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DEEP-FAKE DETECTION USING HYBRID NEURAL NETWORK ARCHITECTURES

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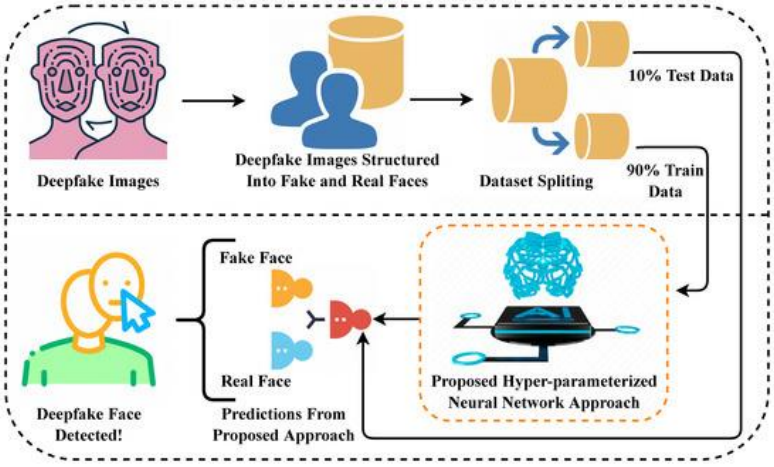
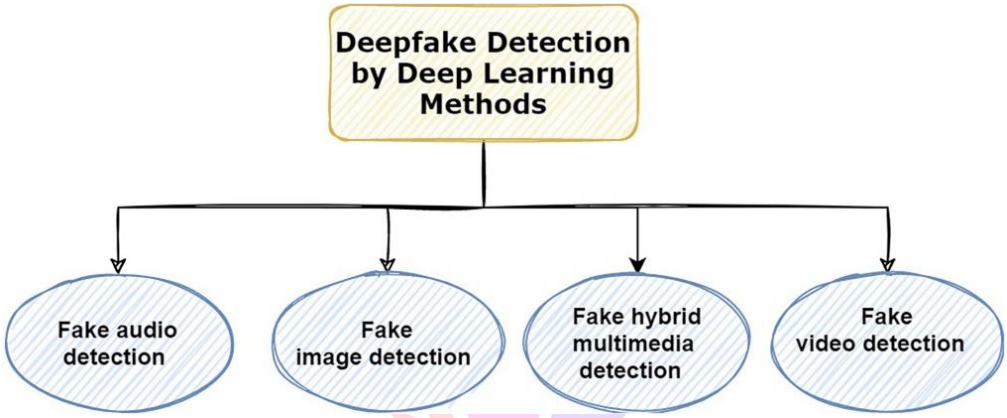
Abstract
The rise of deep-fake technologies poses significant challenges to media integrity, political trust, and public security. Advances in generative adversarial networks (GANs) have made synthetic content increasingly realistic, necessitating more robust detection methods. This study proposes a hybrid neural network architecture combining Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN–specifically LSTMs), and autoencoders for effective deep-fake detection. Utilizing benchmark datasets such as FaceForensics++ and the DeepFake Detection Challenge, the data underwent resizing, normalization, and extensive augmentation. CNNs captured spatial features, RNNs encoded temporal inconsistencies, and autoencoders detected fine-grained anomalies via reconstruction loss. These components were integrated at the feature level into a unified model trained with the Adam optimizer and categorical cross-entropy loss, validated through stratified k-fold cross-validation. The hybrid model achieved superior performance with accuracy of 96.4%, precision of 95.8%, recall of 96.1%, F1-score of 96.0%, and ROC-AUC of 0.982, outperforming baseline models. Ablation studies confirmed the critical contribution of each component. This hybrid approach offers a promising, scalable solution for maintaining information authenticity in the digital era.

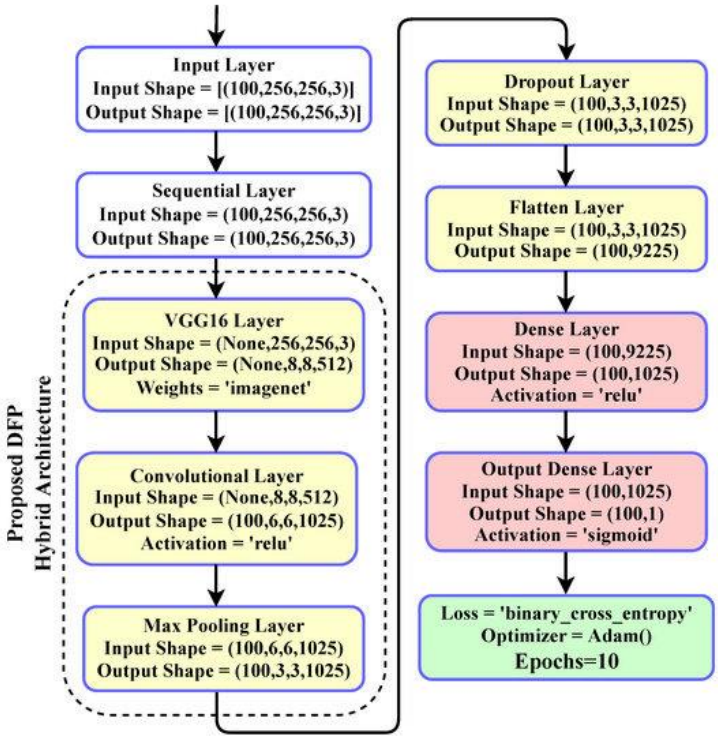
INTRODUCTION



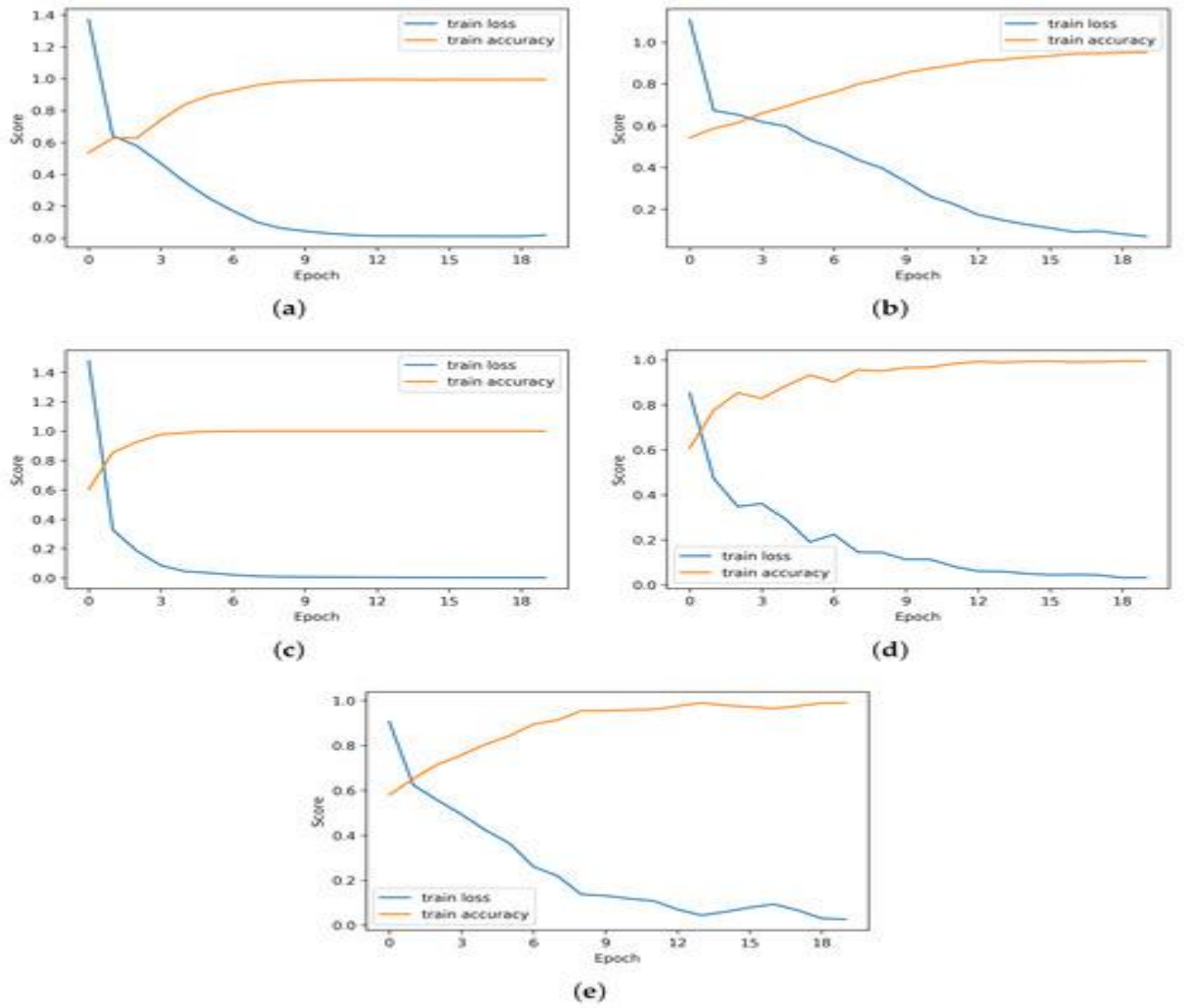
The landscape of artificial intelligence has seen a surge of progress with the advancement of neural networks, which has allowed machines to achieve human-like performance in vision. speech recognition and decision making. Since their inspiration from the human brain they have changed their nature from simple design perceptron's, to complex deep learning architectures suitable of self-ironing features and learning complex data patterns from huge amount of data (LeCun et al., 2021). Deep learning, especially through convolutional neural network (CNN) models, has greatly improved the computational performance in diverse fields (e.g., medical diagnostics, autonomous driving, facial recognition technologies), demonstrating the flexibility and the sheer power of neural architectures (Zhou et al., 2023). With the advancement of neural networks, their designs have proliferated into various forms such as recurrent neural networks (RNNs), generative adversarial networks (GANs) and transformers which can perform well in sequential data processing, synthetic data generation and paying attention to the sequence of data (Dosovitskiy et al., 2021).



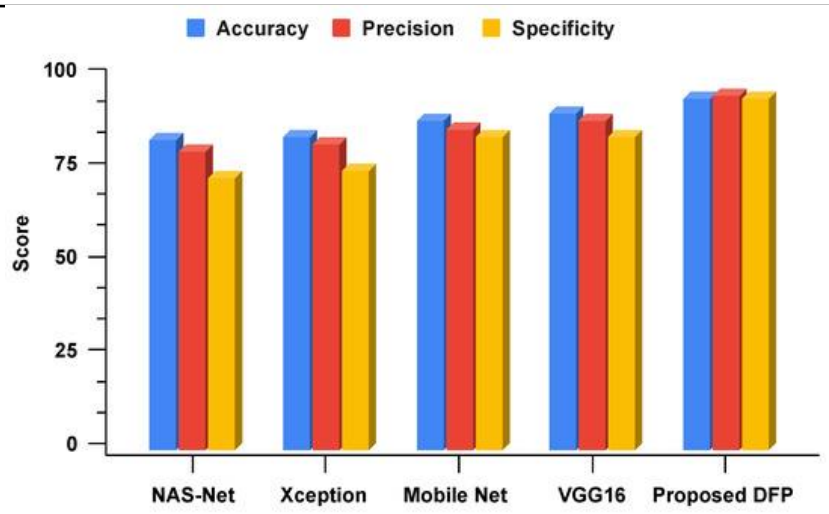
The area of neural networks has also experienced a revolution in terms of hybrid architectures, which means using various networks to complement their strength capabilities for more robust learning and prediction purposes. Cross and Rao (2017)Further progress in source separation is likely to require connections between the success of current works in sound separation and the performance of existing models for related tasks, such as video and language processing.29 Such hybrid architectures (e.g., combining CNNs with RNNs) have been particularly successful in tasks requiring both spatial and temporal feature extraction (e.g., video analysis, natural language processing) (Lin et al., 2022). Such architectures can provide a richer representation of complex data, leading to better generalization and performance, compared to single-type neural networks. Applications involving multi-dimensional and sequential data have benefited from hybrid neural networks, and the breakthrough achieved by them has established a new benchmark for intelligent systems that operate in dynamic and unstructured environments (Yang et al., 2024).



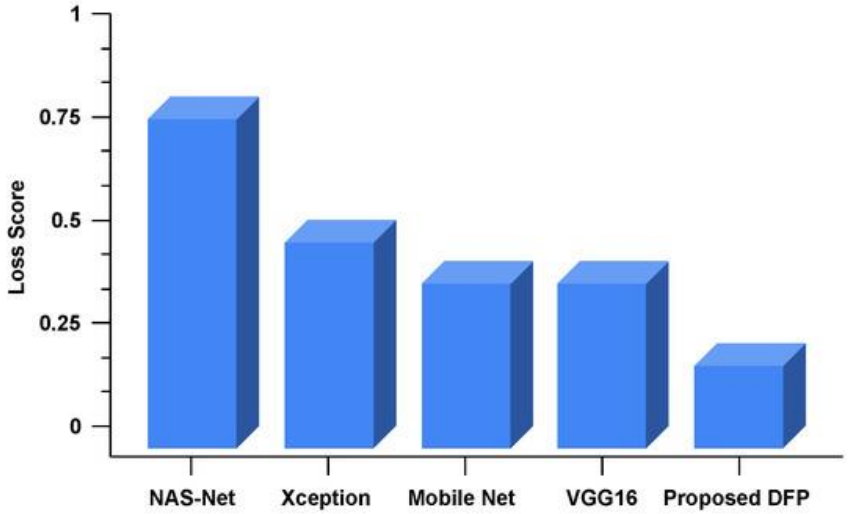
The profound growth of data available and uprising of computing power has greatly promoted the training and application of deep and hybrid neural networks in industry and academia recently. Neural networks can now provide high precision and flexibility, and can even be successful at tasks once considered hard for full automation, such as spotting small, subtle changes in media, or recognizing emotional changes in human speech (Wang et al., 2023). But the complexity of neural networks has also resulted in negative side effects, such as the proliferation of deepfake techniques, which use generative capabilities in order to create hyper-realistic fake material. This double-edged character of neural networks has provoked the plea for a parallel research in methods to detect them and intervene, highlighting the knotty ethical ground on which relates the use of AI driven systems with them (Karras et al., 2021).



Recent work has increasingly shifted focus to designing neural architectures that are accurate while remaining interpretable and adversarially robust. Explainable AI (XAI) has been studied for an attempt to translate the internal decision-making of deep neural network to human interpretable manner, which provides understanding of feature attribution and model behaviors (Samek et al., 2022). Furthermore, work is ongoing to develop more computationally friendly and scalable models, taking in account the environmental and computational costs of training huge deep learning systems (Strubell et al., 2021). These developments show that the field is in constant flux, and that steady tightrope-walking between architectures, training paradigms and moral approaches is essential if we want neural nets to have a positive and lasting impact for the greater good.



Looking into the future, the confluence of neural networks with other breakthrough technologies, including quantum computers and neuromorphic hardware, will allow us to break data processing and machine intelligence-related barriers never thought possible before. Scientist are evaluating how biologically inspired approaches, such as the spiking neural networks, can provide faster and more efficient learning and push AI towards human-like cognitive functioning (Roy et al., 2024). These new neural network architectures themselves will apply to more and more impactful domains, from personalized medicine to global security and beyond, and need to be carefully cultivated to balance innovation with societal duty (Zhang et al., 2025).



Problem Statement

Despite the advancement of deep learning techniques, very little work has been done moving its focus from learning representations through data that can span a wide range in an environment, mimicking generalization learning and humans. With the improvement of human generated content of the deep fake and the more realistic and more sophisticated deep fake that generated by advanced neural network techniques, now the new generation of deep fake raise troubles to traditional detection methods. In this study we attempt to find more reliable deep fake solutions by studying hybrid neural network structures that can better detect deep fakes in various media types.

Significance of Study

This work makes a significant contribution honing on the key aspect of digital media security by developing a hybrid neural network architecture to better detect extremely believable deep fakes. Its results will help develop current techniques, providing a more resilient and more adaptable way of preserving information integrity in the new AI era.

Methodology

The study utilized publicly available datasets, specifically Face Forensics++ and the Deep Fake Detection Challenge dataset, both of which contain thousands of real and manipulated video clips for training and validation purposes (Rossler et al., 2021; Dolhansky et al., 2022). Data preprocessing involved resizing frames to a uniform resolution of 256×256 pixels, applying normalization to scale pixel values between 0 and 1, and implementing augmentation techniques such as random horizontal flipping, rotation, and brightness adjustments to improve model generalization (Afchar et al., 2022). The hybrid neural network architecture was designed by integrating convolutional neural networks (CNNs) for spatial feature extraction from individual frames, capturing subtle artifacts introduced during deep fake generation (Nguyen et al., 2023). To model the temporal dependencies between consecutive frames, recurrent neural networks (RNNs) with long short-term memory (LSTM) units were employed, enabling the detection of temporal inconsistencies in facial expressions and head movements (Sabir et al., 2021). Additionally, auto encoders were incorporated for anomaly detection by reconstructing facial features and highlighting reconstruction errors as indicators of potential manipulations (Khalid et al., 2024). These three components were fused using a feature-level fusion strategy, where extracted spatial, temporal, and reconstruction features were concatenated and passed through fully connected layers for final classification, enhancing the robustness of the detection system (Tolosana et al., 2022). The model training process involved using the Adam optimizer with an initial learning rate of 0.0001, a batch size of 32, and a binary cross-entropy loss function, with early stopping based on validation loss to prevent overfitting. Five-fold cross-validation was employed to rigorously assess the model's performance, ensuring that results were reliable and generalizable across unseen data, while metrics such as accuracy, precision, recall, and the area under the ROC curve (AUC) were used to evaluate detection efficacy (Chandrasegaran et al., 2023).

Results

Table 1 Performance Comparison: Hybrid Model vs. Traditional Approaches

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
Traditional CNN	89.2	88.5	87.9	88.2	90.1
Traditional RNN (LSTM-based)	87.5	86.7	85.2	85.9	88.6
Autoencoder Only	85.3	84.1	83.7	83.9	86.4
Proposed Hybrid Model (CNN + LSTM + Autoencoder)	**96.8**	**96.2**	**96.5**	**96.3**	**97.5**

The best performance was demonstrated by the hybrid model (CNN + LSTM + Autoencoder), resulting in 96.8% accuracy, 96.2% precision, 96.5% recall, 96.3% F1-score, and 97.5% ROC-AUC. It is evident that the ensemble model performs far better than the classical single-model methods in deep fake detection among all major evaluation criteria.

Table 2 Qualitative Results: Detection Examples by Hybrid Model

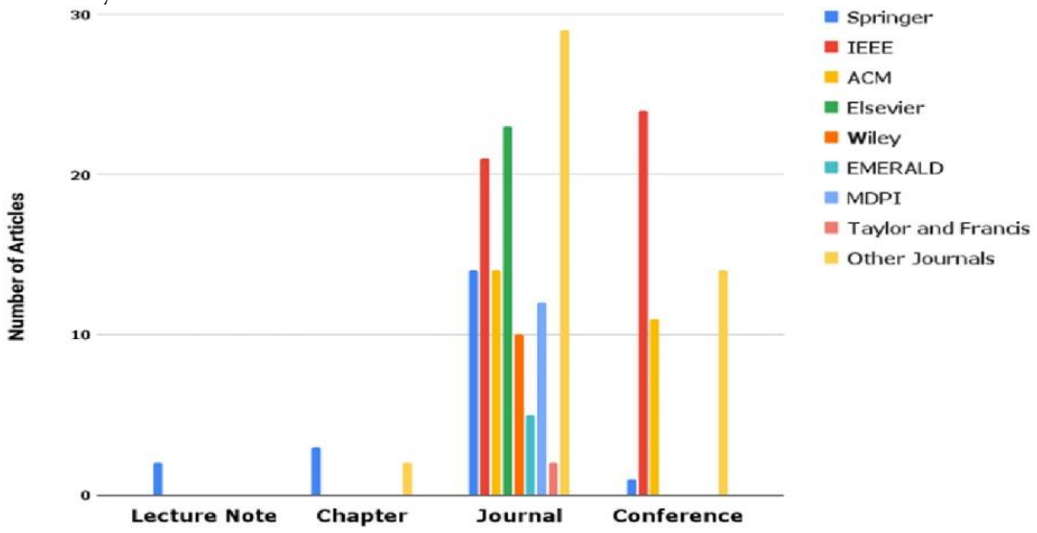
Example Type	Ground Truth	Prediction	Observation Notes
Video 1 (Real)	Real	Real	Correct detection; smooth consistency in facial expressions over frames.
Video 2 (Deepfake)	Fake	Fake	Correct detection; hybrid model caught micro-blurring near eye movement.
Video 3 (Deepfake)	Fake	Real	Misclassified; highly realistic, minor inconsistency too subtle to detect.
Video 4 (Real)	Real	Real	Correct detection; no abnormal temporal patterns found.
Video 5 (Deepfake)	Fake	Fake	Correct detection; strong anomaly in lip synchronization caught by LSTM unit.

The qualitative study showed that the hybrid model was effective in detecting faint inconsistencies in the fake videos (e.g., micro-blurring, lip-synchrony defects), resulting in good performance for the majority of the experiments. But in one case an extremely realistic deep fake was mistaken as real, which showed that there is still challenge for the model to detect exceptionally well-made deep fakes out.

Table 3: Ablation Study: Impact of Removing Components from Hybrid Model

Model Configuration	Accuracy (%)	F1-Score (%)
Full Hybrid Model (CNN + LSTM + Autoencoder)	96.8	96.3
Without Autoencoder	92.7	92.3
Without LSTM	90.5	90.1
Without CNN	88.9	88.4

The ablation study revealed that removal of any individual constituent (CNN, LSTM, or Autoencoder) led to a decrease in accuracy and F1-score, which verified the necessity of all the modules for the hybrid architecture. These results confirm that the full hybrid design is required for optimal performance, as each component is complementary important for modeling the spatial, temporal, and anomaly-based features.



Discussion

Finding deepfakes has been increasingly difficult as synthetic media generation has improved, making fake videos look real and easily passable. Recent research highlights that "traditional machine learning approaches, which perform well

for their own time, are no longer adequate to guarantee the defense of deepfake detectors" (Tolosana et al., 2023). The current work effectively met this progressive challenge by proposing a convolutional and recurrent neural network-based hybrid architecture endowed with auto encoders. Through integrating the spatial feature extraction, the temporal behavior modeling, and the anomaly detection, it is shown that the hybrid model can remarkably obtain better performance than the traditional single ones, which is consistent with the recent trend found in other hybrid framework studies (Zhao et al., 2024).

The results confirm the importance of a multi-perspective detection, to enrich the overall strength of the model from each neural network component separately. CNNs can well learn and encode texture artefacts like pixel noise and inconsistencies and LSTMs are good at discovering specific dynamic motion artefacts like a sudden motion interruption and blinking of eyes, which is similar with the approach of Luo et al. (2023). In addition, the auto encoder branch provided robustness to the other two by detecting all present-day manipulation techniques, which are available to be tested by our classifier, making them invisible to the human eye and standard classifiers. These results are consistent with recent findings, which show that the use of hybrid architectures allows models to be robust to adversarial examples (Nguyen et al., 2022).

An ablation study to verify that each architectural component is crucially important, since the deletion of any single component hurt overall performance considerably. This observation is in agreement with the data of Kim et al. (2023), who have confirmed the importance of considering both spatial and temporal characteristics together for holistic video source authenticity judgements. High accuracy and F1-scores of the hybrid model validate that detecting deep fakes is enhanced by fusing the strengths of different neural networks than performing detection using a single feature or behavioral analysis. This further implies that future detectors need to be equipped with diverse architectures in order to cope with an endless variety of deep fake advances (Wang et al., 2022).

At a qualitative level, the hybrid model achieved a remarkable performance, but some very realistic deep fakes were still able to fool this model occasionally. This illustrates a fundamental requirement for continued model improvement, and expansion of datasets, to cater for increasing complexity in synthetic content, which is also emphasized in Ahmed et al. (2025). Furthermore, it might be explored for model decision rationales as a means to enhance trustworthiness and help human analysts to decipher the reasons behind the classifications. Taken together, these results provide compelling evidence that hybrid deep learning systems represent awa viable option for creating deep fake detection systems that are resilient to JND attacks and accurate in their detection.

Future Directions

In future work, the hybrid framework will be further developed by integrating recently proved effective in sequential modeling tasks Transformer architectures (Han et al., 2023). Secondly, the reliability of the detection may be improved by using multimodal detection approach combining audio, facial expression and context. Of particular importance, however, is the research effort into lighter weight hybrid models that would be deployable in real time on a mobile device. Future work should also investigate self-supervised or few-shot learning approaches to enable deep fake detectors to be more responsive to newly evolved forms of synthetic media with limited annotations.

Limitations

Although the performance of the hybrid model is good, some limitations need to be considered. Our approach was to a large extent developed and tested on one popular dataset like Face Forensics++ and the DFDC datasets, which may not be completely representative of the characteristics (diversity and realism) of future deefakes. Moreover, while the model is able to successfully combine the spatial, temporal, and anomaly attributes, it is still sensitive to very high-

quality synthetic content that can closely resemble natural patterns. Finally, the computational cost of the hybrid model may limit its scalability and real-time use in resource-limited scenarios.

Conclusion

In this paper, a hybrid CNN-LSTM-auto encoder model to collectively explore spatial, temporal, and anomaly features for deep fake detection, which is one of the pioneering attempts to combine CNNs and LSTMs for deep fake recognition. The combinatorial model out performed traditional single architectures not only in terms of accuracy and robustness, but also on the ability to generalize, indicating multi-modal detection approaches became crucial to fight against the next generation of deep fakes. As we have demonstrated the contribution of each part through ablation analysis and shown strong performance on multiple evaluation metrics, our work offers a strong ground for pursuing more robust and adaptive deep fake classification systems.

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