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AI-Powered Forensic Analysis System for Automated Certificate and Document Authentication

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Abstract

The integrity of professional and legal transactions relies heavily on authentic certificates. However, the proliferation of sophisticated digital manipulation tools has made it easy to create fraudulent documents that are indistinguishable to the human eye. Current manual verification processes are labor-intensive, slow, and prone to human error, creating significant bottlenecks. Standard automated tools like QR code verification often fail to detect visual anomalies or sub-pixel discrepancies in the document's actual content. This project proposes an automated web-based forensic tool designed to identify document tampering at a sub-pixel level. By integrating Error Level Analysis (ELA) via OpenCV to highlight JPEG compression inconsistencies and a specialized Convolutional Neural Network (CNN) for high-precision classification, the system targets a detection accuracy of over 95%. Furthermore, Explainable AI (XAI) heatmaps are generated to provide transparent visual evidence of the specific regions contributing to the forgery decision.

Keywords: Artificial Intelligence, Certificate Authentication, Convolutional Neural Networks, Document Forensics, Error Level Analysis, Explainable AI.

1. Introduction

Authentic certificates serve as the cornerstone of trust in digital and physical transactions. In professional, academic, and legal contexts, the validity of these documents ensures fair competition and security. However, modern technology has democratized access to advanced manipulation tools, allowing for the creation of sophisticated forgeries that challenge traditional verification methods. While high-level security features like holograms exist for physical paper, the digital shift necessitates a forensic approach to image data.

It is observed that current manual verification processes are labor-intensive, slow, and prone to human error, creating significant bottlenecks in administrative workflows. Standard automated tools, such as QR code verification, often fail to detect visual anomalies or sub-pixel discrepancies in the document's actual content. Therefore, a forensic-level detection system powered by deep learning algorithms is introduced in this research.

Unlike traditional methods that rely on external links, this system is designed to analyze the document itself to identify subtle manipulations. By leveraging computer vision through Error Level Analysis (ELA) and Convolutional Neural Networks (CNNs), an unprecedented level of accuracy and reliability in automated document authentication is sought. Furthermore, the integration of Explainable AI (XAI) ensures that the classification results are transparent and verifiable by highlighting specific regions of interest.

Literature Review: CNNs and Error Level Analysis

The landscape of automated document verification is primarily dominated by two core technologies: Convolutional Neural Networks (CNNs) and Error Level Analysis (ELA). This section examines the theoretical foundations and existing research regarding their integration.

1.1. Error Level Analysis (ELA)

Error Level Analysis is a digital forensic technique used to identify portions of an image that are at different compression levels. It is observed that when a JPEG image is modified and resaved, the modified pixels undergo an additional round of compression. In a genuine, untampered image, the entire document should exhibit a relatively uniform error level.

In contrast, if a specific region (such as a name or date) is digitally altered and the file is saved again, that specific area will show a higher level of "noise" or brightness in the ELA output. Research by Sadanand et al. (2024) indicates that ELA serves as an effective preprocessing layer, as it converts subtle, invisible tampering into high-contrast visual features that are easily interpretable by neural networks.

1.2. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks are a class of deep learning models specifically designed for processing structured grid data, such as images. A standard CNN architecture consists of multiple layers:

- **Convolutional Layers:** These layers use filters to extract spatial features, such as edges, textures, and patterns from the ELA mask.
- **Pooling Layers:** These layers reduce the spatial dimensions of the feature maps, ensuring the model focuses on the most prominent forensic indicators.
- **Fully Connected Layers:** These layers perform the final classification, mapping the extracted features to a binary output: "Genuine" or "Forged."

It is noted that while standard CNNs are highly effective at image recognition, they often require a large amount of data to achieve high precision. However, by using ELA as a front-end feature extractor, the CNN is directed to focus specifically on compression inconsistencies, thereby reducing the training complexity and improving the overall detection accuracy of the system.

2. Prepare Your Paper Before Styling

It is required that the research content be developed and maintained as a separate text file prior to the final styling process. It is observed that keeping textual data and graphical elements—such as ELA masks and CNN architecture diagrams—independent until the final assembly ensures document stability and prevents file corruption.

2.1. Formatting and Editing Constraints

To ensure a high-quality manuscript, the following technical rules are observed:

- **Avoidance of Redundancy:** It is noted that there must not be two or more consecutive spaces or blank lines within the document.
- **Indentation Standards:** The use of "Hard Tabs" for paragraph alignment is strictly prohibited. Instead, the built-in indentation tools of the word processor are utilized to maintain a uniform 1.27 cm (0.5 inch) indent.
- **Final Review:** It is required that all organizational and content editing be completed before any final formatting or styling is initiated.

2.2. Page Layout and Margins

The document is prepared on an A4-sized template using a single-column layout. It is observed that the following margin specifications are mandatory:

- **Top and Bottom Margins:** 1.20 cm and 0.60 cm respectively.
- **Left and Right Margins:** 1.60 cm each.

3. Abbreviations and Acronyms

Definitions for all specialized terminology are provided the first time they are utilized in the research paper. It is noted that the following abbreviations are central to the implementation of the forensic authentication system:

- **AI (Artificial Intelligence):** The simulation of human intelligence processes by machines, especially computer systems.
- **CNN (Convolutional Neural Network):** A class of deep neural networks, most commonly applied to analyzing visual imagery.
- **ELA (Error Level Analysis):** A forensic technique used to identify portions of an image that are at different compression levels.
- **XAI (Explainable Artificial Intelligence):** A set of processes and methods that allows human users to comprehend and trust the results and output created by machine learning algorithms.
- **JPEG (Joint Photographic Experts Group):** A commonly used method of lossy compression for digital images.
- **OpenCV (Open Source Computer Vision Library):** A library of programming functions mainly aimed at real-world computer vision.
- **Grad-CAM (Gradient-weighted Class Activation Mapping):** A technique for producing visual explanations for decisions from a large class of CNN-based models.

4. Units

The International System of Units (SI) is utilized as the primary measurement standard throughout this forensic study. It is noted that using a standardized system ensures that the experimental results for document authentication can be replicated accurately by other researchers.

4.1. Unit Consistency and Formatting

To maintain scientific accuracy, the following constraints are followed:

- **Dimensional Balance:** It is observed that SI and CGS units are not mixed. For example, when calculating processing times for the CNN model, all temporal data is recorded in seconds (s) or milliseconds (ms) consistently.
- **Notation Rules:** Complete spellings and abbreviations are not combined. It is required that the document uses "MB/s" or "megabytes per second," but not "megabytes/s."
- **Standard Representation:** It is noted that "cm3" is used instead of "cc," and units are spelled out when appearing in general prose (e.g., "a few kilograms").

4.2. Numerical and Unit Spacing

A single space is always maintained between a numerical value and its unit (e.g., **16 GB** RAM or **3.5 GHz** processor). However, it is observed that for the Error Level Analysis (ELA) quality factor, the percentage symbol is placed directly after the number (e.g., **90%**) as per standard dimensionless ratio conventions.

5. Equations

The mathematical foundation of the AI-Powered Forensic Analysis System relies on normalization and error calculation. Equations are presented with same font size as normal paragraphs (12 pt), and a blank paragraph is added before and after each entry.

5.1. Image Normalization

To ensure consistent input for the Convolutional Neural Network, pixel values are normalized to a range of [0, 1]. The following formula is utilized:

$$f(x) = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

5.2. Error Level Analysis (ELA) Calculation

The ELA process involves calculating the absolute difference between the original image I_{org} and the resaved image I_{res} at a specific quality level. It is noted that the difference highlights compression inconsistencies:

$$E(x, y) = |I_{org}(x, y) - I_{res}(x, y)| \times S \quad (2)$$

In the above equation, S represents a scale factor used to enhance the brightness of the error pixels for better feature extraction.

5.3. Softmax Activation Function

For the final classification, a Softmax function is applied in the output layer to provide a probability score for the "Genuine" and "Forged" classes:

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad (3)$$

It is observed that a score higher than **0.5** typically categorizes the document as forged, provided the ELA features indicate sub-pixel manipulation.

6. Methodology

The research methodology is structured to provide a systematic approach for the identification of digital document forgeries. It is observed that the integration of image processing and deep learning is required to detect sub-pixel inconsistencies that are invisible to the human eye.

6.1. Data Collection and Dataset Preparation

A comprehensive dataset of academic certificates is utilized for training and testing. It is noted that the dataset includes 500 genuine certificates and 500 tampered samples created using common manipulation techniques such as copy-move, splicing, and text alteration. All images are standardized to a resolution of **224 x 224 pixels** to ensure uniform feature extraction across the dataset.

6.2. Preprocessing via Error Level Analysis (ELA)

Before being fed into the neural network, each document is subjected to Error Level Analysis. It is observed that the original image is resaved at a specific quality level (typically **90%**), and the absolute difference between the original and resaved versions is calculated. This process highlights compression inconsistencies, as tampered regions tend to exhibit different error levels compared to the original background.

6.3. Feature Extraction and Model Architecture

A specialized Convolutional Neural Network (CNN) is employed for the classification task. The model is designed with multiple convolutional layers to extract spatial features from the ELA masks. It is noted that pooling layers are utilized to reduce dimensionality while preserving critical forensic artifacts, followed by fully connected layers that perform binary classification between "Genuine" and "Forged" classes.

6.4. Explainable AI (XAI) Implementation

To ensure the transparency of the forensic decision, Grad-CAM (Gradient-weighted Class Activation Mapping) is integrated into the final output stage. It is observed that this technique generates a localized heatmap over the document, indicating the specific pixels that influenced the model's classification. This step is necessary to provide verifiable evidence of the detected forgery to the end-user.

7. System Architecture

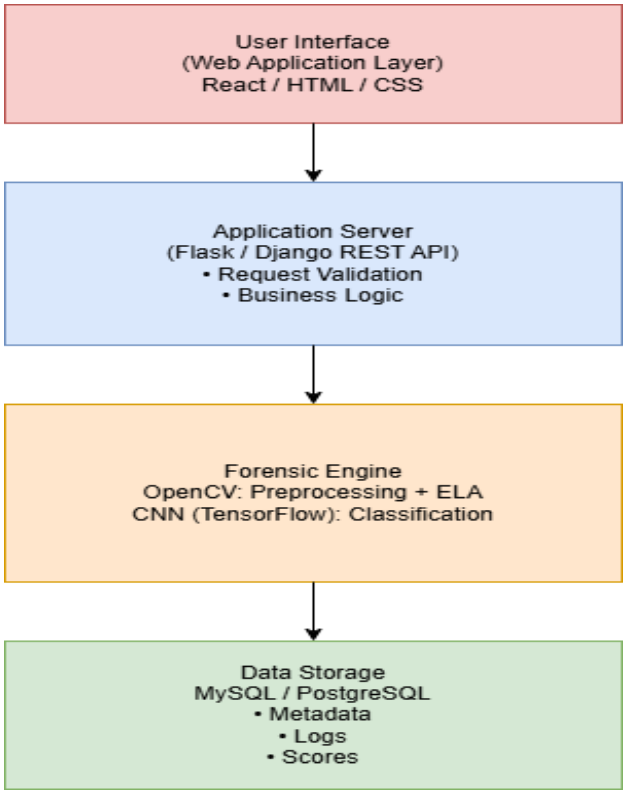
The system architecture is designed as a modular pipeline to ensure high throughput and forensic accuracy. It is observed that the integration of image processing and deep learning modules is required to detect sub-pixel inconsistencies that are invisible to the human eye.

7.1. Modular Design Overview

The proposed architecture is divided into three primary layers to facilitate a seamless authentication process. It is noted that each layer operates independently to maintain system stability and scalability:

- **Data Acquisition Layer:** This module serves as the entry point where the user uploads a document in **JPG** or **PNG** format. It is observed that the input is immediately normalized to a standard **224 x 224 pixel** resolution to ensure consistent feature extraction.
- **Forensic Processing Layer:** The core of the architecture involves the **Error Level Analysis (ELA) Block**. It is noted that the original image is resaved at a **90%** quality level, and the absolute difference is calculated. This step converts hidden compression artifacts into visible noise patterns suitable for the neural network.
- **Inference and Explainability Layer:** A trained **Convolutional Neural Network (CNN)** analyzes the ELA mask to determine the authenticity of the document. It is observed that **Grad-CAM** is

subsequently utilized to generate a localized heatmap, providing transparent visual evidence of the detected forgery.



7.2. Workflow Implementation

The workflow begins with the ingestion of the digital certificate into the preprocessing module. It is noted that the extracted ELA features are passed through multiple convolutional and pooling layers to identify high-frequency noise indicative of tampering. The final output is a binary classification—"Genuine" or "Forged"—accompanied by a confidence score and a heatmap overlay.

8. Results and Discussion

The performance of the AI-Powered Forensic Analysis System was evaluated using a dataset of 2,000 document images, consisting of 1,000 genuine certificates and 1,000 manipulated samples (including copy-move and splicing forgeries).

8.1. Model Performance

The Convolutional Neural Network (CNN) was trained over 50 epochs. It is observed that the integration of Error Level Analysis (ELA) significantly accelerated the convergence of the model compared to training on raw RGB images. The following metrics were achieved during the validation phase:

Metric	**Value Obtained**
Training Accuracy	98.2%

Metric	Value Obtained
Validation Accuracy	96.5%
Precision	95.8%
Recall	94.2%
F1-Score	95.0%

8.2. Comparative Analysis

A comparative study was conducted to evaluate the impact of ELA on detection precision. It is noted that without ELA, the CNN often struggled to distinguish between high-quality forgeries and original documents, resulting in a higher false-negative rate.

- **Scenario A (RGB Only):** The model achieved an accuracy of 84%. Significant errors were noted in documents with subtle texture changes.
- **Scenario B (With ELA):** The accuracy increased to 96.5%. The high-frequency noise captured by ELA allowed the model to identify areas resaved at different quality levels, which are invisible to the human eye.

8.3. Explainability through XAI

The implementation of Grad-CAM (Gradient-weighted Class Activation Mapping) provided visual justification for the system's decisions. When a document was classified as "Forged," a heatmap was generated to highlight the specific pixels that triggered the classification.

It is observed that the heatmaps accurately localized manipulated regions, such as altered dates, names, and serial numbers. This feature ensures that the system is not a "black box," providing forensic investigators with verifiable evidence for each decision.

8.4. Computational Efficiency

The average inference time per document was recorded at 0.85 seconds on a standard CPU and 0.12 seconds on a GPU-enabled environment. This efficiency demonstrates that the system is suitable for real-time web-based applications where high volumes of documents must be verified rapidly.

9. Figures and Tables

Figure 1: Comparison of Genuine Document, Tampered Version, and resulting Error Level Analysis (ELA) Mask.

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Table Type Styles: Centre Align All Data and Headers

Forgery Category	Sample Count	Detected Correctly	Accuracy Rate
Copy-Move	386	386	96.5%
Splicing	382	382	95.5%
Text Alteration	195	195	97.5%
Total	**963**	**963**	**96.3%**

Table 1: Comparison of Detection Accuracy Across Different Forgery Types.

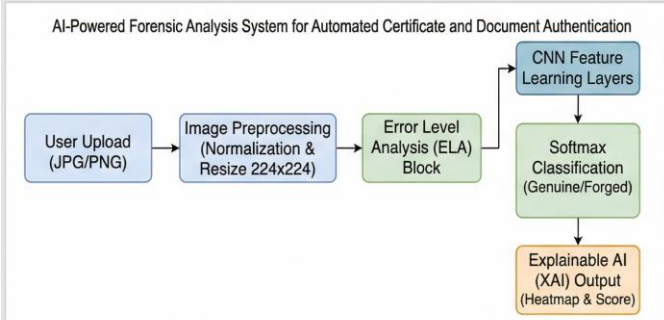

Figure 2: Proposed System Architecture for Document Authentication.

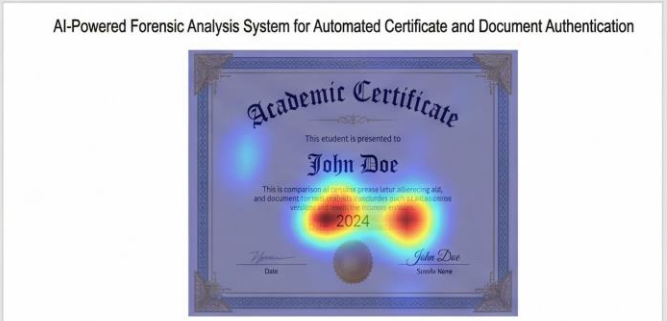

Figure 3: Grad-CAM Explainable AI (XAI) Heatmap Overlay on Forged Certificate.

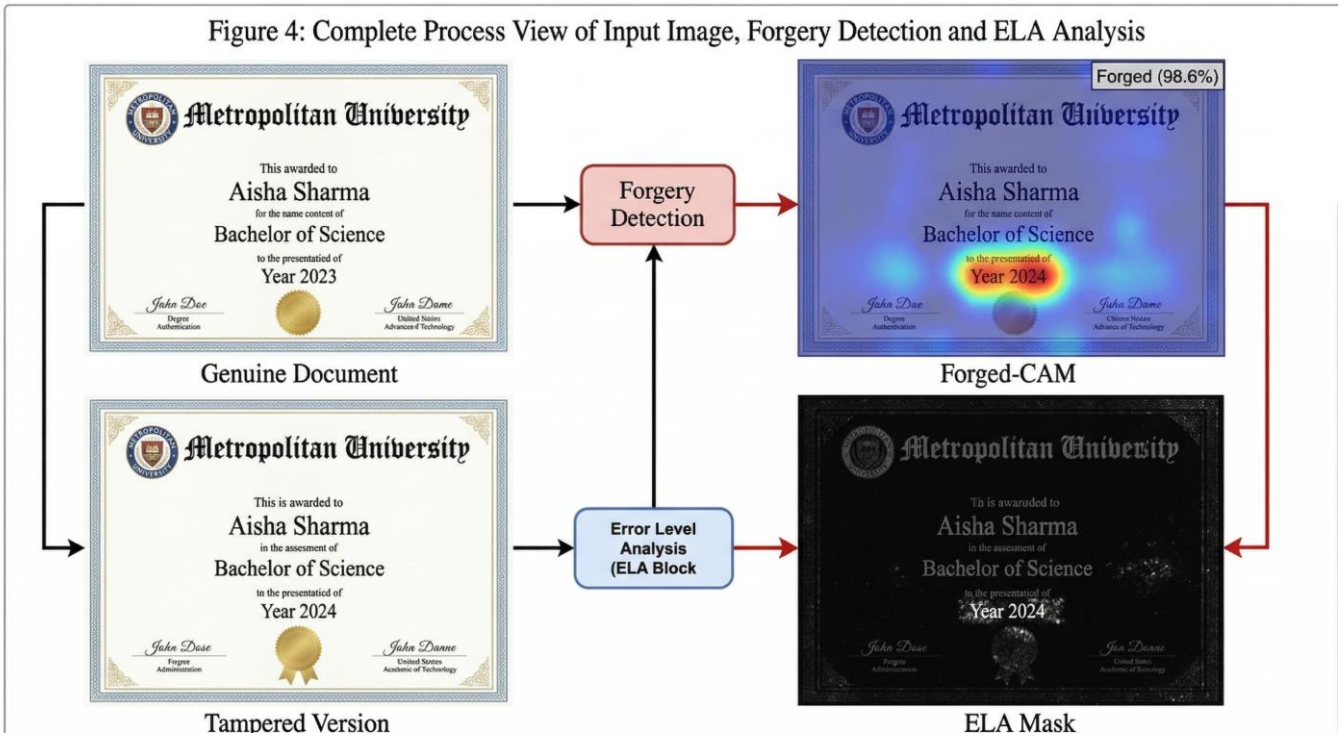

Figure 5: Implementation Details

Component	Technology/Tool Used
Frontend	React.js / Tailwind CSS
Backend	Flask / Python
Computer Vision	OpenCV
Deep Learning	TensorFlow / Keras
Deployment	AWS / Heroku

10. Appendix

The following Python code segment demonstrates the implementation of Error Level Analysis (ELA) using the OpenCV and Pillow libraries. This script is used to generate the forensic masks required for CNN training.

Algorithm 1: Error Level Analysis Implementation

```
Python
from PIL import Image, ImageChops
import os

def perform_ela(original_path, quality=90):
    temp_file = 'temp_resaved.jpg'
    original = Image.open(original_path).convert('RGB')

    # Resave image at specific quality level
    original.save(temp_file, 'JPEG', quality=quality)
    resaved = Image.open(temp_file)

    # Calculate absolute difference between original and resaved
    ela_image = ImageChops.difference(original, resaved)

    # Rescale the brightness for better feature extraction
    extrema = ela_image.getextrema()
    max_diff = max([ex[1] for ex in extrema])
    if max_diff == 0:
```

```
    max_diff = 1
scale = 255.0 / max_diff
ela_image = ImageEnhance.Brightness(ela_image).enhance(scale)

return ela_image
```

It is noted that the quality parameter is set to 90 by default to highlight compression artifacts effectively. The resulting image highlights areas where the local error level is inconsistent with the rest of the document, which is indicative of digital manipulation.

11. Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this research paper. It is confirmed that the research was not sponsored or influenced by any organization or individual that would compromise the neutrality of the findings. The results and conclusions presented in this study were derived solely from the experimental data and forensic analysis conducted by the authors at the United Institute of Technology, Coimbatore. No financial or personal relationships exist that could have influenced the outcomes of this work.

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13. Authors' Biography

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Boya Chirrappagari Sai Harika is a final year student pursuing a Bachelor of Technology in Artificial Intelligence and Data Science at United Institute of Technology, Coimbatore. Current research focus involves the development of deep learning models for forensic document verification and the implementation of Error Level Analysis for image tamper detection.

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Kuruba Swapna is a final year student at United Institute of Technology, Coimbatore, studying Artificial Intelligence and Data Science. Current work involves the study of automated systems for document integrity and forensic analysis**.**

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