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ABSTRACT This paper proposes a new method of tampered image detection by combining the CNN with a backbone of ResNet50 with ELA. Our method is designed for digital forensics, which is a very important domain for the detection and assessment of image modifications in many other domains, such as cybersecurity, journalism, and criminal investigations This procedure comprises image pre-processing to ascertain altered areas by comparing variations in compression levels to find compression artifacts using ELA. It serves as the foundation for reliable feature extraction: the ResNet50 model, pre-trained on ImageNet, has its basic layers frozen to preserve learned weights. For customization with regard to binary classification, some custom layers are appended on top: global average pooling, batch normalization, dense layers with ReLU, and dropout regularization. The architecture here comes up with a generator-based approach so that large datasets can be handled with better memory consumption, enabling real-time data preprocessing during training of models.Our methodology is assured to optimize resource utilization and enhance generalization, which has been evidenced with extensive experiments. The obtained model offers high accuracy and robustness in detecting tampered images; thus, it presents a scalable solution for real-world forensic applications. This integration of ELA and CNN provides the backbone of fast and accurate analysis of digital evidence to help in better decision-making in sensitive situations.

INDEX TERMS Tampered Image Detection, Error Level Analysis (ELA), Convolutional Neural Network (CNN), ResNet50, Digital Forensics, Image Manipulation Detection, Cybersecurity, Journalism, Criminal Investigations, Feature Extraction, Binary Classification, Data Preprocessing, Dropout Regularization, Compression Artifacts, Real-time Analysis, Scalable Forensic Applications.

I. INTRODUCTION

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Use a zero before decimal points: "0.25," not ".25." Use

"cm^3," not "cc." Indicate sample dimensions as "0.1 cm $\times$ 0.2 cm," not "0.1 $\times$ 0.2 cm^2." The abbreviation for "seconds" is "s," not "sec." Use "Wb/m^2" or "webers per square meter," not "webers/m^2." When expressing a range of values, write "7 to 9" or "7–9," not "7~9."

A parenthetical statement at the end of a sentence is punctuated outside of the closing parenthesis (like this). (A parenthetical sentence is punctuated within the parentheses.) In American English, periods and commas are within quotation marks, like "this period." Other punctuation is "outside"! Avoid contractions; for example, write "do not" instead of "don't." The serial comma is preferred: "A, B, and C" instead of "A, B and C."

If you wish, you may write in the first person singular or plural and use the active voice ("I observed that ..." or "We observed that ..." instead of "It was observed that ..."). Remember to check spelling. If your native language is not English, please get a native English-speaking colleague to carefully proofread your paper.

Try not to use too many typefaces in the same article. Also please remember that MathJax can't handle really weird typefaces.

C. EQUATIONS

Number equations consecutively with equation numbers in parentheses flush with the right margin, as in (1). To make your equations more compact, you may use the solidus (/), the exp function, or appropriate exponents. Use parentheses to avoid ambiguities in denominators. Punctuate equations when they are part of a sentence, as in

$$E = mc^2. \tag{1}$$

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$$\frac{47i + 89jk \times 10rym \pm 2npz}{(6XYZ\pi Ku)Aoq\sum_{i=1}^{r} Q(t)} \int_{0}^{\infty} f(g)\mathrm{d}x \sqrt[3]{\frac{abcdelqh^2}{(svw)\cos^3\theta}}. \tag{2}$$

$$\frac{47i + 89jk \times 10rym \pm 2npz}{(6XYZ\pi Ku)Aoq\sum_{i=1}^{r} Q(t)} \int_{0}^{\infty} f(g)\mathrm{d}x \sqrt[3]{\frac{abcdelqh^2}{(svw)\cos^3\theta}}. \tag{3}$$

Be sure that the symbols in your equation have been defined before the equation appears or immediately following. Italicize symbols (T might refer to temperature, but T is the unit tesla). Refer to "(1)," not "Eq. (1)" or "equation (1)," except at the beginning of a sentence: "Equation (1) is ... ."

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Please use "soft" (e.g., `\eqref{Eq}`) cross references instead of "hard" references (e.g., `(1)`). That will make it possible to combine sections, add equations, or change the order of figures or citations without having to go through the file line by line.

Please don't use the `{eqnarray}` equation environment. Use `{align}` or `{IEEEeqnarray}` instead. The `{eqnarray}` environment leaves unsightly spaces around relation symbols.

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Do not use `\nonumber` inside the `{array}` environment. It will not stop equation numbers inside `{array}` (there won't be any anyway) and it might stop a wanted equation number in the surrounding equation.

II. PROPOSED METHOD

In this paper, we demonstrate that combining ELA with CNN model while freezing the base layers and adding custom layers to the base model which will provide a significant increase in the robustness of the final model and significantly improve performance of the classification task to detect images, which are tampered. We explore this idea in the context of digital forensics, where the goals are to analyze the images and detect suspicious activity in the field of crime, journalism etc. Since digital forensics helps uncover activities and patterns, determine the root causes of incidents, and establish a chain of evidence admissible in court, it becomes essential to identify, recover, analyze and present digital evidence from electronic devices and digital storage. Additionally, an ELA based model helps in identifying the difference in various layers of the images to help us uncover the underlying changes made to the image that is suspected to be tampered with. The model allows us to help various fields where criminal investigations, legal disputes and cybersecurity incidents occur and images need to be analyzed quicky to help user make quick informed decisions. The following sections outline the details of each step in the process.

A. INITIALIZATION

The initialization of the framework is preprocessing the images based on the number of images available in the dataset,

Literature	Dataset	Method	Result
Author et al. (2024) [1]	CICDDoS2019	CNNs	97.7%

TABLE 1. Literature Survey

it corresponds to the total number of images which are categorized in two classes specifically: 1) Authentic and 2) Tampered. The classes with their labels are split initially to ensure we have a sizeable amount of image to work with, we ensure that the classes are not biased and are equally balanced to provide a robust model and reduce overfitting. The classes are initialized with ones and zeros, zero if the image is authentic and one if the image has been tampered. For images to get preprocessed, we need to handle a chuck of images at a time, which will require us to take images in batches to preprocess and analyze further.

After reshaping the images according to our input shape which will reduce the size of the image so that our next function would work effectively. Creating batches to handle memory overflow and preprocessing image before feeding them to the ELA function ensures that the system doesn't require a lot of resources and is more optimized to create a more robust model.

Further, we take each resized image and input it to our ELA function, this step is iterated over multiple images to get robust images with reduced quality to take forward for our ELA function.

B. ELA PROCESS WITH GENERATORS

For each image in our ELA function, we generate a buffer to save the original image to a temporary in-memory file with reduced quality, which helps us in reducing the overall memory utilization of the system. We load the compressed image from the buffer and calculate the difference between the original image and the one which was compressed to get the Pillow image object, this is a technique used in image forensics to detect tampering or inconsistencies in an image. We enhance the brightness of the image according to the extrema we get in the pillow image object.

This returns us the ELA image which is a new image that emphasizes regions with differing compression levels, useful for detecting tampering or manipulation. This image will highlight differences due to compression artifacts. To feed the image forward to the model for training, it requires the image to be converted to an array for numerical processing and is normalized making the data compatible with many machine learning models. We close the image further to free up resources and it is a good practice to avoid file locks or memory leaks, especially when processing multiple images in a loop. For the model to handle such large number of images at once would require a lot of resources, to tackle this issue we provide generators to the model.

These generators help in handle image preprocessing and feeding batches of data to the model during training. They are often used in deep learning workflows when the model requires to load images in batches and apply transformations or augmentation. Instead of loading all images into memory at once, generators load and process batches on-the-fly, reducing memory consumption. Generators often include on-the-fly preprocessing, which enhances the dataset and helps the model generalize better, increasing its robustness and generalizability for better performance. We also try to visualize the batch of images after the ELA function to ensure that the shape of the generator and preprocessed images are according to the requirements.

C. RESNET50 MODEL ARCHITECTURE WITH TRAINING EVOLUTION

In this study, we employ a Resnet50 model to classify the images into two categories (Authentic and Tampered), we use a transfer learning approach based on the ResNet50 architecture, pre-trained on ImageNet to solve our classification problem. This method capitalizes on the robust feature extraction capabilities of ResNet50, significantly reducing training time and computational resources while improving model accuracy. The model was customized to adapt the pre-trained base for the task by introducing additional trainable (Custom) layers specifically designed for binary classification.Figure 1: shows the architecture of the base model we have used featuring Resnet50 in a five-stage design to represent the overall function of the layers

The base of our architecture is the ResNet50 model, known for its depth and efficient handling of the vanishing gradient problem through residual connections. The model was loaded without the top layers, removing the full-connected top layers helped us retained only the convolutional layers which are responsible for extracting hierarchical features from the input images. The input shape was fixed to match the requirement of the model while ensuring compatibility with pre-trained weights. The freezing of all layers in the base model during training aimed at preserving the learned weights and keeping the feature extraction capability unaltered by the new task-specific data. To this binary classification problem, we attached five different types of custom layers to the base pre-trained model in an attempt to make it adapt. First, there is a global average pooling layer that reduces the high-dimensional feature maps output by ResNet50 into a single vector for each feature map, reducing the number of trainable parameters and hence improving generalization. Unlike the traditional Flatten layer, this preserves spatial information and improves model performance when using ResNet-based architectures. Further, we added batch normalization to normalize the activations from the pooling layer, reducing internal covariate shift and accelerating convergence.

Once we are done with that, we added a series of two dense

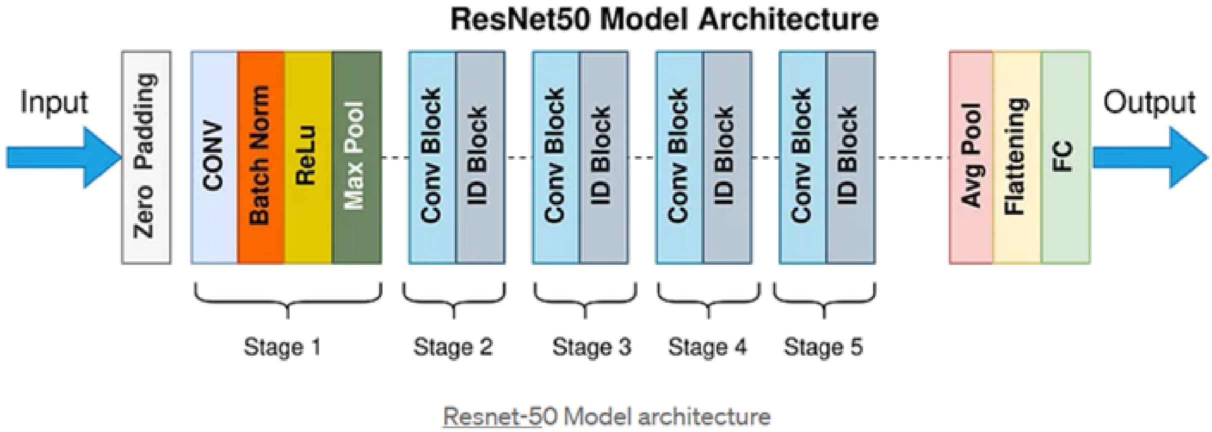

FIGURE 1. Architecture of the base model

layers. The first layer consists of 512 neurons providing substantial capacity to capture complex patterns. The second contains 256 neurons for further refinement of feature extraction. Both are activated by the ReLU activation function, which introduces non-linearity in deep networks and provides output zero for negative inputs, creating sparsity in the activations that could further be helpful in efficient computations with a reduction in overfitting. While being computationally less expensive than sigmoid or tanh function. The custom layers then involved a dropout regularization technique which was employed after each dense layer to with a rate of 0.75 after the first dense layer to impose strong regularization and rate of 0.5 was applied after the second dense layer for moderate regularization. This helped in preventing overfitting of the model during training. After dropout regularization, there was a single neuron in the output layer with sigmoid activation to predict the probability of the positive class, which is suitable for binary classification tasks.

It achieves a very good trade-off among accuracy, training efficiency, and robustness, making it pretty effective in real-world applications. This model was trained for more than 100 epochs with a step size of about 145 while capturing essential evaluation metrics such as accuracy, the f1 score, and validation accuracy. This will make sure we minimize the gap between the training and validation accuracy of the model, which will be robust and very effective in real-world applications.

III. RESULTS AND ANALYSIS

A. DATASETS

The CASIA V2 dataset, created by the Institute of Automation at the Chinese Academy of Sciences, CASIA, is one of the more general resources for research in the area of image forgery detection. Designed to support studies on image tampering, it includes manipulative techniques such as splicing, copy-move forgery, and other methods.The Table 2 outlines the details of the dataset and gives us an overview of what the dataset contains. The dataset is a very diverse collection of 12,614 images of roughly equal amounts of authentic and tampered examples from various categories such as nature, animals, objects, and urban settings. Such diversity will enable models trained with CASIA V2 to generalize rather well across different scenarios. There are also ground truth masks provided for every tampered image in the dataset, highlighting manipulated regions and thus making the dataset indispensable for supervised learning tasks and performance evaluation. The resolution of the images also varies to reflect real-world conditions, as images naturally come from different devices and sources.CASIA V2 has a variety of applications, including training and validation of

Feature	**Description**
Dataset Name	CASIA TIDE v2.0
Purpose	Designed for research and development in image forgery detection
Released By	Chinese Academy of Sciences Institute of Automation (CASIA)
Image Type	Digital images, both authentic and tampered
Number of Images	12,614 images (7,491 authentic and 5,123 tampered)
Forgery Techniques	Splicing, copy-move, and other common image tampering techniques
Resolution	Varies (typically medium resolution)
File Format	JPEG (for compressed images)
Dataset Structure	Contains two folders: one for authentic images and one for tampered images
Applications	Used for image forgery detection, digital forensics, and tampered image localization research
Public Availability	Available for academic and non-commercial use upon request from CASIA

TABLE 2. Overview of the CASIA TIDE v2.0 Dataset

image forgery detection models, testing of pre-processing techniques such as Error Level Analysis, and benchmarking deep learning architectures like CNNs for forgery classification. Features such as these make it invaluable in the field of digital forensics and research on image authenticity.

IV. CONCLUSION

This study is essential in maintaining integrity is crucial in fields like Law enforcement, Cyber security, and Legal investigations. In this project, we aimed to design a robust system capable of determining whether an image is tampered with. The research compares the performance of two widely known CNN models, VGG16 and ResNet50, with traditional preprocessing methods like ELA and data augmentation. The project concludes with viable results that taking colour inconsistencies and compression differences significantly improves model capability compared to conventional grayscale-based ELA methods.The system can be integrated into social media to moderate content in real-time, flagging misleading images and advancing platform integrity. In journalism, it makes sure that media is authentic by verifying images before publication; this helps in debunking fake news and fosters ethical reporting as a way of maintaining the public's trust in digital journalism.Although promising performance may be seen in the CASIA v2 dataset, it does not generalize upon exposure to other datasets or real-world scenarios. This needs to be handled in future work by enrichment of the dataset with diversity and updates for further strengthening the resistance and longevity of the model. Moreover, interpreting it with Explainable AI by using Grad-CAM will illustrate the regions of interest influential in the model's choices for transparent decisions and gaining the trust of the users. The dataset and code for further research are available [here] and [repository link].

ACKNOWLEDGMENT

The preferred spelling of the word ‘‘acknowledgment’’ in American English is without an ‘‘e’’ after the ‘‘g.’’ Use the singular heading even if you have many acknowledgments. Avoid expressions such as ‘‘One of us (S.B.A.) would like to thank . . . .’’ Instead, write ‘‘F. A. Author thanks . . . .’’ In most cases, sponsor and financial support acknowledgments are placed in the unnumbered footnote on the first page, not here.

REFERENCES

[1] A. Chandio, G. Gui, T. Kumar, I. Ullah, R. Ranjbarzadeh, A. M. Roy, A. Hussain, and Y. Shen, ‘‘Precise single-stage detector,’’ 2022.

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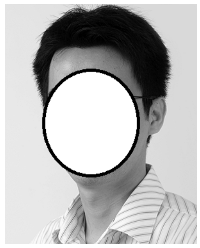

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