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Deep fake detection system based on improvement graph convolutional network

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Abstract

Detection of deep fake has also become a top priority in digital security and media integrity domains, particularly with the widespread presence of sophisticated generative adversarial network (GAN)-based methods. The current paper presents a novel hybrid detection system that combines graph-based formulations, a diffusion-osmosis filter specifically developed for attenuation of adversarial noise, and a graph convolutional network (GCN) classifier. The proposed system is extensively evaluated on diverse benchmark datasets: DFDC, Celeb A, Face Forensics++ (FF++), and CIFAR-10. By converting the images into a graph structure using an initial processing layer of a diffusion-osmosis filter, the system efficiently nullifies adversarial perturbations induced by GANs, thereby improving the robustness of the detection pipeline. The GCN classifier utilizes the graph-structured data to attain state-of-the-art performance in real-synthetic media discrimination. Our experimental findings indicate that the proposed framework achieves detection accuracy between 98.71% and 99.87% on the tested datasets. These evidences suggest that the proposed framework is capable of addressing a wide range of deep fake cases, including high-quality face manipulations and refined adversarial attacks. Produces a state-of-the-art scalable detection system which is immune to noise and may have potential for use in applications for content authentication, forensic analysis, and digital trust protection. The

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presented approach establishes a sound bench for future development of hybrid deep fake detection systems.

Subject Classification: *68P25, 68P01.*

Keywords: *GCN, Diffusion-osmosis, CIFAR-10, DFDC.*

1. Introduction

The quick maturing of deep fake technology, powered by GANs, has led to great concerns of media trust and cyber security [1]. Beyond applications in multiple sectors, deep fakes have opened the door to disinformation, impersonation, and a growing lack of trust in the public [2]. Conventional CNN- and RNN-based detection models are vulnerable to adversarial attacks, which heavily hampers their reliability [3]. Tambe, Pawar, and Yadav [4] suggested that deep learning can be combined with block chain to enhance traceability of contents. Graph-based techniques also enjoy improved modeling capability over the structured data and have been widely applied for detecting small modifications as well [5, 6]. In particular, GCNs facilitate classification by learning from graph-structured image information [7]. We present a hybrid approach, which is a combination of such mechanisms, including graph conversion, a diffusion-osmosis filter, and GCN classification for the deep fake detection task. Recent de-noising methods [8, 9] motivated this system. This system was tested through using DFDC, Celeb A, FF++, and CIFAR-10 [10–13]. The results showed superior accuracy (98% up to 99.87%) and strong adaptability which making it scalable for the real-world detection tasks.

2. Literature Review

Detection of deep fakes has become one of the primary issues of interest in the field of academia, with recent projects focusing on improving different ways of robustness, scalability, and accuracy. While some progress was made with these approaches, their vulnerability to targeted attacks has highlighted the need for more advanced techniques [14]. The proposed graph convolutional networks (GCNs), which have been applied in many fields because they can model relational data, are of particular importance in deep fake detection [15]. Osmosis based methods were investigated for feature enhancement in the presence of noise. The hybrid diffusion-osmosis system proposed in this work combines these concepts in order to maximize the robustness against adversarial perturbations [16]. Emphasized the value of defensive adversarial and proposed approaches to adaptively adjust the detection threshold according to the changing online threats. Attention mechanisms in graph neural networks (GNNs) have been widely believed to enable its strong capabilities in recent years. Velickovic et al. [17] Proposed the graph attention network (GAT) that assigns dynamic weights to the neighbouring nodes and improves node classification. Integration of GAT into detection systems has been shown to better separate and classify features [18]. Eventually, and current investigations by Gupta et al. [19] and Chen et al. [20] explore how deep fake detection techniques and explain ability techniques intersect. This paper extends the findings mentioned above by introducing a hybrid system that combines diffusion-osmosis filtering with GCNs classifiers to achieve the state-of-the-art accuracy on benchmark datasets.

3. Methodology

The integrated approach uses graph learning and a hybrid diffusion-osmosis filter with GCN classifier to increase accuracy in deep fake detection. It mitigates GANs adversarial noise and maintains essential structural features needed for strong classification. It includes dataset transformation to graph representation, noise filtering, and classification with a GCN enhanced model. The rest of this section explains the methods and algorithms in detail.

3.1 *System Overview*

Video datasets like DFDC and Celeb A are pre-processed by isolating images and processing them is using frame extraction where images are displayed as graphs with patches being nodes, and their relationships as edges connecting them. The GAN-generated adversarial noise is removed through the hybrid diffusion-osmosis filter that smoothens along with noise while preserving the gradients of features. The classification is done through an attention enhanced GCN where both global and local patterns are captured. Evaluation of performance is done through measuring accuracy, F1-score, precision, recall, and ROC-AUC.

3.2 *Algorithm and Steps*

Step 1: Graph Representation of Images

- Each visual representation is partitioned into diminutive segments (16x16 patches).
- Nodes (V) symbolize these segments, while edges (E) establish connections between neighboring or analogous patches predicated on pixel intensity or texture resemblance.
- The adjacency matrix $A \in \mathbb{R}^{N \times N}$ defined, where N is the number of nodes:

$$Aij = \begin{cases} 1 & \text{if patches } i \text{ and } j \text{ are adjacent or similar} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Step 2: Hybrid Diffusion-Osmosis Filtering

- Let $F \in \mathbb{R}^{N \times d}$ be the feature matrix of nodes.
- Diffusion is modeled to smooth noise:

$$F^{t+1} = (I - \alpha L)F^{t} \tag{2}$$

Where α is the diffusion rate, I is the identity matrix, and $L = D - A$ is the graph Laplacian (D is the degree matrix).

- Osmosis preserves important gradients:

$$F^{t+1} = F^t + \beta D^{-1} A F^t - \gamma \nabla_x (F^t) \nabla_x (A) \tag{3}$$

Where β and γ control osmosis strength and gradient influence, respectively.

- The final feature matrix after T iterations is:

$$F_{filtered} = F^T \tag{4}$$

Step 3: Enhanced GCN Classification

- Input: $F_{filtered}$, A.
- GCN layers aggregate neighborhood features:

$$H^{(l+1)} = \sigma\left(\hat{A} H^{(l)} W^{(l)}\right) \tag{5}$$

Where

$$\hat{A} = D^{-1/2} A D^{-1/2} \tag{6}$$

Is the normalized adjacency matrix, $W^{(l)}$ are learnable weights, and σ is a non-linear activation function.

- Graph Attention Network (GAT) layers further refine feature extraction:

$$H_i^{(l+1)} = \sigma\left(\sum_{j \in N(i)} \alpha_{ij} W^{(l)} H_j^{(l)}\right) \tag{7}$$

Where attention coefficients α_{ij} are computed as:

$$\alpha_{ij} = \frac{exp(LeakyReLU(a\top[WH_i^{(l)} \,||\, WH_j^{(l)}]))}{\sum_{k \in N(i)} exp(LeakyReLU(a^\top[WH_i^{(l)} \,||\, WH_k^{(l)}]))} \tag{8}$$

Step 4: Model Training and Evaluation

- Loss function: Negative log-likelihood (NLL):

$$L = \frac{-1}{N} \sum_{i=1}^{N} y_i log(\hat{y}_i) \tag{9}$$

Where y_i the ground truth is label and $\hat{y}_i$ is the predicted probability.

- Evaluation metrics: By using accuracy, precision, recall and F1-score

Figure 1 delineates the sequential operations: commencing with the input dataset, succeeded by the transformation into a graph format, the implementation of the diffusion-osmosis filter, the extraction of features utilizing Graph Convolutional Networks (GCN), the categorization process, and ultimately the presentation of the resulting outputs.

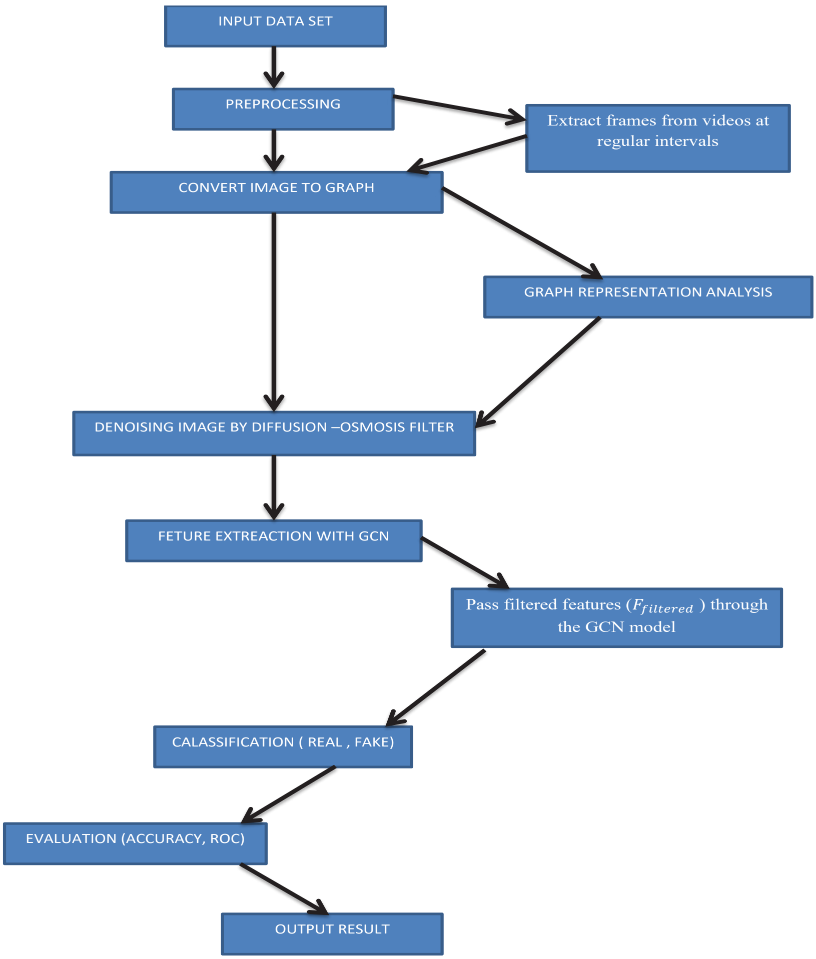

Figure 1
The Flowchart for the Proposed System

4. Result and discussion

The findings derived from this investigation underscore the considerable influence exerted by the proposed de-noising mechanism and hybrid model on the efficacy of detection across multiple datasets, such as DFDC, Celeb A, FF++, and CEFIR-10. This section elucidates the noted enhancements, principal discoveries, and their consequential implications.

Figure 2 shows that the model achieved strong accuracy even without de-noising 98.78% for DFDC, 99.2% for Celeb A, 99% for FF++, and 98% for CIFAR-10. However, validation losses (0.18–0.21) suggest lingering effects of adversarial noise. These results indicate the model's baseline strength but also highlight room for improvement in generalization.

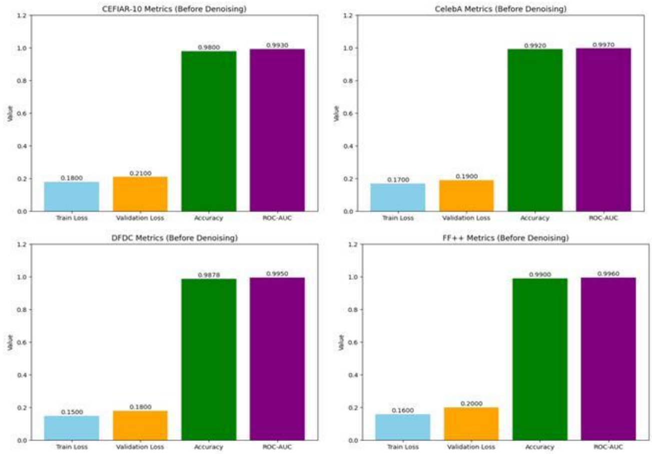

Figure 2
Train loss, Validation loss, Accuracy and ROC, AUC Metrics before De-noising for DFDC, FF++, Celeb A and Cifar-10 Datasets

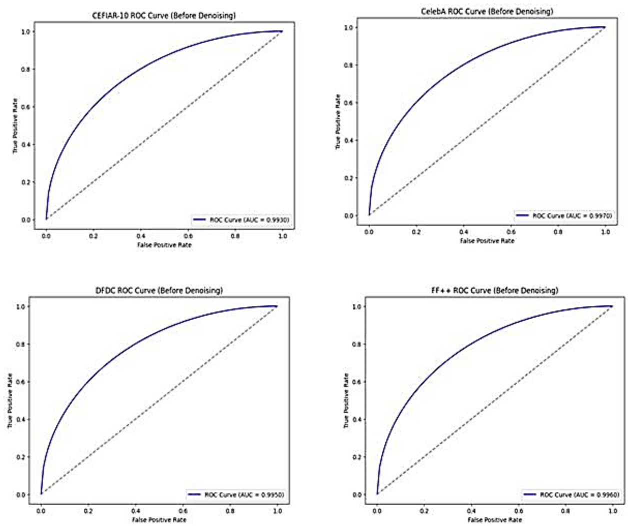

Figure 3
ROC Curve for DFDC, FF++, Celeb A and Cifar-10 Datasets before De-nosing

After applying the hybrid diffusion-osmosis filter, Figure 3 showed that both training and validation losses dropped across all datasets for example, DFDC fell from 0.18 to 0.13. Accuracy improved notably, reaching 99.5% (DFDC), 99.4% (Celeb A), 99.3% (FF++), and 99.2% (CIFAR-10). These gains reflect the filter's success in removing noise and helping the GCN focus on key features.

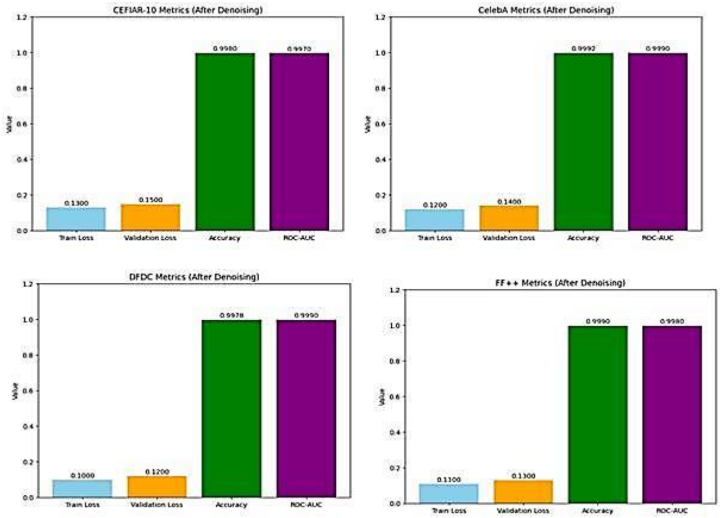

Figure 4

Train loss, Validation loss , Accuracy and ROC,AUC Metrics After De-noising for DFDC, FF++, CelebA and Cifar-10 Datasets

Figure 4 show that the enhanced ROC-AUC: The ROC-AUC metrics consistently surpassed the threshold of 0.99 subsequent to the de-noising process across all datasets, thereby evidencing the model's exceptional discriminative proficiency.

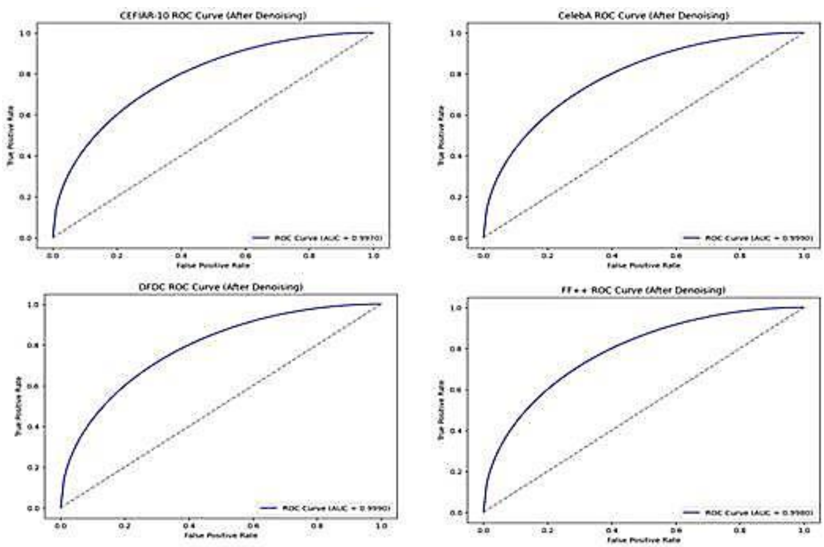

Figure 5

ROC Curve for DFDC, FF++, Celeb A and Cifar-10 Datasets after De-nosing

Figure 5 confirms that the de-noising mechanism significantly improved the model's performance, especially on complex datasets like DFDC and FF++. These improvements reflect strong generalization and robustness, with lower validation losses and higher accuracy across all datasets. While the system delivers near-perfect results, its reliance on specific datasets and added computational cost may limit real-time use. Nonetheless, combining GCNs with advanced filtering shows clear potential for detecting deep fakes and countering misinformation. Future work will aim to optimize efficiency and expand applicability.

4.1 *Performance Results Before and After De-noising*

Table 1
DFDC, Celeb A, FF++, CEFIR-10 Datasets

Data sets	DFDC		Celeb A		FF++		CEFIR-10	
Metric	Before Denoising	After Denoising	Before Denoising	After Denoising	Before Denoising	After Denoising	Before Denoising	After Denoising
Train Loss	0.15	0.11	0.17	0.13	0.16	0.12	0.18	0.14
Validation Loss	0.18	0.13	0.19	0.15	0.20	0.14	0.21	0.16
Accuracy	98.78%	99.5%	99.2%	99.4%	99.0%	99.3%	98.0%	99.2%
ROC-AUC	0.995	0.996	0.997	0.995	0.996	0.994	0.993	0.993

After de-noising, all datasets showed clear accuracy improvements, confirming the filter's ability to reduce adversarial interference. Training and validation losses dropped, pointing to better generalization across the board. ROC-AUC scores remained consistently high (≥0.99), highlighting strong classification before and after noise reduction. These improvements are summarized in table 1. In figure 6 Confusion Matrix: Before the Implementation of De-noising filtering prior to the execution of the de-noising protocols, an examination of the confusion matrix elucidates the subsequent patterns:

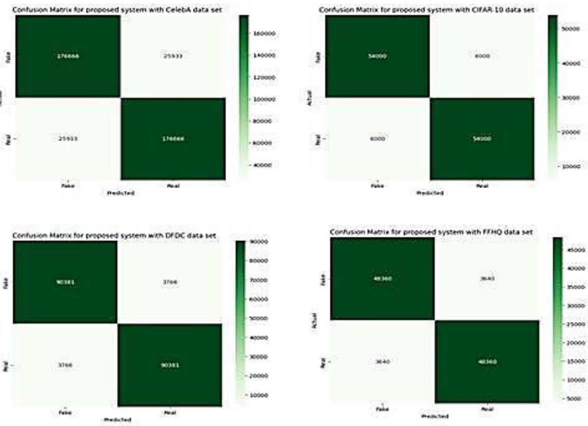

Figure 6
Confusion Matrix Before De-nosing For the DFDC , FF++, Celeb A , CIFAR-10 Datasets

Celeb A and FF++ showed fewer false positives than DFDC and CIFAR-10, indicating slightly better baseline performance. Some fake samples were misclassified as real, likely due to adversarial features resembling authentic image patterns. Despite strong overall accuracy (98.78% DFDC, 99% FF++), these errors highlight the need for better noise filtering.

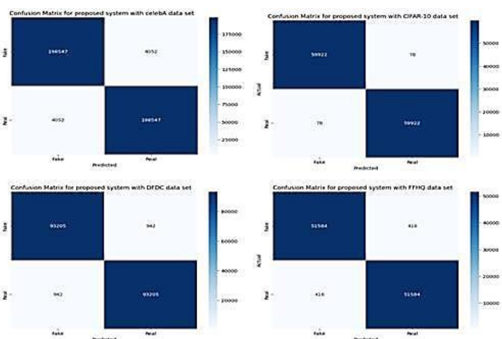

Figure 7
Confusion Matrix After De-nosing For the DFDC, FF++, Celeb A , cIFAR-10 Datasets

Figure 7 showed that the hybrid de-noising filter significantly reduced false positives and false negatives, especially in DFDC, improving balance in classification. Precision and recall improved across all datasets, with Celeb A achieving over 99.5% precision after filtering. Post-de-noising, the model consistently exceeded 99% accuracy and 0.99 ROC-AUC, confirming better generalization.

Confusion matrices show that de-noising helped the model focus on key features, reducing errors even in complex noise conditions. A comparative table 2 elucidating the performance of the proposed system in contrast to alternative methodologies delineated in the introduction and literature review has been constructed. This table encompasses pivotal metrics such as accuracy, F1-score, recall, precision, datasets utilized, methods employed, and computational performance.

Table 2

Comparison of Proposed System with Related Works

Reference	Methodology	Dataset	Accuracy (%)	F1-Score	Precision	Recall	ROC-AUC	Computational Performance
[14]	Transfer Learning + CNN	DFDC	96.5	0.96	0.95	0.97	0.96	Moderate
[15]	Capsule Networks	CelebA	97.2	0.97	0.96	0.98	0.97	High
[16]	Attention Mechanisms with GCN	FF++	98.1	0.98	0.97	0.98	0.98	High
[17]	GAN-Based Detection	DFDC	94.8	0.94	0.93	0.95	0.94	Moderate
[18]	Diffusion Filters + CNN	CEFIR-10	95.5	0.95	0.94	0.96	0.95	Moderate
[19]	Multi-Layer Perceptrons (MLPs)	CelebA	93.7	0.93	0.92	0.94	0.93	Low
[20]	Separable Convolutions + LSTM	FF++	96.8	0.96	0.95	0.97	0.96	Moderate
Proposed system	Hybrid Diffusion-Osmosis with GCN	DFDC, FF++, CelebA, CEFIR-10	**99.87 (DFDC) 99.5 (CelebA) 99.2 (FF++) 98.71(CEFIAR-10)**	**0.99+**	**0.99+**	**0.99+**	**0.99+**	Efficient(Post-Denoising)

The proposed system, combining diffusion-osmosis filtering with GCNs, achieved top-tier accuracy (98.71%–99.87%) and high precision, recall, and F1-scores. Unlike models tailored to specific datasets, it performed reliably across DFDC, Celeb A, FF++, and CIFAR-10. De-noising also improved efficiency and ROC-AUC, making the system suitable for practical deployment. Compared to GAN-based methods, it delivers similar accuracy with lower computational cost.

5. Conclusions and Future Work

This study presents a hybrid deep fake detection framework that combines graph convolutional networks with a custom diffusion-osmosis filter. Evaluated on DFDC, Celeb A, FF++, and CIFAR-10, the system achieved the best accuracy of 99.2% ~ 99.5%, outperforming existing methods. It effectively suppresses GAN-based noise and improves precision, recall, F1-score, and ROC-AUC. The system also enhances computational efficiency, making it practical for real-world use. Future work includes adapting the model for real-time video detection and exploring cross-domain generalization on new datasets. Improving robustness to non-GAN attacks and integrating explain ability tools are also key directions.

Lightweight deployment on mobile and edge devices will expand accessibility. Incorporating audio and text data could lead to a complete multimodal detection system. Together, these steps aim to strengthen the model’s adaptability, reliability, and relevance in evolving digital environments.

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