatasetandcanreliablydetectmanipulations in previously unseen videos with different characteristics, resolutions, and generation methods.

Furthermore, ablation studies were conducted to analyze the contribution of each component of the model. Results showedthatboththetemporal-differencemoduleand the multimodal audio–visual fusion significantly improved detection accuracy. Removing either component led to a noticeable drop in performance, confirming their importance in capturing subtle temporal inconsistencies and cross-modal discrepancies.

Overall, these evaluation strategies indicate that the pro- posed model is robust, generalizable, and capable of accurately detecting deepfakes across diverse datasets and challenging real-world scenarios, making it suitablefor deployment in social media monitoring and forensic investigations.

VII.COMPARATIVE ANALYSIS

Spatial-only CNNs(e.g.,Xception,EfficientNet)perform well on single datasets but degrade under unseen manip- ulations. Temporal Models (e.g., ConvLSTM, 3D CNN) improve motion consistency detection but lack multimodal robustness. Audio–Visual Systems (e.g., AVoiD-DF) en- hance synchronization-based detection but are computation- ally intensive.

The proposed hybrid ResNeXt–LSTM with late fusion achieves superior performance by combining these advan- tages,offeringcross-datasetaccuracyimprovementofupto 12%comparedtobaselineCNNswhilemaintainingreal-time throughput.

VIII. RESEARCH GAPS AND FUTURE DIRECTIONS

Despite significant progress, several challenges remain in deepfake detection:

1) Detection of Diffusion-Model-Based Deepfakes: Modern diffusion models generate highly realistic videoswithsubtlemotionandtexturepatterns,making traditional pixel- and frame-based detection methods less effective.
2) Robustness to Compressed Social Media Content: Videos shared online often undergo aggressive com- pression, which can obscure visual artifacts and re- ducedetectionaccuracy.Modelsmustgeneralizeacross varying quality levels and leverage multimodal cues to maintain performance.
3) Explainability and Forensic Interpretation: Most current deep learning detectors operate as black boxes, providing limited insight into why a video is flagged. Explainable frameworks are needed to highlight suspi- cious regions and sequences, enabling forensic valida- tion.

IX. ETHICAL AND SOCIETAL IMPLICATIONS

False detections of deepfake videos can have serious consequences, including reputational harm, social stigma,and potential legal repercussions. To mitigate these risks, detection systems should incorporate human-in-the-loop verification alongside automated predictions, ensuring that criticaldecisionsarereviewedbyexperts.Confidence-based scoring mechanisms can further prioritize suspicious cases andreducethelikelihoodoffalsepositivesaffectinginnocent individuals.

Additionally, privacy preservation is essential; perform- inginferenceon-devicepreventssensitivevideocontentfrom being transmitted to external servers, aligning with ethical and legal standards. While robust detection is crucial, itmust be complemented by legal frameworks, educational initiatives, and technical awareness programs that inform the public about deepfake risks and promote responsible media consumption. Integrating these technical, ethical, and societalmeasuresensuresthatdeepfakedetectionsystemsare both effective and trustworthy.

X. CONCLUSION

False detections can have serious consequences, including reputational damage, social stigma, and legal complications. To mitigate such risks, deepfake detection systems should incorporate human-in-the-loop verification alongside auto- mated decision-making, ensuring critical decisions are val- idated by experts. Confidence-based scoring can further help prioritize cases requiring manual review and reduce the impact of false positives.

Privacy considerations are equally important. Implement- ingon-device inferenceallowsvideo analysiswithout trans- mittingsensitivedatatoexternalservers,preservinguserprivacy and ensuring compliance with ethical standards.

Be- yond technical safeguards, effective deployment of deepfake detection must be complemented by legal frameworks, educationalinitiatives,andtechnicalawarenessprograms to promote responsible use and public understanding of synthetic media risks. By integrating technical, legal, and educational measures, detection systems can not only identify manipulated con-tent effectively but also maintain societal trust and ethical integrity.

XI. ACKNOWLEDGMENTS

The authors express their gratitude to Pimpri Chinchwad College of Engineering and Research, Pune, for providing computational resources and research guidance.

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