<u>End Semester Project Report</u>

On

Edited Image Detection

BY:

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Abstract:

In this project, we address the challenge of detecting edited images, aggravated by the widespread availability of sophisticated image editing tools. Our approach employs Error Level Analysis (ELA) and Convolutional Neural Networks (CNNs) to identify manipulated images. ELA is used as a preprocessing step to highlight regions with different compression levels, enhancing the detection capabilities of our system. A CNN architecture is then utilized, trained on these ELA-enhanced images to classify them as authentic or edited. While our primary detection methods are ELA and CNN, we also explored the potential integration of additional techniques such as Frequency Analysis, Gradient Analysis, and Image Reconstruction. However, these methods were not implemented but considered for future enhancement of the model's accuracy and robustness. The experimental results showcase the effectiveness of our approach in detecting various types of image manipulations, and we provide a comparative analysis with existing methods. This study underscores the potential of our method as a valuable tool in combating the dissemination of fraudulent visual content in digital media.

Introduction and Significance:

In the digital age, the authenticity of visual content has become a significant concern due to the rapid advancement and accessibility of image editing software. This proliferation has made it increasingly difficult to distinguish between genuine and manipulated images, posing serious challenges to the integrity of digital media. Recognizing the urgency of this issue, our project develops and evaluates a robust methodology for detecting edited images, an essential tool in maintaining the credibility of digital content.

Our approach centers on the use of Error Level Analysis (ELA) combined with Convolutional Neural Networks (CNNs). ELA serves as an effective preprocessing technique that exploits variations in image compression to highlight potential areas of manipulation. This analysis provides a refined input for our CNN, which is specifically trained to discern between altered and unaltered images based on these highlighted discrepancies.

While the core of our detection system relies on ELA and CNN, we also considered the feasibility of incorporating additional analytical techniques such as Frequency Analysis, Gradient Analysis, and Image Reconstruction. These methods were evaluated for their potential to further enhance the detection capabilities of our system. Although they were not implemented in the current phase of our research, they represent promising avenues for future work to improve the model’s accuracy and adaptability.

This report outlines the detailed methodology, experiments conducted, and the results obtained from our study. By comparing our approach with existing state-of-the-art methods, we demonstrate the effectiveness and efficiency of our model in identifying and classifying edited images, thereby contributing to the broader efforts to combat the spread of misleading or fraudulent visual content.

Initial Attempt and Problem Encountered:

Approach:
Our initial approach to detecting edited images involved analyzing sudden changes in the light direction vector. The premise was based on the hypothesis that discrepancies in lighting could indicate potential image manipulation, particularly in regions where edits might disrupt the natural flow of light across the image. This method sought to automatically detect unnatural variations in light direction that typically occur during image splicing or other forms of digital manipulation.

Problem Faced:
Despite the theoretical soundness of the approach, we encountered significant challenges during practical implementation. The primary issue was the complexity introduced by the presence of multiple light sources in an image. Natural environments and many digitally created scenes often contain a variety of light sources, each casting shadows and highlights in different directions. This complexity makes it difficult to determine a consistent baseline for what constitutes a "natural" light direction vector across different images.

Solution - Using ELA:

What is ELA? (Error Level Analysis):
Error Level Analysis (ELA) is a forensic technique used in the field of digital image analysis to detect manipulations or alterations. It is based on the premise that when an image is compressed (for example, as a JPEG), all parts of the image should compress at approximately the same rate. However, if an image has been altered by adding, modifying, or deleting elements, the manipulated sections may exhibit a different compression level compared to the original sections. ELA exploits this discrepancy to highlight areas of potential manipulation.

Why ELA?:
ELA helps highlight regions in an image that have been subjected to different levels of compression. When an image is edited or manipulated, these regions may have different compression levels compared to the rest of the image.

Real Image and its ELA

Edited Image and its ELA

We can see in the edited image the blue and orange book is copied over and a dinosaur is added and in the ELA these areas have really bright spots with high varience.

Steps for Solution:

1. **Preliminary Data Collection and Preparation:** Gather a comprehensive dataset of original and morphed images. This dataset should include a wide variety of manipulations to ensure the robustness of the model. Preprocess the images to a uniform size and format for analysis.
2. **ELA Implementation:**
    a. **Preprocessing:** Before applying ELA, each image in the dataset is preprocessed to ensure consistency. This involves resizing images to a standard dimension and converting them to a uniform format if necessary. Preprocessing is essential for the effective application of ELA, as it reduces variability unrelated to manipulation.
    b. **Application of ELA:** ELA is applied to every image in the dataset. The process involves saving each image at a predefined, consistent compression level (typically as a JPEG) and then comparing this newly compressed version with the original image. The comparison highlights differences in compression levels, which manifest as variations in error levels.
    c. **Generating the ELA Layer:** The outcome of the ELA process is a new image (or layer) for each original image, which visually represents the differences in error levels. Areas of the image that have been edited or manipulated and then resaved will typically show higher error levels, appearing as distinctly brighter or more colorful regions when visualized. This ELA layer serves as a map of potential manipulations within the image.

d.
```python
def convert_to_ela_image(path, quality = 90):
    filename = path
    resaved_filename = 'resaved.jpg'

    im = Image.open(filename).convert('RGB')
    im.save(resaved_filename, 'JPEG', quality=quality)
    resaved_im = Image.open(resaved_filename)

    ela_im = ImageChops.difference(im, resaved_im)

    extrema = ela_im.getextrema()
    max_diff = max([ex[1] for ex in extrema])
    if max_diff == 0:
        max_diff = 1
    scale = 255.0 / max_diff

    ela_im = ImageEnhance.Brightness(ela_im).enhance(scale)
    # gray_ela = image.convert('L')
    return ela_im
```

Calculation of ELA of an Image:

i. Saving the image at 90% the original quality and taking the difference.
ii. Scaling of the image brightness as differences are really small.

e. **CNN Model Design and Training:**
   i. **Model Design:** Design a CNN architecture tailored to the task of morphed image detection. The model should include convolutional layers capable of extracting detailed features from both the original images and their ELA-processed counterparts.
   ii. **Training:** Train the CNN on the prepared dataset, using a split of training, validation, and testing sets to evaluate performance and prevent overfitting. Employ augmentation techniques to increase the diversity of training data and improve model generalization.

f. **Integration and Testing:** Integrate the ELA and CNN components into a cohesive system. Test the system on a separate set of images not seen by the model during training to evaluate its real-world applicability.

g. **Evaluation and Optimization:** Use a range of metrics (e.g., accuracy, precision, recall) to evaluate the system's performance. Analyze misclassifications to identify any patterns or weaknesses in the model. Refine the model architecture and training process based on these insights.

Solution Design:

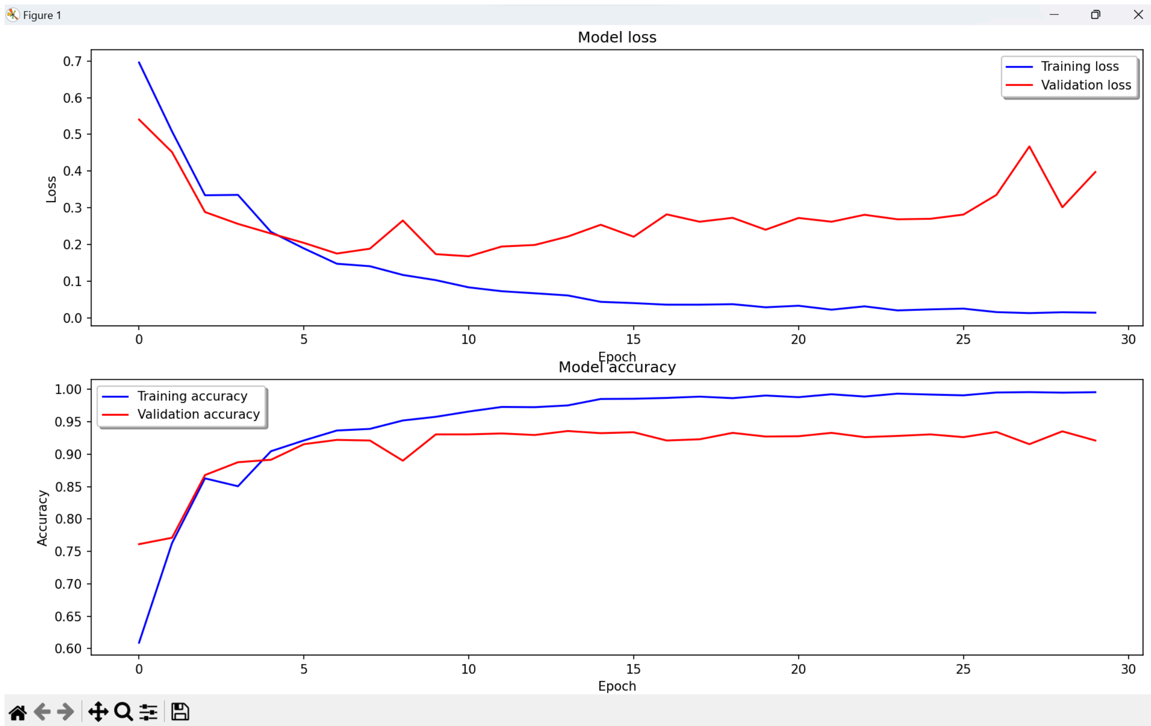
1. **Dataset:** we have used the *CASIA 2.0 Image Tampering Detection Dataset* (https://www.kaggle.com/datasets/divg07/casia-20-image-tampering-detection-dataset/code) for training our CNN Model.
    a. It contains 7492: Real Images and 5123: edited Images.
    b. Which were divided randomly into 80% Train and 20% Test.
2. **Files Description:**
    a. **elagenerator.py:** It has been used to generate the ela Images of the dataset and store them in the corresponding folder (either ‘Real’ or ‘Fake’). It also generates a new file, resaved.jpg which stores the resaved version of an image whose ela is being currently generated.
    b. **model.py:** It trains the CNN model and stores the best model in the ‘Models’ folder which can be used to classify images later.
    c. **loadModel.py:** It loads the ‘best_model.keras’ file from the Models folder and classifies the given Image as real or fake.
    d. **Models folder:** stores the trained best model.
    e. **Results folder:** has the Accuracy graph and Confusion matrix for the previous and final trained models with ‘Accuracy final’ and ‘Confusion Matrix final’ being the submitted and used models accuracy graph and confusion matrix.
    f. **sample folder:** It contains sample test images.

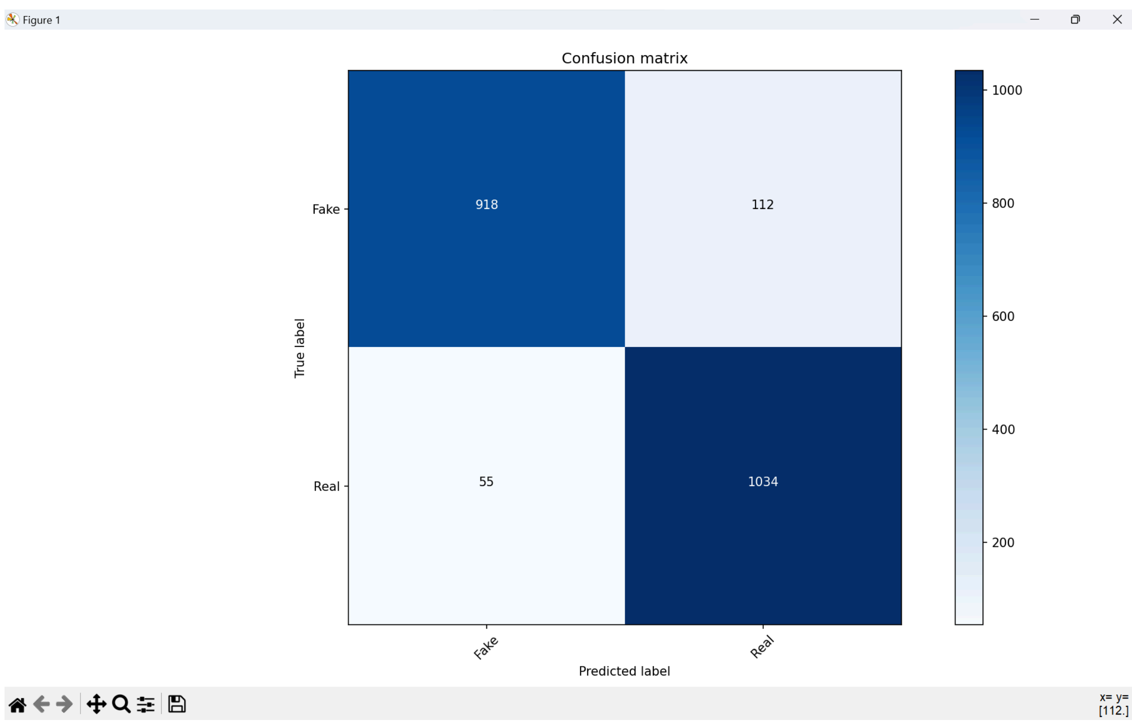
3. **Generating ELA:**
    a. An ela image is generated by resaving the image at 90% quality and taking the difference between the two images which captures the change in compression levels between the two images.
    b. The ela image obtained is usually very dark as minimal difference between the original and resaved image. To enhance the image features we scale the image with max value of a pixel in the ela image being scaled to 255.
    c. The **elagenerator.py** does this for all dataset images and stores in the corresponding folder.

4. **Making the Model:** we have used these layers to build a strong model:
    a. **Convolutional Layers (2 layers):** Extract intricate patterns, such as edges and textures, from input images. Hierarchical feature extraction enhances the model's ability to discern between authentic and manipulated regions.

b. **Pooling Layer (1 layer):** Down-sample feature maps, preserving essential information while reducing computational complexity. This operation enhances the model's efficiency and translational invariance.
c. **Dropout Layer (2 layers):** Mitigate overfitting by randomly deactivating neurons during training. This regularization technique fosters model robustness and generalization across diverse datasets.
d. **Flatten Layer (1 layer):** This layer transforms multidimensional feature maps into a one-dimensional array, facilitating seamless integration with densely connected layers. It prepares the extracted features for classification by reshaping them into a suitable format.
e. **Fully Connected Layers (2 layers):** These layers integrate the extracted features from convolutional layers and make informed classification decisions. By capturing complex relationships between features, they enable the model to learn intricate decision boundaries and classify images accurately.
f. **Output Layer (1 layer):** At the final stage, the output layer generates predictions based on learned features. It typically comprises neurons corresponding to the number of classes in the classification task and applies an appropriate activation function to produce probability distributions over the possible classes. This facilitates inference and decision-making, determining the authenticity of input images.

Results:
After training the Model we were able to achieve an accuracy of 92.11% which can be seen in the Accuracy graph while training the model and the confusion matrix calculated by running the best model for the test data which is 20% of the data.





Results for the sample test images:

Image No.	Actual Class	Classified Class	With Probability

1	Fake	Fake	97.68%
2	Fake	Fake	98.67%
3	Fake	Fake	98.33%
4	Fake	Fake	97.73%
5	Fake	Fake	98.47%
6	Fake	Fake	88.67%
7	Fake	Fake	99.99%
8	Fake	Real	96.99%
9	Fake	Fake	99.42%
10	Fake	Fake	91.03%
11	Fake	Fake	99.84%
12	Fake	Real	66.03%
13	Fake	Fake	89.94%
14	Real	Real	100.00%
15	Real	Real	99.02%
16	Real	Fake	71.77%
17	Real	Real	98.80%
18	Real	Real	94.51%
19	Real	Real	71.23%
20	Real	Real	97.62%
21	Real	Fake	99.83%
22	Real	Real	100.00%
23	Real	Fake	66.41%
24	Real	Real	54.87%
25	Real	Real	80.41%
26	Real	Real	97.71%

White: correct classification
Red: wrong classification.
Yellow: very close probability of being wrong.

Problems Identified:

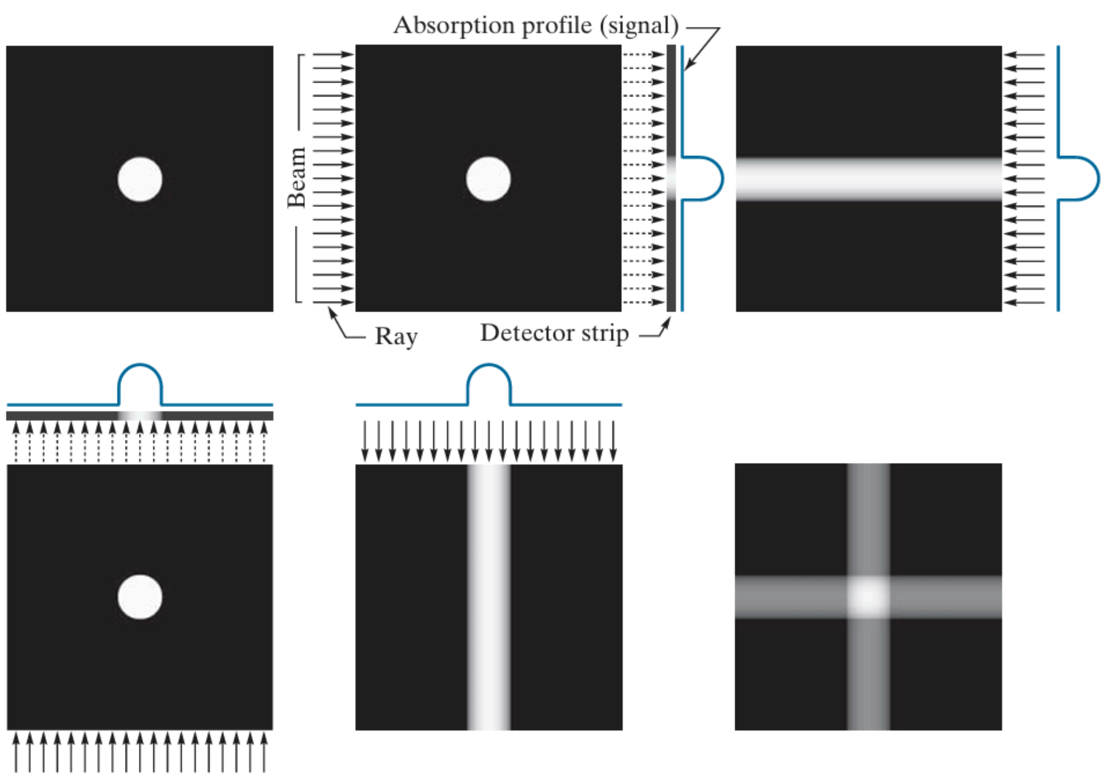
The images classified in the ELA-CNN Model are limited to the dataset which contains only very bright and clean images. In real life photos can vary with lighting, can be noisy or blurry and the model sometimes fail to identify them or identifies them with low probability.

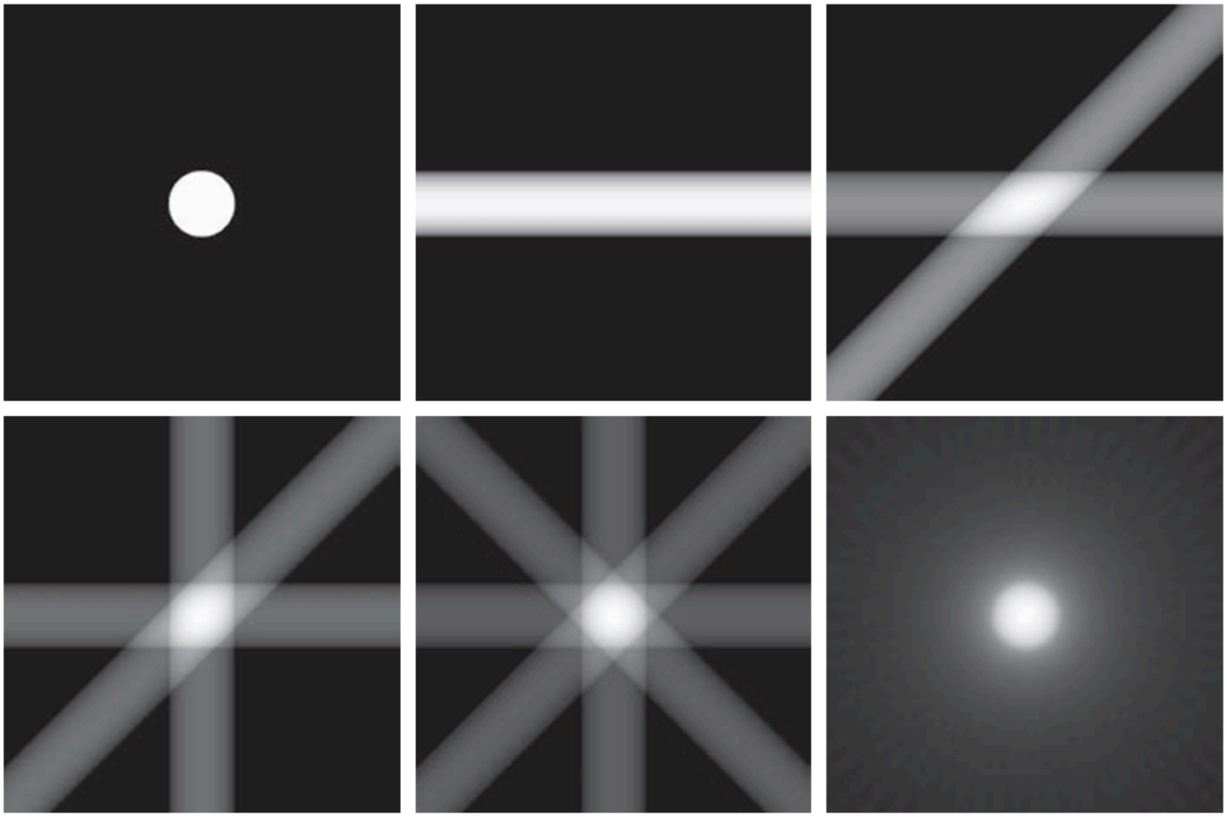
Further Improvements Tried:

To address the limitations encountered in our initial attempts, we explored several advanced techniques aimed at improving the accuracy and reliability of our edited image detection system. These methods were investigated to determine their potential to supplement our primary tools, ELA and CNN, by providing additional data points and analytical perspectives.

Image Reconstruction Using Projections:

Approach: Image reconstruction from projections involves generating a two-dimensional image from a series of one-dimensional projections taken from different angles. This technique, commonly used in medical imaging and other fields, was adapted to assess whether it could help in identifying inconsistencies typical of manipulated images.





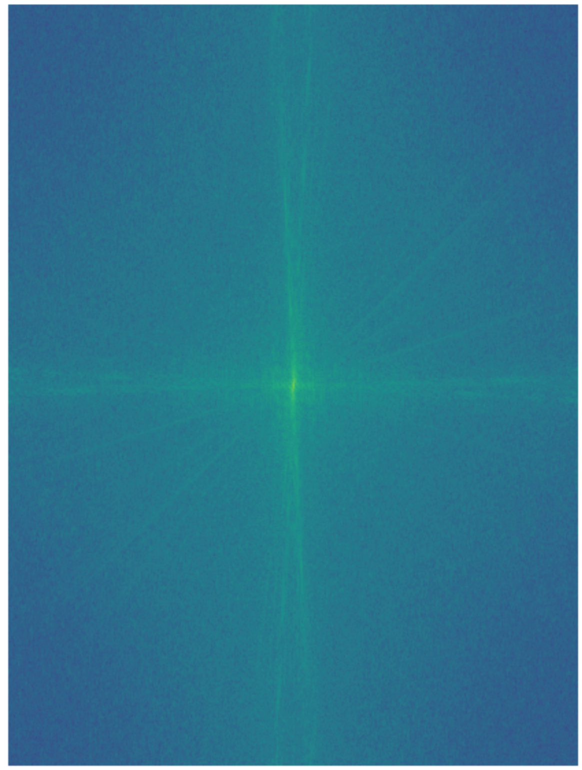
<u>Challenges</u>: While theoretically promising, the application of this method in detecting image manipulations proved complex. The main challenge was differentiating between naturally occurring variations in projections due to legitimate scene elements and those resulting from manipulative editing.

Frequency Analysis:
<u>Approach</u>: We explored the use of frequency analysis to detect edited images by examining the frequency components of an image. Edits often introduce anomalies that can be detected as unusual patterns in the frequency domain, not visible in the spatial domain.

```
def perform_fft(image):
    image = image.convert('L')  # Convert to grayscale
    f = fft2(np.array(image))
    fshift = fftshift(f)
    magnitude_spectrum = np.log(np.abs(fshift) + 1)  # Adding 1 to avoid log(0)
    magnitude_spectrum = (magnitude_spectrum - np.min(magnitude_spectrum)) / np.ptp(magnitude_spectrum) * 255
    return Image.fromarray(magnitude_spectrum.astype('uint8'))
```

Calculating the FFT of an Image.

1. fft2 function: calculated the 2D fast fourier transform of the image.
2. ffshift function: shifts the FFT to the origin.

Dual ELA-FFT model: We calculated the FFT as well as the ELA of the image and tried to make a Dual input CNN model the takes both ELA and FFT of the image to classify if the Image has been edited or is real.

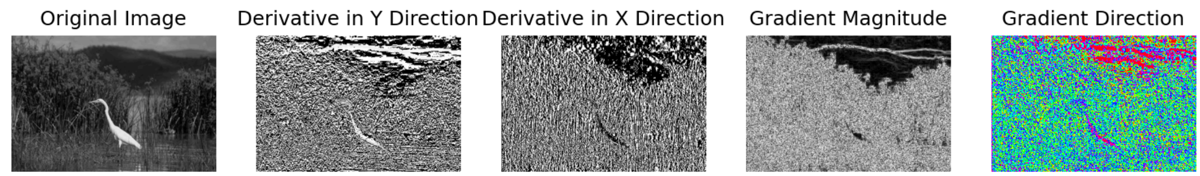
Gradient Analysis:

Approach: Gradient analysis was used to calculate the direction and magnitude of edges in images, providing insights into the natural flow and disruptions typical in edited images. We further enhanced this method by segmenting images into smaller regions, allowing for localized analysis of gradient histograms.

```python
def compute_derivatives(image):
    # Calculate the derivative in the y-direction
    dy = np.diff(image, axis=0, prepend=image[:1,:])

    # Calculate the derivative in the x-direction
    dx = np.diff(image, axis=1, prepend=image[:,:1])

    return dy, dx

def compute_gradient_magnitude(dy, dx):
    # Compute the magnitude of the gradient
    gradient_magnitude = np.sqrt(dy**2 + dx**2)
    return gradient_magnitude

def compute_gradient_direction(dy, dx):
    # Compute the gradient direction using arctan2
    gradient_direction = np.arctan2(dy, dx)
    return gradient_direction
```

1. Calculated the Image's first derivative across the x direction and y direction.
2. And used the derivatives to calculate the magnitude and direction.

Image Gradient - Histogram of Real Image



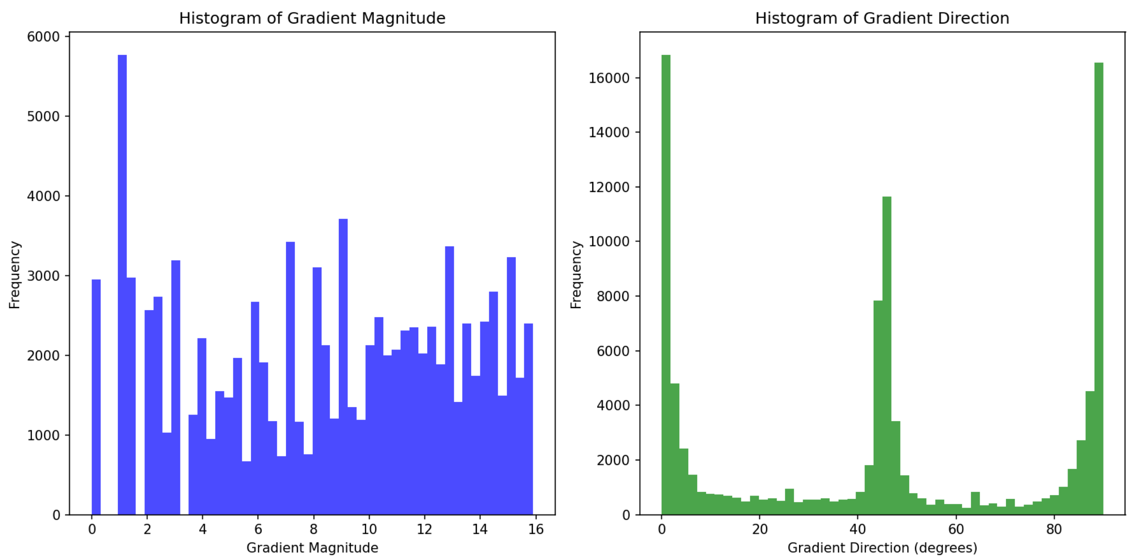
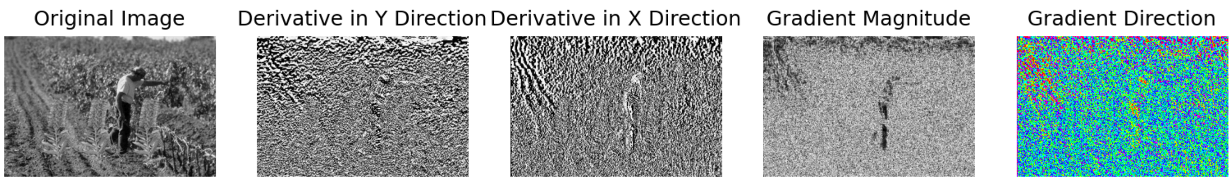
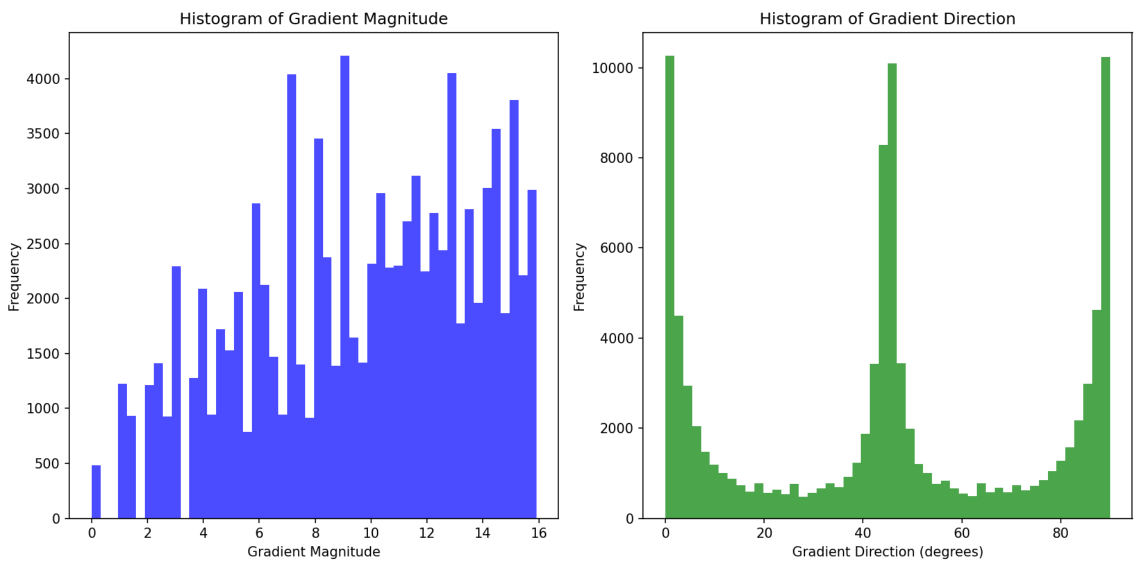


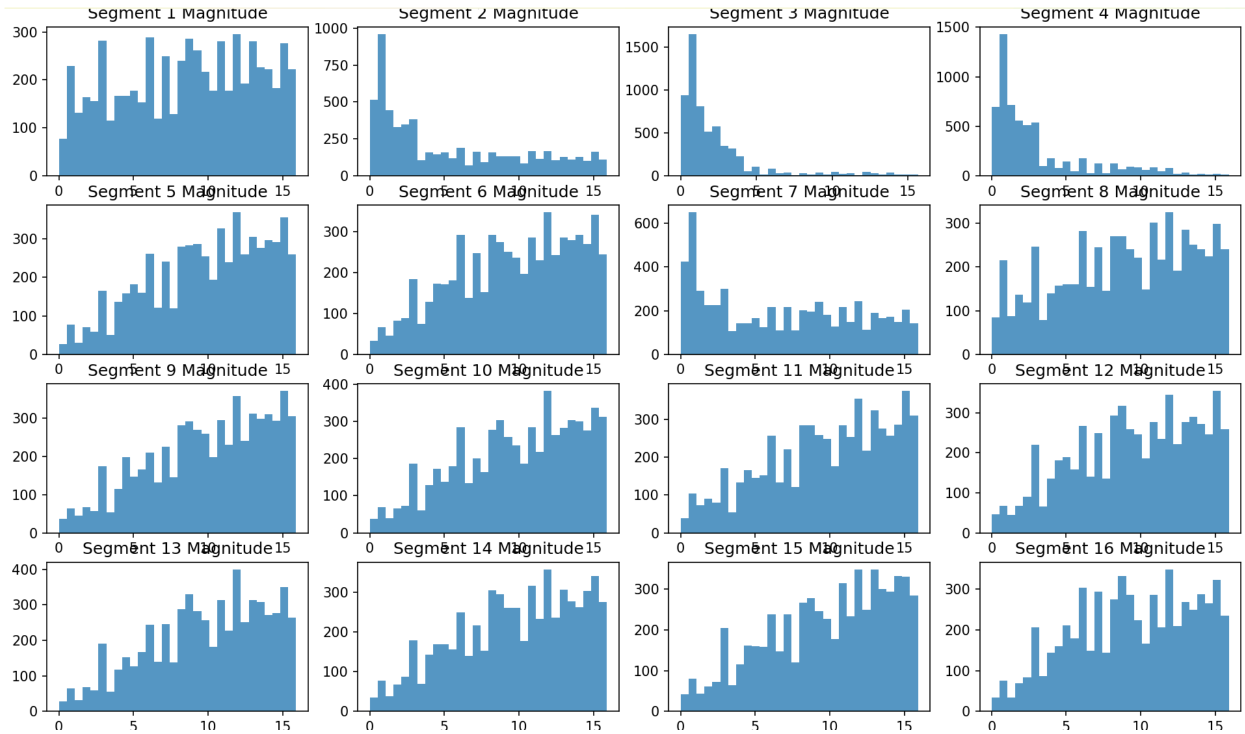
Image Gradient - Histogram of Fake Image



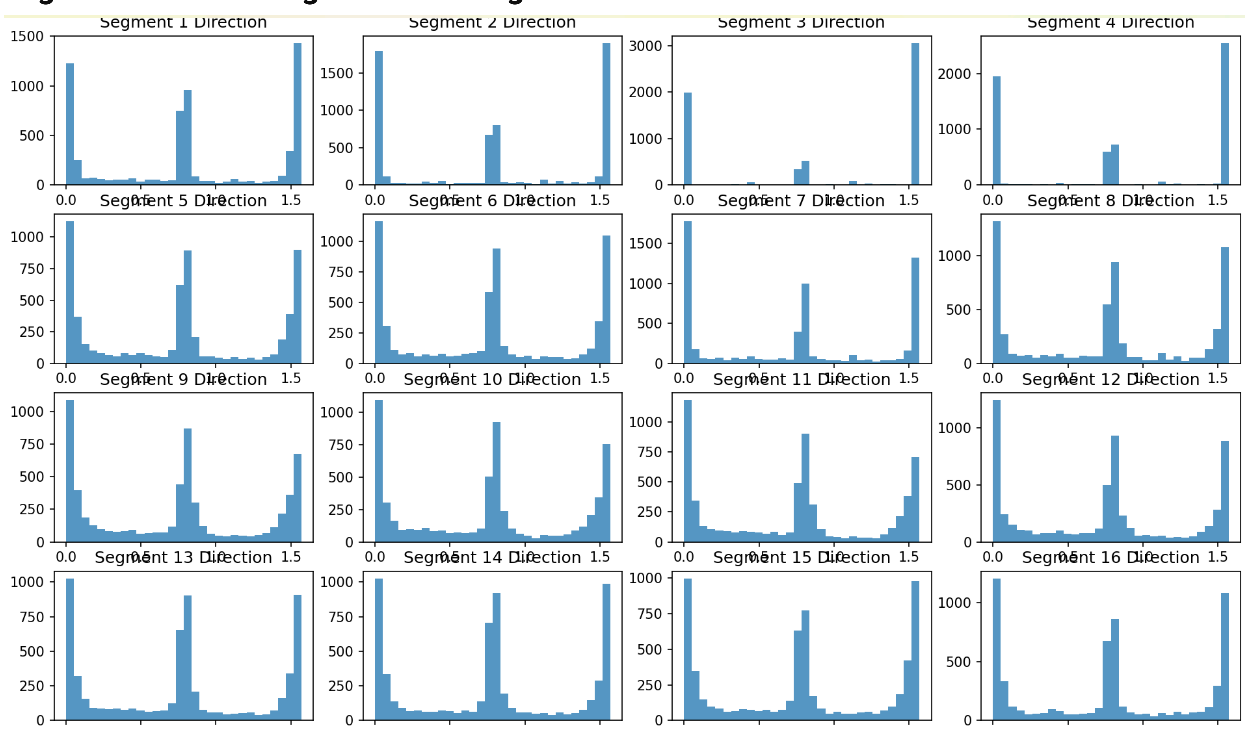


Gradient Analysis with Segmentation: we segmented the image of size N*M into c squared images of size (N/c)*(M/c), and plotted the same gradient histograms.

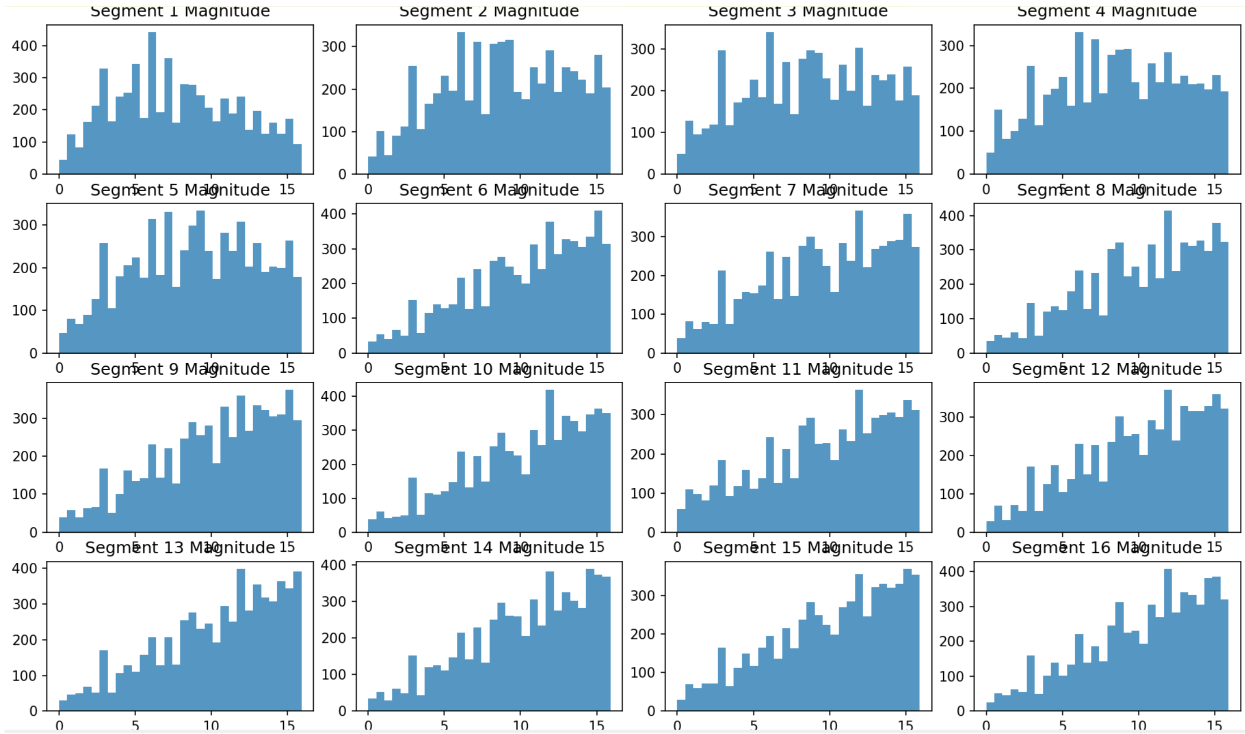
Segmentation of Images - Real image - Magnitude



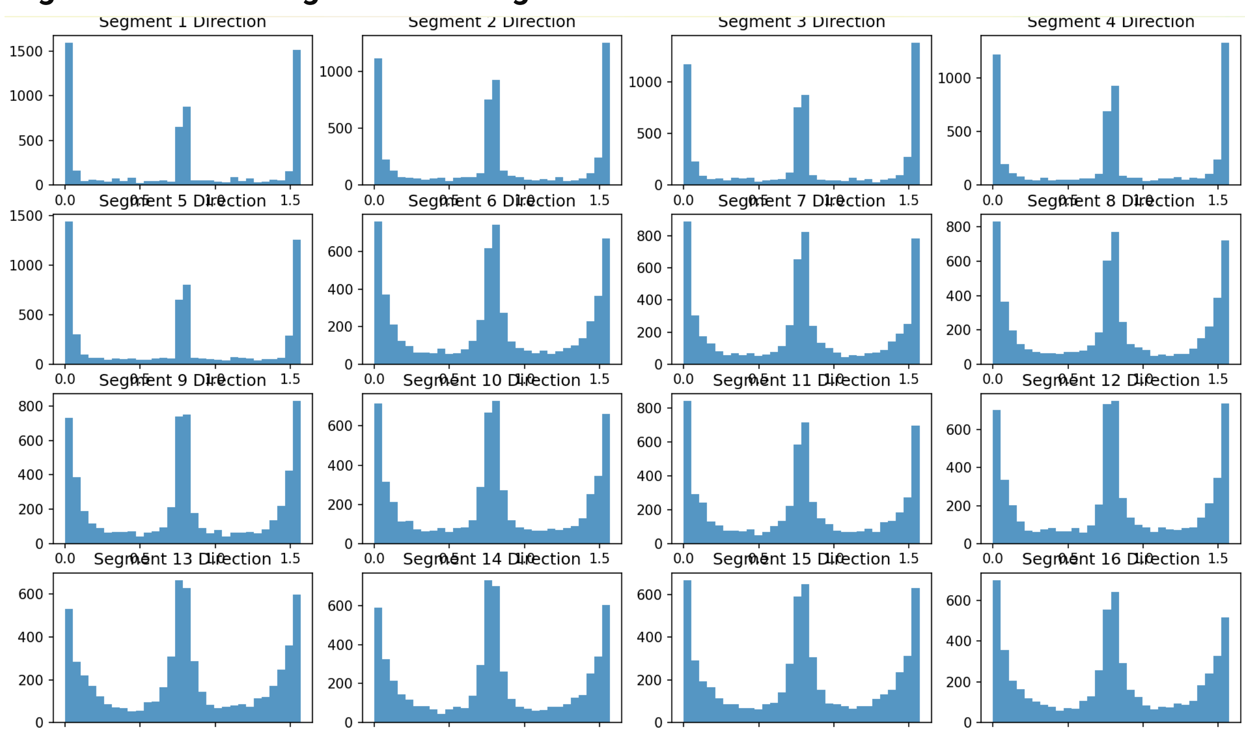
Segmentation of Images - Real image - Direction



Segmentation of Images - Fake image - Magnitude



Segmentation of Images - Fake image - Direction



Conclusion:

Throughout this project, our primary goal was to develop a reliable system for detecting edited images, a challenge exacerbated by the rapid evolution of image editing technology. Utilizing Error Level Analysis (ELA) and Convolutional Neural Networks (CNNs) formed the backbone of our approach, yielding substantial initial success yielding an impressive accuracy of 92.11%. However, recognizing the complexity of image manipulation techniques and their diverse manifestations, we endeavored to broaden our detection capabilities through the exploration of several advanced methods such as Image reconstruction from projections, Frequency analysis, Gradient Analysis with and without segmentation.

The insights gained from these additional techniques suggest pathways for future development. By continuing to refine these methods and fully integrating them into our detection system, we can improve our ability to combat the dissemination of fraudulent digital content.

In conclusion, the project has not only highlighted the effectiveness of ELA and CNNs in detecting image manipulations but also underscored the potential of integrating additional analytical tools to further enhance detection capabilities. The continued evolution of our methods will be crucial in keeping pace with the ever-advancing field of image editing technologies.

References:

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