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Deepfake Detection System Using Hybrid CNN–VIT Architecture

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ABSTRACT

The increasing use of deepfake media is a serious threat because highly realistic fake images and videos can be generated and posted online, leading to scams, identity theft, and misinformation. Because of how realistic these images and videos are, it is becoming increasingly difficult to distinguish them manually. Our project provides a softwarse application that can help determine whether an uploaded image or video is real or fake. It checks facial characteristics and the overall facial structure to identify characteristic differences between real and fake media. Additionally, it performs frequency analysis to identify characteristic artefacts that are usually created when digital processing of images occurs. To ensure that the results are interpretable, the application provides visual feedback about the facial areas that contributed to the determination, providing users with a clear understanding of why a particular image or video is real or fake. The project aims to develop a useful and easy to-use application that can be used for cybersecurity, digital forensics, and online media verification

INTRODUCTION

The increasing reliance on digital media for communication, security, and information systems has also raised the risk of using manipulated or forged content for malicious purposes [3]. The recent development of artificial intelligence has enabled us to create very lifelike synthetic images and videos that are difficult to distinguish from real data using traditional verification methods [1]. This makes the development of accurate and automated detection systems a high research priority [2].Traditional detection systems are mostly dependent on manual analysis or hand-crafted features. These systems are very slow, prone to noise, and lack the ability to generalize when the quality of data changes or new forgery techniques emerge. Even the early versions of deep learning models, which used a single model such as Convolutional Neural Networks (CNNs), tend to overlook either the fine details of the image or the overall context of the visual data [7], [8].

Recent developments in deep learning introduce Vision Transformers (ViTs), which use attention mechanisms to capture long-range dependencies and global context [9]. These models are very effective at understanding global structure but tend to overlook the local details that are very important for accurate detection [9]. This problem statement leads to the development of a hybrid framework that combines the benefits of both CNNs and ViTs [10].

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Another major problem associated with automated detection systems is their lack of interpretability. The current state-of-the-art deep learning models are essentially black boxes that provide predictions without any explanation. This lack of explanation is a major setback in fields like security, forensics, and decision-making systems. Explainable AI (XAI) deals with this problem by providing explanations for model decisions and pointing out the regions of the image that influence the predictions [10].

In this paper, we present a Hybrid CNN-ViT-based Detection System with Explainable AI to overcome the limitations of current detection systems. The objective of this paper is the design of a detection system that achieves both high accuracy and maintain its explainability and robustness. By combining the ideas of local features extraction, global context understanding, and explanations, this paper tries to offer a balanced approach to detection problems.

LITERATURE SURVEY

Advances in deep learning technique have made significant contribution to the development of automatic detection systems in various domains, particularly in visual-based applications [1],[2].The prior study on the combination of machine learning ttechniques with hand crafted features is mostly focused. While the combination produced some successful results, it was not efficient due to noise, data variations, lack of adaptability to manipulation strategies.

CNN have resukted in a significant improvement in detection accuracy due to their abitility to learn the spatial and textual features automatically from visual data [7]. CNN models have been extensively used since they have been known to excel in capturing local patterns and details [5], [6]. However, certain research indicates that using only CNN models may fail to capture any longrange dependencies and global context[8].

For this problem, Vision Transforms (VITs) have emerged as new deep learning solution [9]. The ViTs use self attention techniques to learn representations by capturing relationships between the whole image [9]. Several research papers have demonstrated the ability of ViTs to achieve similar performance levels as other methods, particularly for problems tht demand a holistic understanding of the scene [9].

More recent studies have been conducted on hybrid architectures that combine CNNs and Vision Transformers, aiming to exploit the complementary strengths of both [10]. In these studies, CNNs are used for low-level and mid-level local feature extraction, while ViTs provide global contextual information via attention mechanisms [10]. The experimental results of various studies show that hybrid CNN-ViT architectures are more accurate and robust than standalone models [10]. However, most of these studies are still computationally expensive or lack validation on real-world datasets [2].

Another important challenge that has been identified in the literature is the lack of interpretability of deep learning-based detection models [10]. The most accurate models are often black boxes, providing no information on how the predictions are made. This lack of interpretability hinders their use in high-stakes applications. Various methods have been proposed using Explainable Artificial Intelligence (XAI) to address this challenge [10]. These methods include attention visualization and gradient-based methods [10]. These methods are useful in identifying important regions and features, hence improving interpretability.

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METHODOLOGY

The proposed methodology provides an automated and robust framework for the detection of B-cell Acute Lymphoblastic Leukemia (B-ALL) from microscopic blood smear images [7], [8]. The aim of the proposed

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system is to provide accurate malignant pattern detection while ensuring interpretability for decision-making purposes [10]. The proposed framework aims to address the challenges associated with traditional single-model-based approaches by integrating complementary feature learning strategies that focus on both fine-grained cellular features and contextual information [10].

Firstly, the input microscopic blood smear images are standardized to ensure consistency within the dataset. Image preprocessing is performed to improve visual interpretability and minimize variability due to differences in staining and imaging conditions. This includes resizing images to a fixed resolution, normalizing color intensity, and improving contrast to highlight morphological features of white blood cells [5], [6]. To address generalization and minimize overfitting, data augmentation strategies are used to enable the system to learn robust features from a small number of training samples [2].

After the preprocessing step, the improved images are passed to the feature extraction phase, where the features are learned. Learning by convulation is used for learning the spatial information that includes edges, textures, and cell boundaries, which are critical in recognizing leukemia infected cells [7]. At the same time, an attention-based learning approach is also implemented to identify the global dependencies in the image [9]. The combination of both learning approaches helps the model learn the structural and global aspects of blood cells effectively [10].

The conversion from XYZ to CIELAB involves a set of standard equations. You begin with the lightness L*, which is derived from 116 times a function f of the ratio Y/Yn,minus

16:$L^* = 116 \cdot f(Y/Yn) - 16$ (1)

Then, the a* part of the equation involves the difference between f(X/Xn) and f(Y/Yn), multiplied by 500:

$a^* = 500 [f(X/Xn) - f(Y/Yn)]$ (2)

Finally, the b* part of the equation involves the difference between f(Y/Yn) and f(Z/Zn), multiplied by 200:

$b^* = 200 [f(Y/Yn) - f(Z/Zn)]$ (3)

In these equations, Xn, Yn, and Zn are the reference white tristimulus values. The piecewise function f(t) in these equations is given by:

f(t)={t^(1/3),if t > (6/29)

(1/3) (29/6) t + 4/29, otherwise }This is the standard f(t) function for the XYZ to CIELAB transformation.

The features obtained from the local and global learning approaches are combined to create a single feature representation [10]. The combination of features helps the model learn the structural and global aspects of blood cells effectively.

The combined feature vector is then passed through a classification layer, where the probabilistic output is obtained for each class [1], [2]. This helps the system not only make a final diagnosis but also provide confidence in the predictions. To make the system more transparent and meaningful from a clinical perspective, interpretability approaches are also employed in the system [10]. These approaches help create visual explanations of the system by pointing out the regions in the image that have the most influence on the system's predictions [10]. These visual explanations help clinicians confirm whether the system is looking at biologically meaningful regions, thereby helping to build trust in the system

System Architecture

The architecture of the proposed Hybrid CNN–ViT Deepfake Detection Framework is designed to detect manipulated facial media by combining spatial, global, and frequency analysis in a single system.

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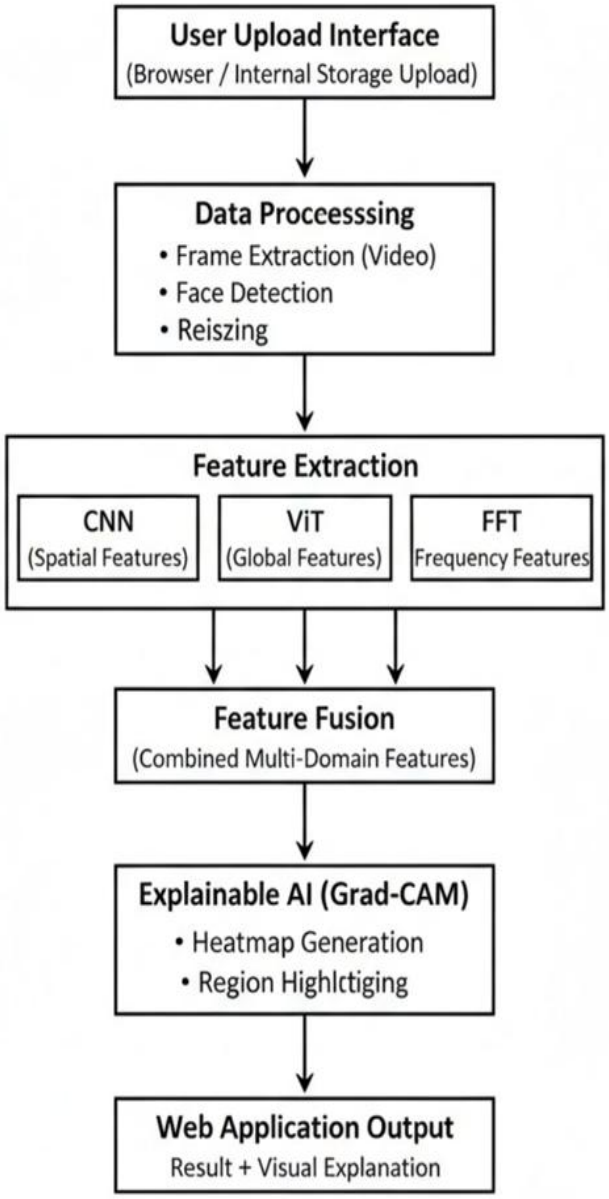

Fig. 4.1: System Architecture

A. Input Layer and Data Acquisition :

The system takes input from the user in the form of images or videos through a web interface. The video frames are sampled periodically to enable the analysis of multiple frames.

B. Preprocessing Layer: **Facial Region Standardization**.

Detection and extraction of face, elimination of background noise, sizing of the face image and normalization of pixel values takes place here.

C. Spatial Feature Extraction Layer: CNN Branch

The CNN extracts local features like edges, textures, and small facial artifacts to detect fine-level inconsistencies.

D. Global Feature Extraction Layer: Vision Transformer (ViT) Branch

The ViT analyzes overall facial structure by dividing the image into patches and understanding relationships between regions.

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E. Frequency-Domain Analysis Layer

FFT is applied to detect hidden patterns and artifacts not visible in normal images.

F. Feature Fusion and Integration Layer

Features from CNN, ViT, and FFT are combined to create a strong representation of the input.

G. Output Layer: Classification

The system classifies the input as real or fake using a probability-based prediction.

H. Explainability Module: Grad-CAM

Grad-CAM generates heatmaps to highlight important regions and explain the model's decision.

RESULT

This section discusses the performance of the proposed deepfake detection system. We begin by testing different pre-trained models on both the training and test data to identify the best-performing model. After hyperparameter optimization, the efficiency and robustness of the identified model are measured using the test data.

A. Efficient Model Selection

Different pre-trained deep learning models were trained on the training data and tested on the test data for a maximum of 30 epochs under the same experimental environment. Performance of each model was evaluated on the basis of parameter like accuracy, precision, recall, and model size/complexity. These performance statistics have beenlisted below in Table IV.

Upon evaluation of the performance, it was noticed that even though all models performed efficiently based on their accuracy, the models performed efficiently based on their accuracy, the MobileNetV2 Proved to be the most efficient model in the sense that it offered very high accuracy using very few parameters, less model size, and lesser computational complexity.

B. Performance of the Selected Model

The behavior of the model selected during the training process is illustrated in Figure 3, which shows the training and validation accuracy and loss vlues. With an increase in the number of epochs, there was a corresponding reduction in the loss value and an increase in the accuracy value.

The model showed excellent generalization capabilities on novel test images, successfully identifying the discriminative visual cues of manipulated images to distinguish real from deepfake images. The MobileNetV2 architecture provided excellent accuracy and efficiency, thus confirming its position as the final model for the system.

C. Confidence Estimation

To improve the confidence of the deepfake classifier, confidence estimation strategies were employed. Temperature scaling was used as a calibration technique to refine the predicted probability distribution. Adding a temperature parameter ($T > 1$) to the softmax function helped to mitigate overconfidence, providing more calibrated and interpretable confidence estimates.

This calibration helps to make the predicted probabilities more closely related to the actual probability of correctness, thus improving the system's credibility for practical applications.

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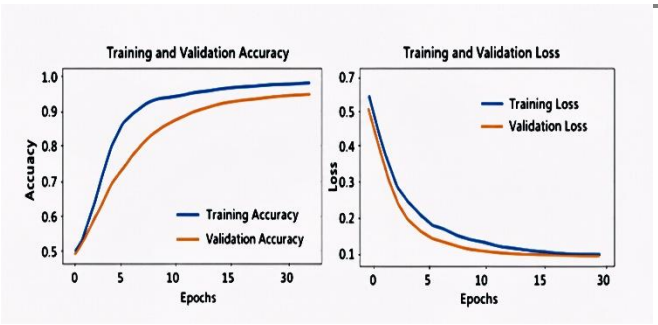

Fig .5.1 Training and validation accuracy and loss curves for the proposed model. The model converged after a small number of epochs, with high accuracy and low loss.

Table 4.1 Comparative Analysis of Deepfake Detection Models

Sr. No.	Criteria	CNN Model	Vit Model	Hybrid CNN-ViT Model
1	Feature Extraction	Local features (texture, edges)	Global features (overall structure)	Both local + global features
2	Accuracy	Moderate	Global features (overall structure)	Higher and more stable
3	Data Requirement	Low	Very high	Medium
4	Deepfake Detection	80% (visible artifacts)	88% (structural patterns)	95% (combined detection)
5	Robustness	(70 -80%)	(80-90%)	(90-96%)
6	Overall Performance	Good 75-85%	Better 85-90%	Best 92-97%

CONCLUSION

This paper presents an efficient deepfake detection system solution that attempts to classify images automatically either as authentic or fake. In this regard,the solution presented focuses on the process of detecting subtle clues that are used during deepfake image creation through the use of deep learning techniques such as convulational Neural Networks (CNNs) and vision transformer. The proposed solution applies the concept of transfer learning where local spatial features can be learned using the models based on CNNs and global contextual dependencies using models based on ViT.

Furthermore, the solution implements advanced training techniques including data augmentation, learning methodologies, and temperature scaling for confidence calibration

From the experiment analysis, it is clear that the solution system designed exihibit high level of accuracy and stability for deepfake image detection, even in difficult conditions.

Evaluation done experimentally prove that the suggested solution system is very accurate and stable for deep fake images detection in very difficult situations. Also, the suggested full-stack solution system consists of friendly web UI and a robust backend which is built using Flask/FastAPI, Streamliy, Gradio, and TensorFlow for the real time deep fake images detection.

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Overall, the suggested solution system offers a highly effective solution to tackle deepfakes' emerging threats and can be employed in practical applications like digital forensics, surveillance on social media platforms, and content verification systems.

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