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Toward Trustworthy Multimedia: Detecting Deepfake Images and Videos Using Integrated SVM–CNN Models

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Abstract—The rapid advancement of deep learning techniques has significantly enhanced the realism of synthetic multimedia, giving rise to *deepfakes* that pose serious threats to information integrity, cybersecurity, and digital trust. This paper proposes a hybrid framework for the detection of deepfake images and videos by integrating Convolutional Neural Networks (CNNs) with Support Vector Machines (SVMs) to leverage the strengths of both deep feature extraction and robust classification. The proposed model utilizes CNN architectures to automatically learn discriminative spatial and temporal features from multimedia data, while SVM is employed as a high-performance classifier to improve generalization and decision boundaries in complex feature spaces. A comprehensive dataset comprising both authentic and manipulated images and video sequences is used to evaluate the performance of the model. Preprocessing techniques, including frame extraction, normalization, and data augmentation, are applied to enhance model robustness. Experimental results demonstrate that the integrated SVM–CNN approach outperforms standalone CNN and traditional machine learning models in terms of accuracy, precision, recall, and F1-score. Additionally, the proposed framework shows improved resistance to adversarial manipulations and compression artifacts commonly found in real-world scenarios. The study contributes to the growing field of trustworthy multimedia by presenting a scalable and efficient detection mechanism capable of addressing emerging challenges in deepfake generation. The findings highlight the importance of hybrid architectures in achieving reliable and interpretable deepfake detection systems, thereby supporting the development of secure digital ecosystems.

Keywords—Deepfake Detection, Convolutional Neural Network (CNN), Support Vector Machine (SVM), Hybrid Models, Multimedia Forensics, Image and Video Analysis, Artificial Intelligence, Digital Trust, Cybersecurity, Adversarial Robustness

I. INTRODUCTION

The proliferation of synthetic media generated through advanced deep learning techniques has fundamentally transformed the landscape of digital content creation and dissemination. Among these innovations, deepfakes—highly realistic manipulated images and videos created using deep neural networks—have emerged as a significant challenge to the authenticity and trustworthiness of multimedia information. Leveraging architectures such as Generative Adversarial Networks (GANs) and autoencoders, deepfake technologies can convincingly alter facial expressions, speech patterns, and identities, making it increasingly difficult to distinguish between real and fabricated content [1], [2].

The widespread availability of powerful computing resources and open-source tools has accelerated the production and distribution of deepfakes across social media platforms, posing severe risks in areas such as misinformation, identity theft, political manipulation, and cybersecurity [3]. As a result, ensuring the integrity of multimedia content has become a critical concern in both academic research and practical applications. Traditional digital forensics techniques, which rely on handcrafted features and statistical inconsistencies, have proven insufficient in detecting sophisticated deepfake artifacts generated by modern algorithms [4].

To address these challenges, recent research has focused on leveraging deep learning-based approaches, particularly Convolutional Neural Networks (CNNs), for automated feature extraction and classification of manipulated media. CNNs have demonstrated remarkable success in identifying subtle spatial inconsistencies and compression artifacts in images and videos [5]. However, despite their effectiveness, CNN-based models often suffer from limitations such as overfitting, lack of interpretability, and reduced generalization when exposed to unseen manipulation techniques [6].

In parallel, classical machine learning methods such as Support Vector Machines (SVMs) have been recognized for their strong generalization capabilities and effectiveness in high-dimensional feature spaces. SVMs are particularly advantageous in scenarios with limited training data and can provide well-defined decision boundaries for classification tasks [7]. Integrating SVM with deep learning frameworks offers a promising hybrid approach that combines the representational power of CNNs with the robustness of traditional classifiers.

Motivated by these observations, this paper proposes an integrated SVM–CNN framework for detecting deepfake images and videos. The proposed approach utilizes CNNs for hierarchical feature extraction and employs SVM as a classifier to enhance detection performance and robustness. By combining these techniques, the study aims to overcome the limitations of standalone models and improve the reliability of deepfake detection systems in real-world scenarios.

The remainder of this paper is organized as follows: Section II reviews related work in deepfake detection methodologies. Section III presents the proposed hybrid SVM–CNN model. Section IV discusses the experimental setup and results. Section V concludes the paper and outlines future research directions.

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II. LITERATURE REVIEW

The rapid evolution of deepfake generation techniques has led to a parallel surge in research focused on developing reliable detection mechanisms. Early studies primarily emphasized traditional image forensics and statistical analysis; however, these approaches were soon outperformed by data-driven machine learning and deep learning techniques. Recent literature highlights a transition toward hybrid and multimodal frameworks that improve robustness and generalization across diverse datasets.

Deep learning-based approaches, particularly Convolutional Neural Networks (CNNs), have been widely adopted for deepfake detection due to their ability to automatically extract hierarchical spatial features. Several studies demonstrate that CNN models can effectively identify subtle visual inconsistencies such as blending artifacts, abnormal textures, and facial distortions introduced during manipulation [8], [21]. Furthermore, the use of Generative Adversarial Networks (GANs) for data augmentation has been explored to enhance CNN training, enabling models to learn intrinsic image characteristics more effectively and improve detection accuracy [8].

Despite their success, CNN-based methods often struggle with temporal inconsistencies in video data. To address this limitation, researchers have proposed hybrid architectures that combine CNNs with sequence modeling techniques such as Long Short-Term Memory (LSTM) networks. These models capture both spatial and temporal features, significantly improving detection performance in video-based deepfakes by analyzing frame-to-frame inconsistencies [5], [13]. Similarly, spatiotemporal convolutional networks have been introduced to jointly learn spatial and temporal representations, outperforming frame-based methods in benchmark datasets [23].

In addition to deep learning, classical machine learning algorithms such as Support Vector Machines (SVMs) have been utilized for classification tasks due to their strong generalization capabilities. Recent studies have explored integrating CNN feature extraction with SVM classifiers, demonstrating improved classification accuracy and robustness compared to standalone CNN models [2]. This hybrid approach leverages CNNs for deep feature representation while utilizing SVMs to construct optimal decision boundaries in high-dimensional feature spaces.

Comprehensive surveys and systematic reviews further emphasize the growing importance of hybrid and multimodal detection frameworks. These studies analyze a wide range of techniques, including CNNs, recurrent neural networks, transformers, and ensemble methods, highlighting that hybrid models often outperform single-model approaches in terms of accuracy and adaptability [1], [9]. Additionally, modality fusion techniques—combining visual, audio, and physiological signals—have been identified as a promising direction for enhancing detection reliability in complex real-world scenarios [9].

Recent advancements also include the integration of attention mechanisms, vision transformers, and diffusion-based models to improve feature representation and detection performance. These methods aim to capture fine-grained inconsistencies and enhance model interpretability while maintaining high accuracy [4], [19]. However, challenges such as generalization to unseen datasets, adversarial robustness, and computational complexity remain significant obstacles in deploying deepfake detection systems at scale.

Overall, the literature indicates a clear trend toward hybrid frameworks that integrate deep learning with traditional machine learning techniques. The combination of CNN-based feature extraction and SVM-based classification emerges as a promising approach for achieving high accuracy, robustness, and scalability in deepfake detection systems. This motivates the development of the proposed integrated SVM–CNN model for trustworthy multimedia analysis.

TABLE 1: LITERATURE REVIEW TABLE BASED ON PREVIOUS YEAR RESEARCH PAPER METHODOLOGY, DATASET USED AND KEY FINDINGS

Author (s) & Year	Title	Methodology	Dataset Used	Key Findings
Li et al. (2018)	In Ictu Oculi: Exposing AI Generated Fake Face Videos by Detecting Eye Blinking	Eye-blinking pattern analysis	Custom YouTube dataset	Eye-blink detection helps identify deepfakes with missing natural blinking.
Matern et al. (2019)	Exploiting Visual Artifacts to Expose Deepfakes	Handcrafted feature analysis	FaceForensics	Visual inconsistencies (e.g., reflections, lighting) are useful for detection.
Nguyen et al. (2019)	Capsule-forensics: Use of Capsule Network to Detect Fake Images	Capsule Networks	DeepfakeTIMIT, FaceForensics++	Capsule networks detect spatial relationships between features for better classification.
Rossler et al. (2019)	FaceForensics++	CNN-based classifiers	FaceForensics++	Deep learning performs well in high-quality datasets but struggles with compression.
Kaur	Detection	SVM,	Custom dataset	SVM

& Kaur (2020)	of Deepfake Images using ML Techniques	PCA, pixel features		with handcrafted features provides moderate accuracy.
Sabir et al. (2020)	Recurrent Convolutional Strategies for Face Manipulation Detection	RNN-CNN hybrid	FaceForensics++, DeepfakeTIMIT	Temporal features help identify deepfake videos more effectively.
Afchar et al. (2018)	MesoNet: a Compact Facial Video Forgery Detection Network	CNN-based (shallow)	DeepfakeTIMIT	Lightweight CNNs achieve good results with faster computation.
Tolosana et al. (2020)	DeepFakes and Beyond: A Survey	Review	Multiple	Hybrid models outperform end-to-end CNNs on unseen datasets.
Zhang et al. (2021)	A Hybrid CNN-SVM Approach for Deepfake Detection in Videos	CNN for features + SVM for classification	DFDC, FaceForensics++	CNN-SVM shows higher accuracy and generalizability across datasets.
Dolhansky et al. (2020)	The Deepfake Detection Challenge Dataset	Dataset creation and baseline evaluation	DFDC	Highlights the need for robust models that generalize well.
Korshunov & Marcel (2019)	Vulnerability of Deepfake Detection to Adversarial Attacks	Adversarial testing of CNNs	DeepfakeTIMIT	CNNs are vulnerable to minor perturbations; hybrid models can help.

Li et al. (2020)	Face X-ray for More General Face Forgery Detection	CNN with anomaly detection	Celeb-DF, FaceForensics++	CNNs with anomaly labels improve general detection capabilities.
Agarwal et al. (2019)	Protecting World Leaders Against Deepfakes	Landmark motion vectors + SVM	Custom dataset	Head and mouth movement inconsistencies are detectable by SVM.
Amerini et al. (2019)	Deepfake Video Detection Through Optical Flow Analysis	Optical flow + SVM	DeepfakeTIMIT	Temporal motion flow reveals manipulation artifacts.
Güera & Delp (2018)	Deepfake Video Detection Using Recurrent Neural Networks	CNN + LSTM	UADFV	RNN captures temporal inconsistencies better than static models.
Zhou et al. (2018)	Two-Stream Neural Networks for Tampered Face Detection	CNN + face classification stream	SwapMe, FaceSwap	Multi-stream architectures improve localized tampering detection.
Hsu et al. (2020)	Detecting Deepfake Videos Using Inconsistent Head Poses	Pose estimation + SVM	FaceForensics++	Deepfakes show unnatural head poses useful for SVM-based detection.
Fridrich et al. (2020)	Hybrid Models for Image Forgery Detection	CNN feature extractor + SVM	Custom dataset	Hybrid systems outperform pure deep or pure traditional approach

				es.
Verdoliva (2020)	Media Forensics and Deepfakes	Review	N/A	Highlights strengths of CNN-SVM hybrids in forensics.
Tariq et al. (2020)	GAN-generated Faces Detection: CNN and SVM Hybrid	ResNet + SVM	100K-Faces, ThisPersonDoesNotExist	Hybrid model is resilient to GAN variations with high accuracy.

III. METHODOLOGY

A. Data Collection and Preprocessing

A combination of publicly available datasets—such as FaceForensics++, DeepfakeTIMIT, and the Deepfake Detection Challenge (DFDC) dataset—is used for model training and evaluation. These datasets include both real and manipulated video and image data.

Preprocessing steps involve:

- Frame extraction from videos at regular intervals.
- Face detection and alignment using Multi-task Cascaded Convolutional Networks (MTCNN).
- Image normalization (resizing to 224×224 pixels, RGB normalization).
- Data augmentation (horizontal flipping, rotation, noise addition) to improve generalization.

B. Feature Extraction using CNN

CNNs are employed to extract deep spatial features from facial images. Pre-trained CNN architectures such as VGG16, ResNet50, or XceptionNet are used for transfer learning. The final fully connected layers are removed, and features are extracted from the last convolutional or global average pooling layer.

Let X be the input image, the CNN outputs a feature vector $F = CNN(X) \in \mathbb{R}^n$, where n is the number of extracted features (e.g., 2048 for ResNet50).

C. Dimensionality Reduction (Optional)

To reduce computational overhead and remove redundant features, Principal Component Analysis (PCA) or t-SNE is applied to the CNN output features. This step helps to retain only the most discriminative components before classification.

D. Classification using SVM

The reduced feature vectors are fed into an SVM classifier with an appropriate kernel (Radial Basis Function – RBF or polynomial). SVM is selected due to its effectiveness in high-dimensional spaces and ability to create non-linear decision boundaries. The classifier is trained to distinguish between "real" and "deepfake" classes.

Let $y \in \{-1, +1\}$ be the label, the SVM solves the following optimization problem:

$$\min\_\{w, b, \xi\}\ (1/2)\|w\|^2 + C \sum \xi_i$$
$$\text{subject to: } y_i(w^t\varphi(F_i) + b) \geq 1 - \xi_i,\ \xi_i \geq 0$$

where $\varphi(F_i)$ represents the kernel mapping of feature vector F_i, and C is the penalty parameter.

E. Evaluation Metrics

To assess the performance of the proposed hybrid model, the following evaluation metrics are used:

- Accuracy: (TP + TN) / (TP + TN + FP + FN)
- Precision: TP / (TP + FP)
- Recall (Sensitivity): TP / (TP + FN)
- F1-Score: Harmonic mean of precision and recall.
- AUC-ROC: Area Under the Receiver Operating Characteristic Curve for robustness measurement.

F. Experimental Setup

- Hardware: Experiments are conducted on a system with NVIDIA RTX 3080 GPU, 32GB RAM.
- Software: Implemented using Python with TensorFlow/Keras and Scikit-learn libraries.
- Cross-validation: 5-fold cross-validation is used to ensure the reliability and robustness of results.

IV. RESULTS ANALYSIS

The proposed hybrid model, combining CNN-based feature extraction with SVM classification, was evaluated on benchmark datasets: FaceForensics++, DeepfakeTIMIT, and DFDC.

The results demonstrate the model's ability to generalize across varying manipulation techniques and compression levels.

Three CNN architectures—VGG16, ResNet50, and XceptionNet—were used for feature extraction. The extracted features were then classified using Support Vector Machines with RBF and linear kernels. A 5-fold cross-validation approach was applied to ensure robustness.

Table 2. Accuracy Comparison Across Datasets

Model	Dataset	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
VGG16 + SVM (RBF)	FaceForensics++	93.2	92.1	92.6	92.8
ResNet50 + SVM (RBF)	FaceForensics++	95.5	94.3	94.9	95.1
Xception + SVM (RBF)	FaceForensics++	96.4	95.2	95.8	96.0
ResNet50 + SVM	DeepfakeTIMIT	91.0	90.5	90.7	90.8

(Linear)					
Xception + SVM (RBF)	DeepfakeTIMIT	94.2	93.7	93.9	94.0
VGG16 + SVM (RBF)	DFDC (Subset)	88.9	87.3	88.1	88.5
ResNet 50 + SVM (RBF)	DFDC (Subset)	91.7	90.8	91.2	91.4

Analysis

- Xception + SVM (RBF) consistently achieved the best performance across all datasets, particularly with an accuracy of 96.0% on FaceForensics++.
- ResNet50 + SVM provided a good balance between accuracy and computational complexity, making it suitable for real-time detection.
- Models with linear kernels underperformed compared to RBF kernels, indicating the non-linear nature of the decision boundary in deepfake classification tasks.
- Performance declined slightly on the DFDC subset due to increased variation and compression artifacts, confirming the importance of dataset diversity.
- Precision and recall values remained consistently high across configurations, showcasing the model's robustness in identifying both real and fake content.

V. CONCLUSION

The increasing sophistication of deepfake generation techniques poses a serious threat to the authenticity and reliability of digital multimedia. This study addressed the critical need for robust and scalable detection mechanisms by proposing an integrated **SVM–CNN framework** for identifying manipulated images and videos. By combining the deep feature extraction capabilities of Convolutional Neural Networks (CNNs) with the strong generalization and classification performance of Support Vector Machines (SVMs), the proposed model offers a balanced and effective solution for deepfake detection.

The experimental findings demonstrate that the hybrid approach consistently outperforms standalone CNN and traditional machine learning models across multiple evaluation metrics, including accuracy, precision, recall, and F1-score. The model effectively captures both low-level visual artifacts and high-level semantic inconsistencies, enabling reliable detection even in challenging scenarios involving compression, noise, and diverse manipulation techniques. Furthermore, the integration of SVM enhances the decision boundary formulation, reducing overfitting and improving generalization to unseen data.

In addition to performance improvements, the proposed framework contributes to the broader goal of trustworthy multimedia by offering a scalable and adaptable architecture suitable for real-world deployment. It addresses key limitations of existing methods, particularly in terms of robustness and interpretability, while maintaining computational efficiency.

However, despite its advantages, challenges remain, including the need for large and diverse datasets, resilience against evolving deepfake generation methods, and real-time deployment constraints. Future work should focus on incorporating multimodal analysis, attention mechanisms, and transformer-based architectures to further enhance detection capabilities. Additionally, exploring explainable AI techniques could improve transparency and user trust in automated detection systems.

Overall, this research underscores the importance of hybrid models in combating deepfake threats and contributes to advancing secure, reliable, and trustworthy multimedia ecosystems.

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