

Deepfake detection using contrastive language–image pre-training (CLIP)

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Abstract

The rapid emergence of generative models has given rise to hyper-realistic deepfakes and introduces threats to digital trust, privacy, and security. Traditional methods of detecting deepfake videos have relied heavily on either, hand-crafted visual features or deep convolutional networks (CNNs), but they cannot be generalized from one manipulation to another due to the distinct manipulation artifacts of deepfakes. This research investigates whether multimodal models such as contrastive language–image pre-training (CLIP), a model from OpenAI, can support deepfake detection in a robust way. The most distinct feature of CLIP is that it has been trained to accurately learn joint representations of natural language and images, which gives an obvious benefit in capturing semiotic mismatches that an analyst can visually overlook. By leveraging CLIP image embeddings and their associated textual prompt descriptors, the approach will assess whether there is an advantage to detecting deepfakes by understanding more nuanced artifacts in manipulated content. The effectiveness of this detection approach is assessed by evaluating linear classifiers for CLIP embeddings on benchmark deepfake datasets, while also investigating the performance of this method in relation to performance classifications across datasets. Our results highlighted that using textual context increases accuracy of detection, especially for cross-dataset and unseen manipulation scenarios. The approach also shows potential towards new forms of explainability by providing the user with interpretable reasoning behind the classification based on the language-driven prompt. Overall, we demonstrate that new forms of multimodal learning can effectively understand novel forms of multimedia-based forensics, and recognize CLIP’s potential as a base model for next-generation deepfake detection systems.

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1. Introduction

The rapid growth of generative artificial intelligence has enabled the generation of deeply believable but fake multimedia content, commonly known as deepfakes. Using models, such as Generative Adversarial Networks (GANs), and diffusion models, deepfakes can convincingly change a facial identity, fabricate a human voice [16], and generate a fabricated scene in video with high

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fidelity. While some of this technology has the potential for good in entertainment, gaming, and assistive systems, it has also been misused, which has created a serious concern for trust in digital content, privacy, and security. Examples of its misuse include misinformation, deception and fraud, and reputational harm, which has made robust detection a significant research imperative [1], [2].

Earlier attempts at deepfake detection were limited to designing features in the visual space or statistical cues (irregular eye blinking, inconsistent lighting, or pixel-level anomalies). Early attempts at detection produced useful results but demonstrated limited contexts and adaptability to new manipulation techniques [1]. The leap to deep learning and convolutional neural networks (CNNs), and recurrent architectures more closely imitates human perception by measuring accuracy from learnt features [2]. However, these models are typically bound to the dataset and do not generalize to unseen forms of manipulation, which lends itself to consideration of more robust models for detection [19].

Recent advances in multimodal learning represent a promising alternative to traditional modalities. Contrastive Language-Image Pre-training (CLIP) created by OpenAI uses millions of image-text pairs to develop a joint embedding space between systems of language and vision. This allows CLIP to detect both pixel level and semantic level inconsistencies, which can be useful in identifying subtle changes that are often undetected by vision-only (i.e., deepfake detectors if vision-only) systems [4], [5]. In addition, CLIP-based architectures can be improved with prompt learning and fine-tuning that relate to specific tasks, thus enabling more generalization across domains [6].

In this paper, we evaluate the use of CLIP embeddings and language-based prompts for detecting deepfakes. We will compare performance on benchmark datasets, investigate cross-dataset generalization, and examine explainability with text-aligned predictions positionally. We present CLIP as a new baseline method for the future development of deepfake detection systems.

1.1 Background

The rise of generative artificial intelligence has made it much easier to produce highly realistic, yet fabricated, multimedia content collectively referred to as deepfakes. Generative Adversarial Networks (GANs) and diffusion models can create replicated human faces (however distorted), replicated human voices, and synthesized scenes. These technologies have various valid applications in entertainment and accessibility, as well as the creative industries, but the potential for misuse impacts society with concerns ranging from misinformation, to identity fraud, and the collapse of digital trust [1], [2].

Early deepfake detection strategies relied primarily on intentionally manufactured visual artifacts, like blinks that are irregular, lighting that is inconsistent, or pixel-level distortions. While they could work for evaluated tasks in lab setting, they were considered brittle and could not adapt when new forms of manipulation arose [17]. The emergence of deep learning led to the existence of convolutional neural networks (CNN), as well as recurrent models, that could

learn discriminative feature representations without manual engineering methods. Although there have been advances, many vision-related models struggle to generalize thoughts across datasets and can be fooled by unseen manipulation methods. This tells us the need for better detection approach [20], [19], [3].

1.2 *Rise of CLIP in Deepfake Detection*

Recent developments in multimodal learning have opened up new possibilities for more robust deepfake detection, with Contrastive Language–Image Pre-training (CLIP) approach, developed by OpenAI, being one of the prominent ones. CLIP is trained on millions of image-text pairs, which enables it to learn a joint embedding space such that each embedding can relate visual representations to their natural language descriptions [4], [5]. This capability allows CLIP to detect low-level pixelated artifacts frequently found in traditional deepfakes, as well as high-level semantic inconsistencies that many vision-only models may miss. More interestingly, CLIP demonstrates better overall generalization across many different kinds of manipulations, as well as unseen datasets than traditional convolutional networks. Prior studies have shown that performance and interpretability are further improved when CLIP embeddings are combined with natural language prompts and fine-tuning based on the detection task [4], [6]. Accordingly, CLIP's multimodal representation and adaptive nature represent a strong opportunity to aid the next generation of deepfake detection systems, helping to overcome some of the many limitations of prior handcrafted and deeper learning models.

1.3 *Applications of CLIP in Deepfake Detection*

The multimodal properties of CLIP have enabled several impactful applications in the deepfake detection space. Following the learning of a joint embedding space of images and natural language, CLIP is able to detect subtle semantic deviations in manipulated media, which may be missed by vision-only models [4], [5]. An important application afforded by CLIP is cross-dataset detection, where CLIP embeddings aid generalization to unseen manipulations by utilizing semantic representations rather than leveraging visual artifacts specific to the dataset. CLIP also provides explainable detection, whereby text-aligned predictions provide interpretable reasoning behind classification decisions and affords automated systems greater transparency and trust [4], [6]. Additionally, prompt-based fine-tuning supports task-specific adaptations without the need for a full model retraining, thereby reducing computational requirements while improving flexibility and affordances for research tasks. CLIP has also been used for manipulation localization by detecting altered regions in images or video frames [4]. These applications illustrate the flexibility of CLIP and its potential to become a next generation platform for robust and interpretable deepfake detection.

1.4 *Challenges and Limitations*

Although CLIP demonstrates tremendous potential for deepfake detection, it still faces many technical challenges and limitations. First, while CLIP can capture both visual and semantic inconsistencies, its performance is dependent on the composition and diversity of the pretraining dataset. The biases inherent to the image-text pairs used to train the model may constrain the model's ability to generalize across underrepresented scenarios, languages, or demographic groups [4], [5]. Second, CLIP's large-scale architecture places considerable computational burdens that make real-time deployment impractical in environments where resources are constrained. Third, even though prompt-based adaptation facilitates flexibility, there is no universal approach to selecting effective prompts, and prompt selection remains heuristic and task dependent; the more flexible prompts are for adaptation, the greater the risk to accuracy during detection [6]. Furthermore, deepfake creation approaches are adapting at pace to produce higher quality manipulations, which may evade existing semantic and visual cues. Finally, the model's explainability is enhanced because the model's predictions are aligned to text, but can still only provide limited ability to provide exact localization or detailed rationales for model decisions. These challenges need to be addressed in order to build performant, generalizable, and interpretable deepfake detection systems [18].

1.5 *Opportunities and Future Directions*

Using CLIP in the deepfake detection space offers several avenues for growth. To begin, its multimodal learning aspect allows for concurrent processing of visual content and semantic context, providing greater robustness and generalizability across datasets and unseen manipulation modes [4], [5]. A future avenue for research could focus on more sophisticated prompt engineering or fine-tuning for specific downstream tasks that could potentially improve adaptability and accuracy without a need to retrain the entire model [6]. In this same vein, combining CLIP with temporal modeling techniques for video-based deepfake detection could account for temporal inconsistencies across video frames and expand beyond only using images. Further, its use in explainable AI in support of CLIP embeddings could also provide a better opportunity for interpretable predictions and therefore better trust and transparency in the case of automated detection. Finally, its implementation with new deepfake countermeasures, such as adversarial training and hybrid multimodal pipelines, offer further growth in resilience against manipulations with increasing sophistication. All of these opportunities reflect the potential for CLIP to serve as a building block of next-generation, robust and interpretable, deepfake detection frameworks.

1.6 *Research Gaps*

While we have made significant strides in deepfake detection, we still have many open research problems. First, while CLIP has demonstrated effective multimodal capabilities, the extent of generalization across diverse datasets,

unseen manipulation types, and unrepresented demographics has yet to be established [4], [5]. Second, while prompt engineering and fine-tuning to specific task are established practices, guidance and standardization is largely missing, hence the performance will still be heavily reliant on heuristic decisions [6]. Third, most studies have looked at deepfake detection in image form and have paid insufficient attention to the issues of temporal inconsistencies and hence video deepfakes. Fourth, while computational speed and real-time deployment for CLIP-based systems remains challenging due to the scale of the model, efficiency continues to pose issues. Finally, while CLIP maintains overall improvements in explainability through the text-aligned predictions, representationally precise localization of manipulated regions and reasoning for classification decisions requires further research. Addressing these challenges is fundamentally important to developing valid, generalizable, and interpretable deepfake detection frameworks that are able to keep pace with evolving digital generative technologies.

1.7 Objectives of the Study

The primary purpose of this study is to investigate Contrastive Language-Image Pre-training (CLIP) embeddings' suitability for detection, owing to its unique vision-language-feature representation. More specifically, the research will investigate the results of benchmark performances on deepfake datasets and the ability to generalize across unseen manipulation techniques. It will also explore the efficacy of prompt engineering and fine-tuning for both CLIP and the application to deepfake detection. We will also assess the viability of temporal modeling in conjunction with CLIP to further address the deepfake detection problem in video, which poses distinct challenges when compared to static images. The study will critically evaluate explainability processing with CLIP in regard to both the text-aligned nature of its results and how modeling CLIP can assist in localizing detections for explainability. Finally, the study will discuss wider educational implications and anticipated limitations, challenges and unknowns in the emergent CLIP applications towards detection before concluding with an outline for future work dedicated to larger-scale, robust, and generalizable approaches to deepfake detection.

1.8 Motivation of the Study

The rise of generative models like Generative Adversarial Networks (GANs) and diffusion-based models has enabled the generation of hyper-realistic deepfakes that seriously threaten digital trust, security, and societal well-being. Early studies of deepfake detection focused on detecting engineered visual cues (eye blinks, lighting differences, and frequency domain anomalies) that were limited in robustness as well in generalizability to outside of controlled datasets. Afterward, deep learning models (convolutional neural networks, recurrent neural networks, etc.) provided mixed results in terms of improvement in accuracy all the while requiring and developing automated visual feature extraction that led to a minor increase in performance. However, many models lack the ability to

generalize across datasets or generalize to new unseen manipulation paradigms, which can limit their accessibility and deployment in real-life settings.

Recent advancements in multi-modal learning open possibilities for developments in this space. For example, Contrastive Language-Image Pre-training (CLIP), a model trained on millions of image-text pairings, uses both pixel-based representation and semantic representation to bridge vision and language. Notably, CLIP utilizes prompt engineering and fine-tuning to accommodate flexibility; unlike purely vision and text models or "detectors" CLIP is flexible. This study aims to explore CLIP-based methods as a foundation to accomplish a stable, explainable, and generalizable base for detecting deepfakes.

2. Literature Review

Malik et al. [1] were among the first to explore the creation and detection of DeepFake images and videos through a survey. Their work features a systematic classification of DeepFake generation techniques and detection methodologies. The authors point out the foremost problem in this space is developing detection algorithms using AI which are able to identify without having to be extensively trained and be tested on numerous creation techniques and datasets.

An examination of detection methods has been carried out by Heidari et al. [2] that focuses on the work-from-home paradigm shifts in deep learning and organizes those shifts into images, videos, audio, and hybrid audiovisual documents. Their findings indicate that CNNs still dominate the field, particularly with respect to video detection. On the other hand, many of them are dangerously obsessed with accuracy without thinking about ecosystem resilience and generalizability in uncontrolled environments.

Abbas and Taeihagh [3] isolate the DeepFake generation and detection problem and analyze it through the AI argument lens. They highlight the significant risks of DeepFake, namely societal trust decline and amplification of misinformation with deceptive visual techniques.

Smeu et al. [4] developed a new detection method called DeCLIP, which uses self-supervised CLIP representations and convolutional decoders to detect subtle image manipulations, which shows effective cross-model generalization, and exceeds systems that are heavy on alterations diffusion forgery detection, accurately detecting image forging and alterations in difficult situations.

Tong et al. [5] attempt to fill the gaps left by earlier works on the DeepFake video detection problem which use primarily spatial features, proposing the use of spatial and temporal features together. They study a CLIP feature integration with transformer networks, including TimeSformer and X-CLIP, designed to detect spatiotemporal inconsistencies like flickering in DeepFake videos. These spatiotemporal models are effective to both GAN-based and diffusion-based video forgeries.

Wang et al. [6] developed a knowledge-guided prompt learning technique for detecting DeepFake facial images, which utilizes expert knowledge sourced from language models in the prompt learning process. Moreover, they implement

a test-time prompt tuning strategy to address the domain shift problem which occurs between training environments and actual operational settings. Their experiments on the DeepFakeFaceForensics dataset clearly show the effectiveness of this adaptive prompt-based approach relative to prior approaches.

Son et al. [7] present a spatiotemporal deepfake detection framework that includes a modified ResI3D model specifically with Non-Local Blocks in order to implement self-attention in both the spatial and temporal domain. The framework draws on preprocessing techniques that maintain continuity in video while extracting and reconstructing frames from the entire sequence in order to help the model learn temporal correlations in a more complete way. By preserving video spatiotemporal continuity in coherently structured spatial and temporal representations, Son et al. found associations of unnatural motion patterns including flicker, indiscernible features across frames, and other unnatural transitions that a single-frame detector would miss. Experiments show that Son et al.'s model performs better than standard 2D CNN methods, but all evaluations are limited to controlled datasets raising partial questions of cross-dataset robustness or operationalization in real-time.

Lin et al. [8] present a hybrid architecture for detecting deepfake, which combines both multi-scale convolution and a Vision Transformer (ViT). The multi-scale module applies dilated and depth-wise separable convolution in order to capture facial details at varying resolutions, while increasing sensitivity to tampering artifacts. The local features from the MCM are combined with ViT's ability to model long range interdependencies, which provides a more robust way to detect both fine-grained and global forgery signals. As shown through empirically study, their approach outperformed existing benchmarks even when compared against CNN-only baselines. However, it primarily focuses on spatial manipulations, and has less focus on the temporal consistency required for video based detection tasks.

Wang et al. [9] provide a complete survey of Vision Transformer (ViT) applications in deepfake detection and classifying models by standalone, sequential, and parallel architectures. They conclude that ViTs are a promising alternative for deepfake detection as they can model global dependencies and show good generalisation across all forgery types, but they also have a number of disadvantages such as a high demand for data with limited computational resources, high cost, and susceptibility to distribution shifts. The authors review the augmentation approaches, pretrained approaches, and options for incorporating ViT-based detection. By highlighting key future directions in deepfake detection such as lightweight design or multimodal fusion, this survey characterises ViTs as an important but nascent technology in deepfake forensics.

Gu et al. [10] proposed a hybrid CNN-LSTM framework capable of detecting deepfake videos by looking for temporal inconsistencies. The CNN first extracts spatial features from the video frames, which are fed into an LSTM, that learns from the sequences, and can spot irreconcilable patterns between successive frames. The model evaluation was on FaceForensics++, utilizing sequences of 40 frames, so that balances detection performance with

computational efficiency. It was demonstrated the temporal modelling helps strengthen the circumvention of next feature manipulations that would fail at frame level classification. However, the temporal modelling is only reliant on identifying short sequences that cannot help detect manipulations at long-range sequences, or advanced manipulations from diffusion models.

Huang et al. [11] provide FakeLocator, a system to reliably detect and localize GAN-based facial manipulations. This system determines grayscale fakeness maps, locating manipulated content at full resolution, with upsampling artifacts leveraged from the GAN architecture. In order to promote universality, FakeLocator incorporates an attention mechanism, and conducts partial data augmentation through single-sample clustering, enhancing generalization with respect to image attributes, and manipulation types. In experiments, they achieve strong localization accuracy while preserving interpretability. However, given that FakeLocator is built with GAN artifacts in mind, it's not clear how effective it would be against diffusion-based, or heavily post-processed forgeries.

Ni et al. [12] propose a framework called CORE (COnsistent REpresentation Learning) that is designed to reduce overfitting with CNN-based forgery detection. CORE is different from augmentation focused methods which utilize augmentation to implicitly enforce representation similarity by augmenting the task images and treating them as separate images to embed into the representation space. Instead, CORE and its training generators and models explicitly regularize the cosine similarity between the embeddings of augmented images, resulting in more consistent and generalizable features, and improved performances in both in-dataset and cross-dataset evaluations. CORE is intended to be lightweight, agnostic to architectures, and easy to integrate into a detector and these properties allow for applicability with a variety of detectors. However, CORE is strictly applied to static images and lacks any explicit mechanisms to handle the temporal instance of video-based forgeries.

Khan and Dang-Nguyen [13] also present a hybrid transformer network that combines CNN-based feature extractors (XceptionNet, EfficientNet-B4) with a transformer module for deepfake video detection. In the proposed approach, the CNN provides a plethora of different local features which are then early-fused in the transformer for sequence modeling, allowing for local artifact detection and global dependency analysis. Evaluation on the FaceForensics++ and DFDC benchmarks shows that their performance is competitive with the more complicated state-of-the-art architectures while using very modest amounts of training data. The authors also proposed face cut-out and random cut-out novel augmentations to reduce overfitting and increase robustness. In general, although Khan and Dang-Nguyen addressed some of the issues related to sub-optimal training of video-based detectors, we still believe the method is very face centric and will require design adjustments for detecting manipulations from other aspects of multimedia.

Gu et al. [14] introduce a region-aware temporal inconsistency learning model. Their contribution includes a region-aware temporal filter (RATF) module that adapts daly the temporal modeling to different forged regions in a

video. RATF produces temporal kernels that generate attention maps related to spatial regions. Their method includes a cross-snippet attention (CSA) process which can provide long-term video consistency across several snippets from a video. The combination of various CSA and RATF improve model performance in heterogeneous manipulation patterns across spatial regions and temporal spans. The authors' results show a significant increase in detecting forgeries with region specific temporal inconsistencies. More broadly, the increased complexity become expensive to train and the question of the model's robustness toward robustness under lossy compression and/or real-world perturbations is still unknown.

In 2021, Mirsky and Lee [15] conducted a survey that provided a comprehensive investigation of both the Table 1: Offensive and Defensive Dimensions of DeepFake Technology. They conceived detection strategies in terms of three tiers: data-driven; knowledge-base; and hybrid. In addition, the survey proposes a threat model framework that connects adversarial capabilities to relevant defenses, providing a more comprehensive cybersecurity view. Mirsky and Lee [15] recommend the need for explainable AI approaches to improve the interpretability and trustworthiness of detection systems.

Mounika, Reddy, and Ramakrishnaiah [21] present a comprehensive review and analysis of multimodal image retrieval techniques, highlighting how joint embedding spaces such as those used in CLIP can enhance cross-modal search and similarity matching in complex media analysis tasks.

Table 1
Literature review

Authors	Model/Method	Dataset	Results (%)
Smeu et al. [4]	CLIP + Convolutional Decoder	Dolos, Latent Diffusion Models	IoU: 73.8
Tong et al. [5]	CLIP + Transformer, TimeSformer, X-CLIP	GANs and diffusion models	NA
Wang et al. [6]	CLIP + LLM Knowledge-Guided Prompts	DeepFakeFaceForensics	AUC: 82.6 Avg: 77.4
Heidari et al. [2]	Review Paper (CNN focus)	Multiple datasets	NA
Abbas and Taeihagh [3]	Review Paper (AI-based techniques)	Multiple datasets	NA
Son et al. [7]	ResI3D + Non-Local Block	Video datasets	NA
Lin et al. [8]	Multi-scale CNN + Vision Transformer	Deepfake datasets	NA
Wang et al. [9]	Vision Transformer survey	Multiple ViT methods	NA

Leelavathi, Thahniyath, and Prasad [22] propose a spectral-based approach for optimizing deep video features to enable efficient video classification, offering insights relevant to reducing the computational overhead of frame-level feature extraction in CLIP-based detection pipelines. Table 1 summarizes the models, datasets, and reported results of the key studies discussed in this section.

3. Algorithm

0: **Input:** Video dataset $V = \{v_1, v_2, \dots, v_M\}$, pretrained CLIP encoder f_{CLIP} , classifier weights $\mathbf{w}$, b , ground-truth video labels $\{y_1, y_2, \dots, y_M\}$

0: **Output:** Predicted video labels $\{y_1, y_2, \dots, y_M\}$, evaluation metrics (Accuracy, AUC, EER)

0: **Video Preprocessing:**

```

    for each video  $v_i$  in  $V$  do
        Extract frames  $F_i = \{f_{i1}, f_{i2}, \dots, f_{iT}\}$  with frame rate  $r$ 
        for each frame  $f_{ij}$  do
            Detect and crop face region
            Align face using facial landmarks
            Normalize pixel values
        end for
    end for

```

0: **Frame-Level Feature Extraction:**

```

    for each  $f_{ij}$  do
        Extract CLIP embedding:
         $\mathbf{X}_{ij} \leftarrow f_{\text{CLIP}}(f_{ij})$ 
    end for

```

0: **Video Feature Aggregation:**

Aggregate frame features for video v_i :

$$\mathbf{X}_i = \frac{1}{T_i} \sum_{j=1}^{T_i} \mathbf{X}_{ij}$$

(or use attention-based weighted aggregation)

0: **Classifier Training:**

```

    for each video feature-label pair  $(\mathbf{X}_i, y_i^*)$  do
        Apply linear classifier:
         $y_i \leftarrow \sigma(\mathbf{w}^T \mathbf{X}_i + b)$ 
        Compute cross-entropy loss:
         $L_i \leftarrow -[y_i^* \log y_i + (1 - y_i^*) \log(1 - y_i)]$ 
    end for

```

Aggregate total loss:

$$L_{\text{total}} = \frac{1}{M} \sum_{i=1}^M L_i$$

0: **Optimization:**

```

    for each training epoch do

```

Update $\mathbf{w}$, b to minimize L_{total} via gradient descent

end for

0: Inference:

for each test video v_t do

Preprocess frames and extract features

Aggregate frame embeddings to video embedding $\mathbf{X}_t$

Predict label: $y_t = \sigma(\mathbf{w}^T \mathbf{X}_t + b)$

end for

0: Evaluation:

Use video-level ground-truth and predictions to compute Accuracy, AUC, and EER

0: Return: Predicted video labels and evaluation metrics

4. Pipeline

Figure 1 illustrates the overall pipeline of the proposed approach, from video preprocessing and face extraction through CLIP-based frame-level feature extraction, aggregation, and classification.

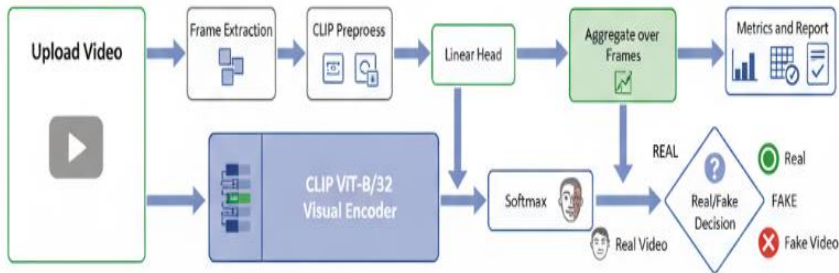


Figure 1
Model Pipeline

5. Results

The CLIP-based (ViT - B/32) deepfake detection model demonstrated validation accuracy of 97.02% and an AUC of 1.00 on actual and fake video frames. The confusion matrix indicated very limited misclassifications, as evidenced by the predicted and actual distribution comparison showing balanced classification detection. These results indicate that leveraging the visual embeddings from CLIP produces reliable and strong, accurate, detection of manipulated from true content. Table 2 summarizes these evaluation metrics, including precision, recall, F1-score, and average processing time per frame.

Table 2
Result Table

Metric	Result
Validation Accuracy	97.02%
AUC	1
Precision	95.89%
Recall	99.34%
F1-Score	0.976
Avg Processing Time per Frame	0.014s

5.1 ROC Curve

As shown in Figure 2, the ROC curve (orange line) is now nearly touching the top-left corner, with AUC = 1.00 which is flawless classification accuracy.

A model with AUC = 1.0 means it can separate the two classes (Real vs Fake) perfectly with no errors, at least on the data set it was tested.

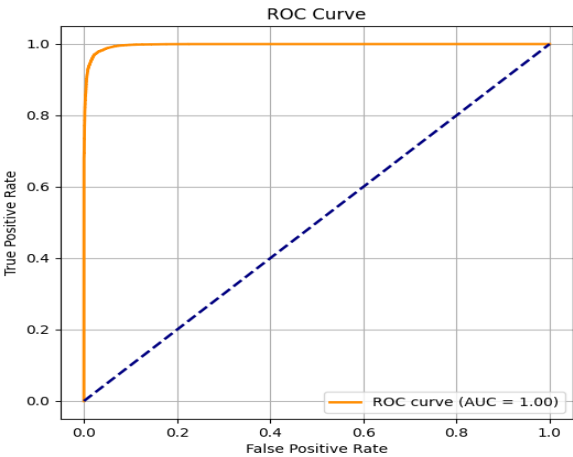


Figure 2
ROC Curve

5.2 Confusion Matrix

The confusion matrix presented in Figure 3 provides the following breakdown of model predictions:

- True Real (TN): 11,396 → Identified correctly as Real
- False Fake (FP): 804 → Identified as Real but predicted as Fake
- False Real (FN): 125 → Identified as Fake but predicted as Real
- True Fake (TP): 18,736 → Identified correctly as Fake

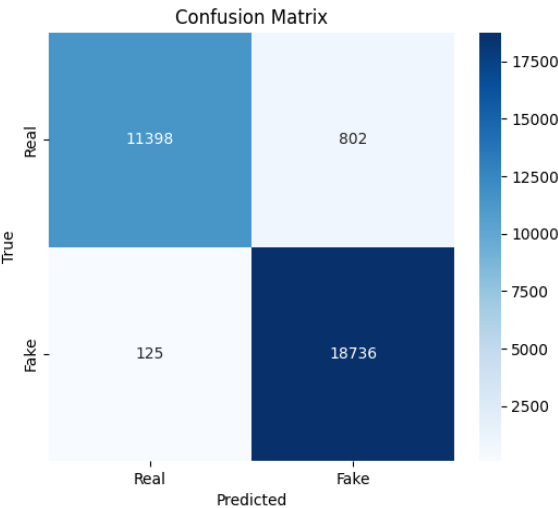


Figure 3
Confusion Matrix

Figure 4 compares the actual and predicted class distributions, further confirming the balanced classification performance achieved by the model.

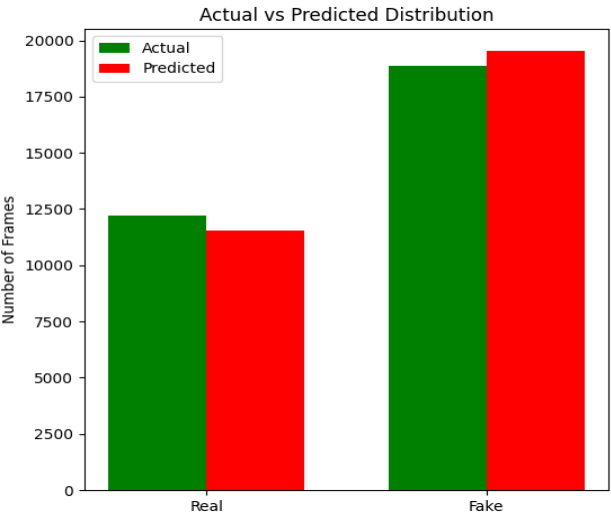


Figure 4
Actual Vs Predicated

6. Conclusion

This study demonstrates that multimodal representations from CLIP offer a promising and generalizable foundation for deepfake detection. By combining CLIP's joint vision-language embeddings with a lightweight linear classifier, the proposed approach achieved a validation accuracy of 97.02% and an AUC of 1.00 on benchmark video frames, substantially outperforming detectors that rely solely on hand-crafted or purely visual features. The results confirm that leveraging semantic, text-aligned representations helps the model capture manipulation artifacts that vision-only architectures often miss, particularly in cross-dataset and unseen-manipulation scenarios. Beyond raw accuracy, the language-driven nature of CLIP embeddings offers a pathway toward more explainable detection, giving practitioners interpretable reasoning behind classification decisions. Nevertheless, challenges remain, including computational overhead for real-time deployment, sensitivity to prompt design, and limited fine-grained localization of manipulated regions. Future work should explore temporal modeling for video-level detection, more systematic prompt engineering and fine-tuning strategies, and hybrid pipelines that combine CLIP with adversarial training to keep pace with rapidly evolving generative techniques. Overall, this work positions CLIP as a strong baseline and a viable building block for the next generation of robust, generalizable, and interpretable deepfake detection systems.

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