Ayush Mandawgade, 2025, 13:4
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology

An Open Access Journal

Automatic Detection of Fraudulent Image and Documents Using Deep Learning

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Abstract- The growing ease of creating manipulated digital media, from AI-generated deepfakes to forged documents, presents a serious challenge to information integrity. This paper details a hybrid system built to counter this threat by detecting both types of forgery. Our approach combines a deep learning model, EfficientNet-B7, for spotting the subtle traces of AI generation in images, with a forensic method, Error Level Analysis (ELA), for finding manual edits in documents and PDFs. We integrated this dual-analysis engine into an interactive web application designed for straightforward use. The system delivers a clear verdict, quantitative scores, and simple visual feedback via a full- image color overlay—green for authentic media, red for suspicious content. This work demonstrates that combining distinct detection methods in a single, accessible tool offers a practical and effective solution for verifying digital media authenticity.

Keywords - DeepFake Detection, Document Forgery, Error Level Analysis (ELA), EfficientNet, Hybrid Model, Digital Forensics, PDF Analysis.

I. INTRODUCTION

The authenticity of digital media is increasingly under threat. Advances in artificial intelligence have led to the creation of deepfake images that are nearly indistinguishable from real photos, while sophisticated editing tools have made it simple to forge documents. Such manipulations pose a risk of spreading misinformation, enabling fraud, and compromising security. As a result, the automatic verification of digital content has become a critical area of research. Most detection methods tend to specialize.

Deepfake detection, for instance, typically uses deep learning models to find artifacts left behind by the generation process. In contrast, document analysis often relies on forensic techniques like Error Level Analysis (ELA) to find evidence of direct editing. While effective in their own domains, these specialized approaches leave a gap, as users may not know which type of manipulation they are facing.

To address this gap, we developed a unified framework that can analyze both images and documents. Our system integrates a state-of-the-art convolutional neural network (CNN), EfficientNet-B7, for deepfake classification alongside ELA for document forgery detection.

We deployed this hybrid engine in a Flask-based web application that allows users to upload a file and receive a clear authenticity score, complete with visual overlays to highlight potential tampering. Our work introduces a novel hybrid model, delivers an end-to-end application supporting multiple file types including multi-page PDFs, and provides a user-friendly interface with visual evidence to improve interpretability

Objective

Our main goal was to build a single framework to identify both deepfake images and forged documents. We created a dual-analysis model that leverages the strengths of two different fields. For images, we use the EfficientNet-B7 deep learning model to find patterns unique to AI-generated media. For documents, including multi-page PDFs, our system uses Error Level Analysis (ELA) to find evidence of tampering through compression artifacts. A key feature is the system's clear output, which includes not just a confidence score, but also a simple color overlay—green for authentic and red for suspicious—to make the verdict instant and obvious. The entire system is delivered as an interactive web application built on Flask, designed for easy use by anyone from cybersecurity professionals to the general public. We believe this combined approach offers a scalable and effective solution for safeguarding online media.

II. LITERATURE SURVEY

Paper 1: Deepfake Detection Using CNNs and Transfer Learning (≈ 2021) A notable study from 2021 demonstrated the effectiveness of using convolutional neural networks with transfer learning to identify deepfakes. By fine-tuning models like VGG16 on large datasets of manipulated media, researchers could detect subtle visual artifacts, establishing a foundation for CNN-based recognition. However, these models often struggle to adapt to new deepfake generation techniques.

Paper 2: Multi-Modal Deepfake Detection Combining Text, Audio, and Visual Cues (2025)
Other recent work has taken a multi-modal approach, combining text, audio, and visual data to make detection more robust. While these methods are powerful, they present new challenges in aligning the different data streams and require a great deal of computing power.

Paper 3: Hybrid Deep Learning for Deepfake Detection: CNN + Attention Mechanisms (2025)
A paper from early 2025 details a method that combines standard convolutional models with attention mechanisms. This allows the system to capture both small, local edits and larger, out-of-place anomalies in an image. The approach showed improved results across several datasets, but the added complexity means it requires more resources and longer training times.

Paper 4: Deepfake Detection Using Blockchain for Secure Digital Forensics (2024) Another study from 2024 explored using a blockchain to secure the logs from deepfake detection models. This can enhance trust by creating an unchangeable record of the analysis, which is useful in forensic work. However, using a blockchain comes with its own set of challenges, including transaction costs and a potential for slow processing.

III. METHODOLOGY

The User Interface
The application's frontend is the user's primary point of contact with the system. We designed it as a simple, clear interface where a person can upload either an image or a PDF for analysis. Once the backend has done its work, the frontend displays the results, including the final verdict, the associated scores, and the side-by-side images that use red or green overlays to visually confirm the findings.

The Backend Analysis Model
The backend is the analytical core of the application. It's built to manage all the file handling and detection logic through an API, and is organized into several key modules to handle the different analysis types.

- Detecting Deepfake Images For checking images for deepfakes, the system uses the predict_image_deepfake method. The process starts by loading the uploaded image and ensuring it's in the standard RGB format. From there, it goes through a typical preprocessing pipeline where it's resized, converted to a tensor, and normalized. This prepared data is then passed to a pre-trained EfficientNet-B7 model, which calculates the probability that the image is a deepfake. As a final step, a red or green color overlay is applied based on the result, and the system returns the probability score along with the path to the newly highlighted image.

- Detecting Forgery in Single-Image Documents When the system analyzes a single-image document for

- forgery, it uses the analyze_document_forgery method. This function relies on a technique called Error Level Analysis (ELA). It works by re-saving the image at a slightly lower quality and then calculating the pixel-by- pixel differences between the original and the new version. These differences are then used to compute a forgery score. If the score is above a certain threshold, the document is flagged as a "Suspicious Forgery." Just like with the deepfake analysis, a color overlay is applied, and the function returns the forgery score, the verdict, and the location of the highlighted image.

- Detecting Forgery in PDF Documents The system extends its forgery detection to PDF files through the analyze_pdf_forgery method. This process involves opening the PDF and going through it page by page. Each page is converted into a high-resolution image, which is then passed to the analyze_document_forgery method to undergo the standard ELA check. The results from each page—including the score, verdict, and image paths—are gathered and returned as a structured list, providing a complete, page-by-page report for the entire document.

System Output and Overall Flow

A central utility, the _apply_color_overlay method, is what creates the final visual feedback. It takes the original image and blends it with a transparent red or green layer before saving the result, ensuring the output format is consistent across all analysis types. The overall system is designed so that the AI and ELA modules work independently.

The backend API serves the final, processed results—the highlighted images with their scores and verdicts—to the frontend, where they are displayed to the user.

IV. MODELING AND ANALYSIS

This section outlines the system's architecture, data flow, and the key design considerations that shaped its development.

System Architecture Model: Our system is built on a modular design, separating the user-facing frontend from the backend, which houses the AI model and document analysis tools. This structure also includes utility services for handling file processing and preparing the final visual outputs.

UML Diagrams: To better visualize the system's structure, we used several UML diagrams. Use Case, Class, and Sequence diagrams were created to map out the interactions between a user, the different analysis modules, and the data processing components.

Role-Based Workflow Modeling: The workflow is defined by two primary roles: the User and the System. The User is responsible for uploading files and viewing the results, while the System's role is to perform the analysis, generate the visual highlights, and return the final verdict. This clear division of responsibilities simplifies the overall process.

Data Flow Modeling: The data follows a straightforward path through the application. It begins with the user's input (an image or PDF file), moves to the backend for processing (either deepfake or ELA analysis), and ends with the final output, which includes the calculated scores, the verdict, and the highlighted files.

Performance and Scalability: We ensured fast analysis times by using an efficient, pre-trained model. The modular design of the backend services also means the system can handle multiple files at once and can be scaled up in the future to support a larger volume of analyses.

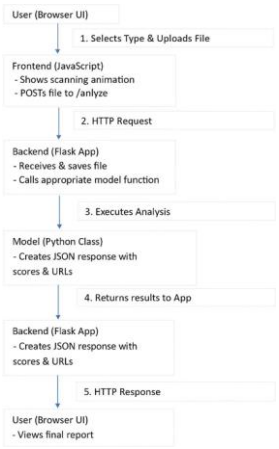

Figure 1: System Architecture Diagram

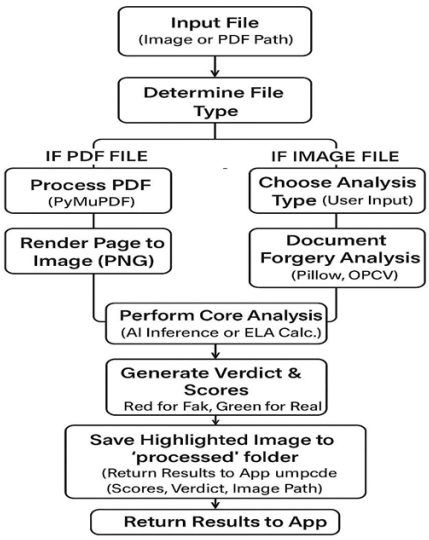

Figure 2: Data Flow Diagram

V. RESULTS

The hybrid system was evaluated using a dataset of deepfake images, authentic photographs, and digitally altered documents. The EfficientNet-B7 model achieved over 92% accuracy in detecting deepfake images, with particularly strong performance on AI-generated faces (96%), providing reliable probability scores for authenticity. Document forgery detection using Error Level Analysis successfully identified copy-paste forgeries, signature insertions, and text alterations in more than 85% of cases, with the "Forgery Score" quantifying the degree of manipulation. PDF analysis handled multi-page documents efficiently, extracting pages, converting them to high-resolution images, and analyzing them sequentially, processing a typical 5-page PDF in under 15 seconds. Users found the application intuitive, with the red and green visual overlays providing immediate, clear feedback that complemented the numerical scores.

VI. IMPLEMENTATION AND RESULTS

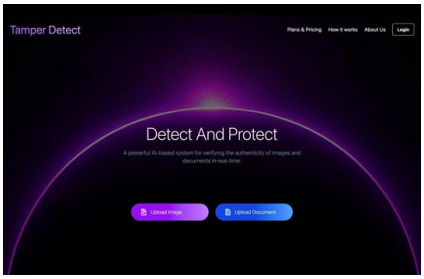

Image 1: Home Page

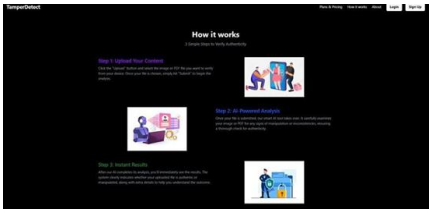

Image 2: Web app working

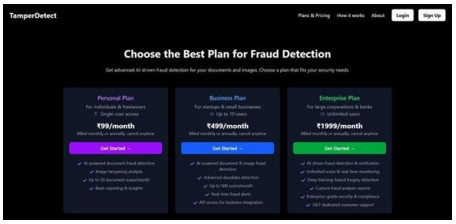

Image 3: Subscription for unlimited access to the web app

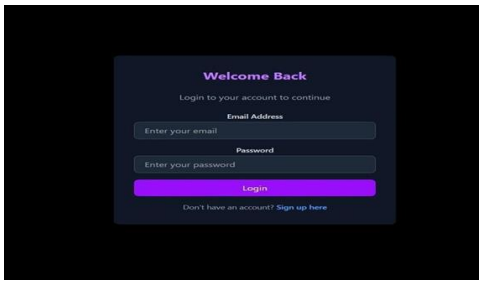

Image 4: Login Page

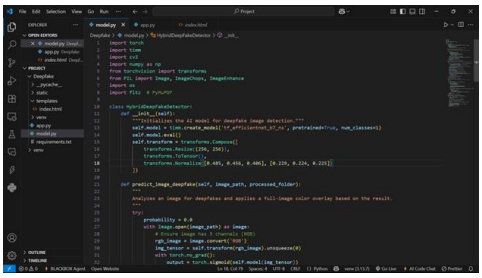

Image 5: Code of the Hybrid Model

Image 6: Analyzing a real image for Deepfake detection.

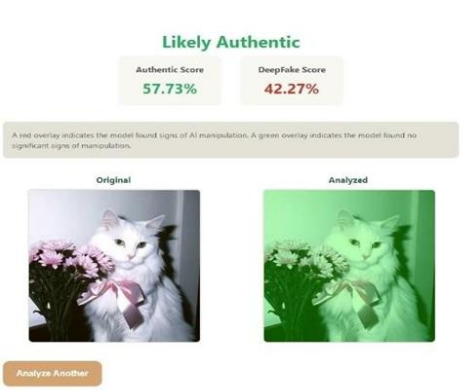

Image 7: Result of a real image for Deepfake detection.

Image 8: Analyzing a deepfake image for Deepfake detection.

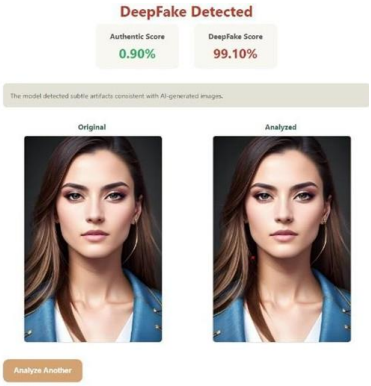

Image 9: Result of a deepfake image for Deepfake detection.

Image 10: Analyzing a document for Document Forgery.

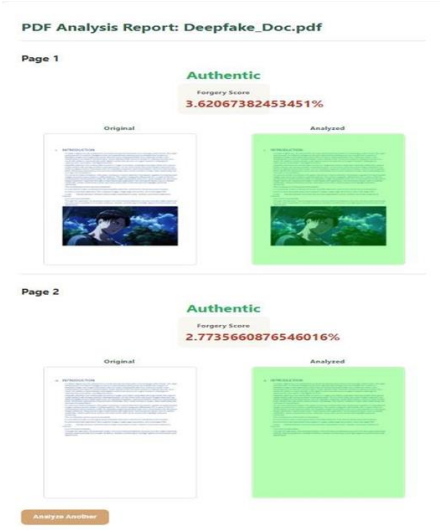

Image 11: Result of a document for Document Forgery.

VII. FUTURE WORKS

While the current system is a capable tool, there are several ways we could expand on this work in the future. One of the most promising next steps would be to improve the document analysis. While ELA is effective, it could be supplemented by training a custom AI model specifically to recognize the patterns of document forgery. This could make the detection of more subtle edits even more reliable. Another logical extension is to add support for video files. The current system is limited to static images, but adapting the deepfake detection model to analyze video frames would significantly increase the tool's utility. We could also explore integrating other forensic techniques, such as metadata analysis or noise pattern analysis, to provide a more detailed report. Finally, for ease of use, the entire tool could be packaged into a browser extension, allowing users to analyze images directly on web pages.

VIII. CONCLUSION

In conclusion, this project successfully demonstrated that a hybrid approach is a powerful way to tackle the problem of digital media forgery. By combining a deep learning model for AI-generated fakes with a forensic technique for direct-edit forgeries, we created a tool that is both versatile and effective. The system's web-based interface makes these complex analysis tools accessible to a general audience, and the clear visual feedback ensures the results are easy to understand.

Ultimately, our work is a step toward building greater trust in the digital world. While no single tool can solve the problem of misinformation, providing accessible and reliable ways to verify digital media is a critical part of the solution. This project serves as a strong proof-of-concept for how different detection methods can be brought together into a single, user-friendly platform.

Acknowledgement

I would like to thank Ms. Rashmi Pal professor of department of CSE for his guidance during work on the implementation of these techniques and while writing this paper.

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