Recognising Image Manipulations Utilising CNN and ELA

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ABSTRACT- Tampering of digital photos or images is known as image forgery. The ability to create phoney images or information has become easier due to the rapid advancement of technology. In order to detect image forgeries, this paper proposes a model that employs Error Level Analysis (ELA) with Convolutional Neural Networks (CNN). ELA is used as a preprocessing step to highlight regions of an image that may have been tampered with. CNN is then trained on this enhanced data to classify images based on their authenticity and detect digital modifications. This initiative's main goals include image classification, attribute extraction, image authenticity verification, and digital image modification detection. Our suggested solution makes use of CNNs' deep learning capabilities and the refinement found by ELA.

KEYWORDS: Image Forensics, CNN, ELA, Deep Fake Detection, Image Authentication, Image Prediction.

I. INTRODUCTION

Image forgery, the malicious act of altering visual content with the intent to deceive, poses a significant challenge in today's digital era. As the accessibility to sophisticated picture editing tools increases, the need for robust forgery detection methods becomes paramount. In this context, Convolutional Neural Networks (CNNs) and Error Level Analysis (ELA) emerge as the promising technologies for enhancing the accuracy and efficiency of image forgery detection. In an era dominated by digital media and social networking platforms, the ease with which images can be manipulated raises concerns about the authenticity of visual content. Image forgery encompasses various forms, including but not limited to copy-move, splicing, and retouching, necessitating advanced detection mechanisms to safeguard the integrity of CNNs have proven to be powerful tools in the field of image processing, computer vision, object detection, and feature extraction. Their key ability to learn relevant features from data automatically makes CNNs particularly well-suited for tasks like image forgery detection. By leveraging the spatial relationships within images, CNNs can effectively discern patterns associated with tampering. ELA, on the other hand, is a pixel-based forensic technique that analyses the error introduced during image compression. When an image is modified, the error levels in different regions change, creating distinctive artifacts. ELA helps identify these irregularities by highlighting areas with significantly altered error levels, thus aiding in the detection of image forgeries. The combination of CNN and ELA presents a synergistic approach to image forgery detection. While CNNs excel at learning complex spatial features, ELA provides a quick and effective means to identify regions of interest within an image.

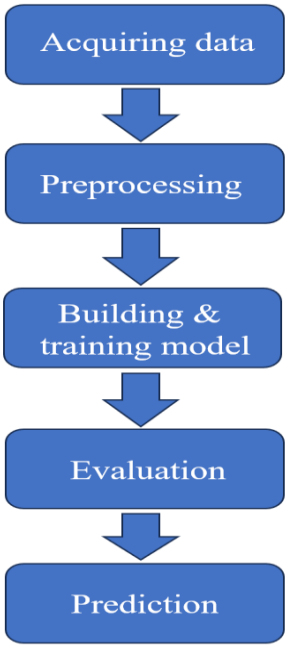

Fig. 1. Steps involved in our Model

Image forgery detection is a critical aspect of digital image analysis aimed at identifying alterations or manipulations made to images. With the proliferation of image editing tools and the ease of manipulating digital images, there is a growing need for robust techniques to detect and prevent image forgeries. These forgeries can range from minor alterations to sophisticated manipulations aimed at deceiving viewers or distorting the truth.

Types of Image Forgery:

Several techniques are employed to forge digital images, each presenting unique challenges for detection:

A. Splicing Forgery: Splicing, In [1] involves blending or merging two or more images to produce an image that is combined. Detecting splicing requires analyzing of inconsistencies in lighting, color, and texture across different parts of the image.

B. Copy Move Forgery: It is a type of manipulation where a part of a picture is copied and pasted onto another part, often with the intention to deceive. Detection of these type of forgeries is challenging due to the need to identify duplicated regions with identical properties and distributions [2].

C. Retouching Forgery: Retouching involves modifying specific features of an image, such as brightness, color, or contrast, to enhance or conceal certain aspects. Detecting retouching forgery requires identifying unnatural alterations in image attributes.

D. Resampling Forgery: Resampling involves altering the dimensions of objects or sections within an image to distort its appearance. Detecting resampling forgery involves analyzing geometric inconsistencies within the image.

E. Morphing Forgery: Morphing involves blending elements from different images to create a new scene. Detecting morphing forgery requires identifying inconsistencies in the composition and structure of the merged elements.

Challenges in Image Forgery Detection:

Detecting image forgeries poses several challenges, including:

A. Computational Complexity: Image forgery detection algorithms often require significant computational resources, leading to long processing times and high memory requirements.

B. Detection of Multiple Forgery Types: Detecting multiple types of image forgeries simultaneously can affect the accuracy of detection algorithms,[3] as each type may require different analysis techniques.

C. Accuracy-Speed Trade-off: Balancing detection accuracy with processing speed is a challenge, as more complex algorithms may offer higher accuracy but require longer processing times.

D. Complexity of Detection Techniques: Many image forgery detection techniques are complex and may require specialized knowledge to implement and interpret.

E. Handling Post-Processing Operations: Images subjected to post-processing techniques such as scaling, rotation and compression present additional challenges for forgery detection, as these operations can alter the image's properties and distributions.

Motivations for Image Forgery Detection:

[4] Image forgery detection is driven by the need to guarantee the integrity and validity of digital photographs used in variety of applications.

Legal Proceedings: Authenticity is crucial in legal proceedings where images are used as evidence.

News Reporting: Detecting image forgeries helps prevent the spread of misinformation and fake news.

Military Applications: In military contexts, authenticating images is essential for intelligence gathering and analysis.

Medical Diagnostics: Authenticity is critical in medical imaging for accurate diagnosis and treatment planning.

Contributions in Image Forgery Detection:

Recent advancements in image forgery detection include:

Simultaneous Detection of Multiple Forgery Types: Some research focuses on developing algorithms

capable of detecting multiple types of image forgeries simultaneously, enhancing the practicality and efficiency of forgery detection systems [5].

Contributions also include the creation of datasets and benchmarking methods to evaluate the performance of detection algorithms objectively. Additionally, researchers contribute by exploring new avenues, such as deep learning models and advanced image processing techniques, to improve the overall effectiveness of image forgery detection while ensuring originality.

Attaining superior accuracy rates [6] compared to existing benchmarks documented in the literature stands as a key objective. Additionally, leveraging pre-trained models and harnessing transfer learning principles, while keeping the model lightweight with minimal parameters, enhances its suitability for environments constrained by memory and CPU limitations. This attribute adds significant value to the proposed architecture.

The study employs the CASIAV2 dataset, renowned for its benchmarking capabilities, representing a notable challenge in itself. Moreover, the forged images include manipulated cropped segments subjected to additional processing like distortion, rotation, and scaling, aimed at simulating realistic scenarios. Notably, blurring is applied to the edges of spliced regions, further complicating the detection process.

II. LITERATURE SURVEY

A literature review on image forgery detection summarizes and evaluates existing research on methods and technologies used to detect manipulated or fake images. It explores various techniques in deep learning approaches. The review discusses the challenges faced in detecting image forgeries and suggests future research directions. It also highlights the importance for training and evaluation in forgery detection algorithms and discusses the evaluation metrics commonly used in this field.

In [3], a comprehensive review discusses the role of deep learning, including CNNs, in image forgery detection. It covers various aspects, including dataset creation, network architectures, and performance evaluation metrics. It specifically discusses the role of CNNs and highlights the importance of feature learning for accurate forgery detection.

In [10], the approach aims to enhance the detection and control of deepfake images, which are digitally altered images that can be used to deceive viewers. By leveraging MCACNNs, the authors demonstrate an effective strategy to address this growing concern, potentially contributing to the development of more reliable methods for detecting and mitigating the impact of deepfake images in various applications. contributing significantly to the field of image forensics and authenticity verification.

Motivation for Deep learning:

One key motivation, in [11] is its capacity to automatically learn features, where higher layers combine the features from lower layers. This hierarchical representation learning is particularly useful in handling the inherent complexity and variability of real-world data. Additionally, deep learning models can generalize well to unseen data, making them suitable for diverse applications. Another motivation is the availability of powerful computational resources, such as GPUs and TPUs, which have significantly accelerated deep learning training and made it more accessible. These factors, combined with the continuous advancements in algorithms and architectures, make deep learning a compelling approach for solving complex and data-rich problems across various domains.

Deep learning approaches:
Deep learning techniques can automatically extract discriminative features from the data, they have demonstrated impressive performance in the detection of image forgeries.

A. Convolutional Neural Networks (CNNs): These have been applied extensively to a variety of image identification tasks. Their effectiveness stems from their ability to automatically learn features at various level of abstraction for identifying different kinds of fakes. CNNs are very good at tasks like picture

production, object detection, and image fraud detection since they are mostly utilised in visual imagery tasks, where the spatial relationships between elements are important.

B. Transfer Learning: It involves in using pre-trained models and fine-tunes them for forgery detection tasks. This approach can reduce the amount of labeled data required for training.

Motivation for Transfer Learning:

One of its key motivations is to overcome data limitations by leveraging knowledge from pre-trained models trained on large datasets. The primary driving force behind transfer learning is the ability to get beyond data constraints by utilising the expertise of previously learned models that have been trained on sizable datasets. This method lessens the requirement for enormous volumes of labelled data by enabling models to transfer learned features and patterns to other tasks. By reusing previously learned model parameters, transfer learning further improves computational efficiency and can drastically cut down on training time and resource requirements for new tasks. Furthermore, by optimising the current knowledge, it makes it easier for the model to be adjusted to certain tasks or domains, which enhances performance. Transfer learning enables feature learning by leveraging the general features learned from the pre-trained model, which can be particularly beneficial for complex datasets. By utilising the general characteristics that have been learned from the pre-trained model, transfer learning facilitates feature learning. This is especially useful for complicated datasets. Additionally, it facilitates domain adaptation, which lessens the requirement for domain-specific labelled data by allowing models trained on one domain to be applied successfully to related domains. All things considered, transfer learning is an effective method that can enhance model performance in a variety of situations, especially when data or computational resources are scarce.

C. Recurrent Neural Networks (RNNs)**:** RNNs can be used for detecting temporal forgeries in videos. They can learn temporal patterns and detect inconsistencies that indicate tampering.

Additionally, a different study [12] presented a novel method using convolutional neural networks (CNNs) to identify copy-move and splicing image forgeries. Three different models were used in the study: VGG16, VGG19, and ELA (Error Level Analysis). Using preprocessing techniques, the photos were the model to be trained for the classification of authentic versus forged images.

For copy-move forgery detection, Smaller VGGNet and MobileNetV2 which were used in [13], providing an effective usage of time and memory resources. Furthermore, [14] presented the Optimal Deep Transfer Learning based Copy Move Forgery Detection method. This method comprised extraction of a deep learning model for the categorization of the target picture and the localization of the copied regions afterward. For feature extraction, the MobileNet model was utilised in conjunction with a political optimizer (PO), and for classification, two models are combined with each other. The Multiclass Support Vector Machine (MSVM) technique's parameter adjustment was made easier by the EBSA method, which improved classification performance.

Additionally, [15] presented a fusion model based on automated deep learning for the purpose of identifying and pinpointing copy-move frauds. The outputs of both densely connected networks (DenseNet) and generative adversarial networks (GANs) were combined in this model to produce a layer for encoding input vectors using the first layer of an classifier. The artificial fish swarm method (AFSA) was used to modify the weight and bias values of the ELM model. The merging unit was then filled with the network outputs.

A review of forgery detection techniques based on the two types of learnings, deep learning and transfer learning is provided in TABLE 1 respectively. It underscore previous research efforts indicating promising results in detecting image splicing forgery with high accuracy using the CASIAv2 dataset with in various models and algorithms. Conversely, detecting copy-move forgery presents challenges and has received considerable attention in the literature. Notably, few studies have focused on detecting both splicing and copy-move techniques simultaneously, with lower detection accuracy rates observed compared to single-technique approaches.

TABLE 1. Synopsis of Techniques for Detecting Image Forgeries

Year	Feature Extraction Technique	Classification technique	Dataset	Evaluation
2022	ELA	CNN	CASIAv2	Accuracy =70.6%
2021	Regularizing U-net	Regularizing U-net	CASIAv2	F1-score = 0.9486
2023	CNN	CNN	CASIAv2	Accuracy =99.3%
2021	Smaller VGGNet	Smaller VGGNet	CASIAv2	Accuracy = 87%
2022	Difference Compression Quality+ CNN	CNN	CASIAv2	Accuracy =92.23%
2020	CNN-Based Local Descriptor Construction	SVM	CASIAv2	Accuracy = 96.97%

III. PROPOSED SYSTEM

Our proposed approach utilizes deep learning, specifically Convolutional Neural Networks (CNNs), which are primarily used for tasks related to image recognition, classification, and segmentation of the data. Leveraging or Feature Extraction techniques such as Error Level Analysis (ELA) and data augmentation, our model learns to differentiate between authentic and manipulated images, enhancing digital forensics capabilities with robust and efficient detection methods. In this proposed system we deal with the concept of Pixel-based Image forgery detection.

A. Data Acquisition:

The proposed approach utilizes the CASIA2 dataset, which contains a vast collection of authentic and manipulated images for training and validation [16]. Initializing the paths for real and fake image directories, and os.listdir() is used to lists their contents or to retrieve the list of files in each directory. Finally, it prints the count of images in both real and fake directories. CASIA2 has a total of 12617 images, where it consists of 7492 original images and 5125 forged images.

Fig.2. Some of the images in dataset

Utilizing Matplotlib to display a grid of images from the specified directory. It sets the number of images to display as 6 and creates a Figure with a size of 12x6 inches. It iterates over the first 6 images in the specified directory, opens each image using PIL, and displays it within a subplot. Finally, it displays the grid of images. Fig.2. provides a visual overview of the some of the images stored in the specified directory.

B. Preprocessing:

Pre-processing involves cleaning and transformations that are applied to the dataset before feeding it to the algorithm or model. During this preprocessing, these images undergo ELA. ELA is a technique that is used to detect regions in the image that may have been manipulated or altered, the compression levels of the modified regions often differ from those of the original areas.

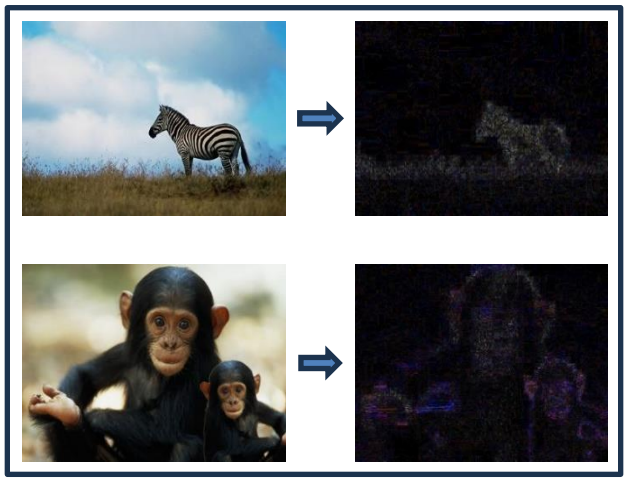

Fig. 3. Images before and after ELA

Figuring out the variation between the original and the compressed version. The difference is enhanced to visualize variations. ELA images highlight areas with differing compression levels, aiding in the detection of digital alterations. ELA highlights these discrepancies by accentuating the areas where compression levels deviate significantly. By extracting images from both the 'Au' (authentic) and 'Tp' (tampered) directories ELA is applied to each image. Overall, the code facilitates data preparation and labeling for a machine learning task, likely for training a model to classify image authenticity.

C. Model Building:

Model building refers to the process of designing and constructing neural network architectures to solve specific tasks such as classification, regression, or generation. Deep learning models typically consist of multiple layers of neurons organized in a hierarchical fashion, it enables the model to learn different patterns and representations from the data.

Using the Keras Sequential API, the proposed model specifies an architecture for a Convolutional Neural Network (CNN) [17]. It is composed of two convolutional layers, each with 32 filters and a 5x5 kernel size. The non-linearity is introduced via rectified linear unit (ReLU) activation functions. To extract salient features and reduce spatial dimensions, max-pooling layers with a 2x2 pooling window are used. In order to reduce overfitting, dropout layers are used, which deactivate neurons randomly during training. The 2D feature maps are transformed into a vector by a flattening process that comes after the convolutional layers. Two dense layers that are fully connected are then used. These layers have 256 neurons that have ReLU activation and a dropout rate of 0.5. Ultimately, the output layer's softmax activation function makes it easier to classify data into two groups, such as Real and Fake.

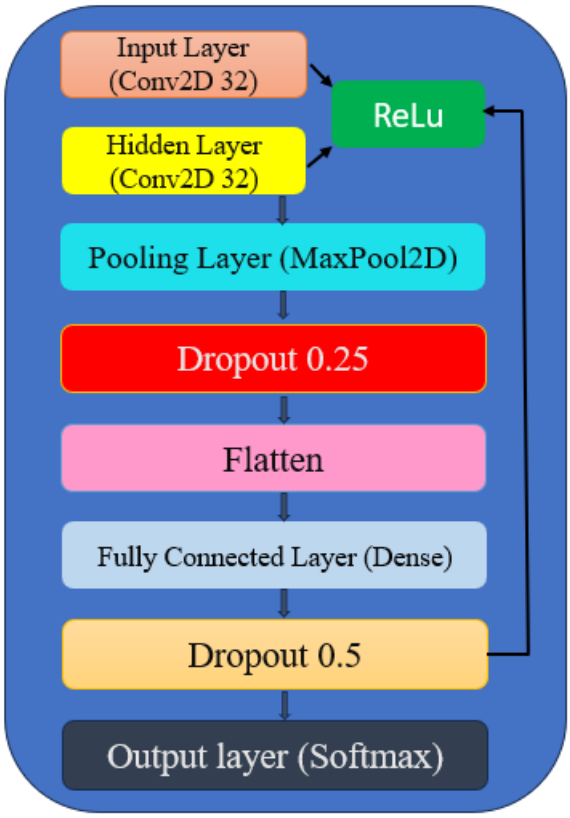

Fig. 4. Model Architecture

The dataset undergoes division into two distinct sets: training and validation set, with respective proportions of 80 and 20 ratio. The testing set serves the dual purpose of testing and validation, mirroring the methodology outlined in the referenced paper.

Specifically, the training set ideally comprises a diverse range of both real and fake images. Conversely, the validation set consists of images, subdivided into real images and fake images. This partitioning strategy enables comprehensive evaluation of the model's performance, ensuring that it is trained on a sufficiently diverse dataset and rigorously assessed on unseen data during testing and validation phases.

CASIA2 Dataset	
Training-80%	Testing-20%

EVALUATION METRICES:

The evaluation of the proposed model involves assessing its performance using various metrics, as outlined. These metrics provide insights into different aspects of classification effectiveness:

Accuracy: The ratio of correctly categorised examples from both instances to the total number of instances.

Accuracy = $TP+ TN / TP+ FN+ FP+ TN \times 100$

Recall: It expresses the proportion of manipulated photos correctly identified relative to the total number of manipulated images

Recall = $TP / FN+TP$

Precision: The percentage of photos marked as forged that are indeed forged is quantified by precision. It is calculated using the formula:

Precision = $TP /TP+FP$

F1 Score: It is a combined measure of precision and recall, providing a harmonic mean that indicates the overall accuracy of the test. It's calculation:

F1 score =
2×Recall×Precision/Recall+Precision×10

IV. MODEL EVALUATION

Figures 5, 6, and 7 illustrate the link between training accuracy and validation accuracy, and training loss and validation loss for the models ELA & CNN, VGG16, and Resnet101. A model's training accuracy curve, which shows an overall rising trend as the model gets better at matching the training set, indicates how well it can learn from training data over time.

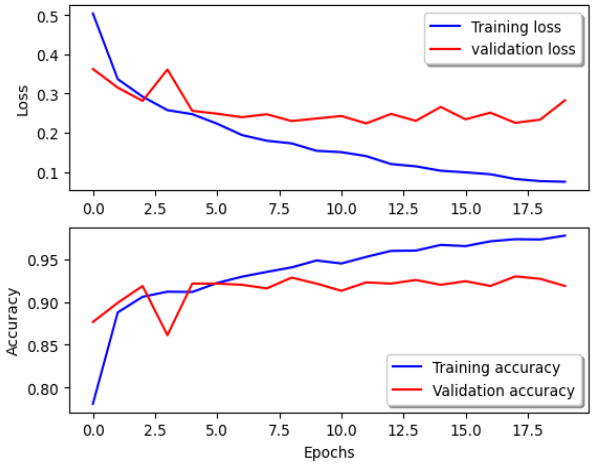

Fig. 5. ELA & CNN model

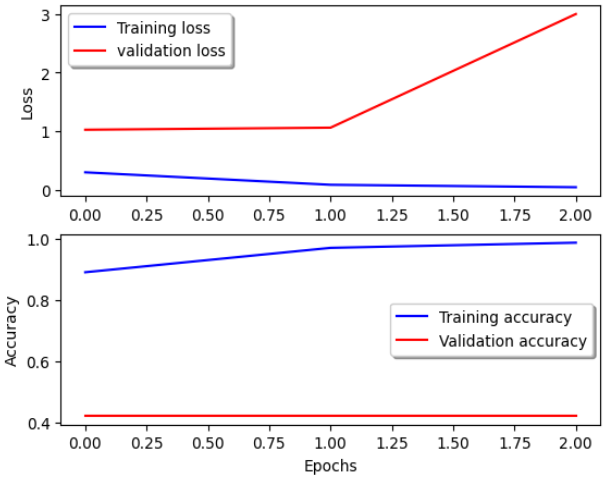

Fig. 6. VGG16 model

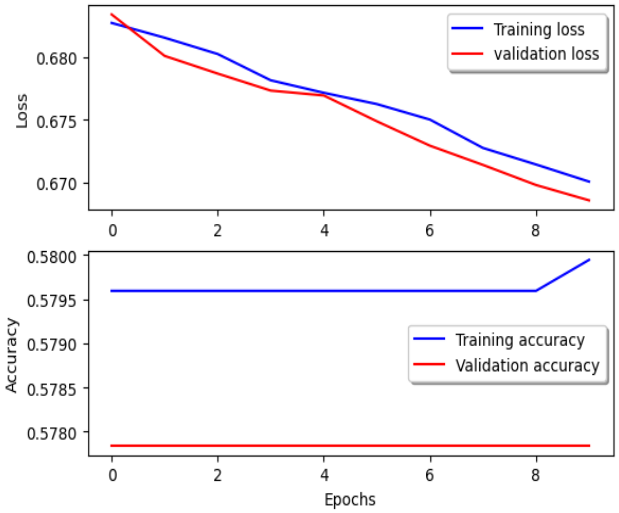

Fig. 7. Resnet101 model

In contrast, the percentage of accurately categorised samples using a different validation dataset that was not utilised for training is known as validation accuracy. This aids in assessing the model's generalisation performance to fresh, untested data. A measure of the model's performance during training is called training loss. It shows the discrepancy between the training dataset's actual labels and the model's anticipated outputs. In order to show that the model is improving its prediction accuracy, the training process aims to minimise this loss. Though it is determined using the validation dataset, validation loss is comparable to training loss.

Throughout training, tracking accuracy and loss curves gives you a better understanding of how well the model absorbs information from the data and applies that knowledge to fresh datasets. Dataset is divided in an 80:20 ratio for the experiment. The validation set serves as a stand-alone dataset for performance assessments, overfitting prevention and hyperparameter adjustments.

Training can stop when validation error is minimised by tracking validation performance, which enhances generalisation and avoids overfitting. The conditions are all represented graphically in Figures 5, 6, and 7. Evaluation metrics plays a crucial role in comparing the effectiveness of classification models. TABLE 2 outlines these indicators.

TABLE 2. Evaluation metrics [19]

	Total params	Accuracy	F1 Score	Precision	Recall	AUC
Reference[17]	28,577,474	92.23%	0.91	85.00%	91.00%	0.92
VGG16	15,502,914	93.83%	0.94	93.93%	93.71%	0.94
VGG19	20,812,610	94.77%	0.95	94.81%	94.73%	0.95
Xception	23,222,570	92.88%	0.93	92.92%	92.96%	0.93
DenseNet 121	8,350,018	94.14%	0.94	94.03%	94.10%	0.94
MobileNet	4,541,378	94.69%	0.94	94.21%	94.74%	0.95
ResNet50	25,948,802	94.61%	0.95	94.50%	94.69%	0.95
ResNet101	45,019,266	93.60%	0.94	93.36%	94.00%	0.94
ResNet152	60,692,738	93.43%	0.93	93.49%	93.12%	0.93

TABLE 3. Comparison of Existing models

	Accuracy	F1score	Precision	Recall
ELA&CNN	93.13%	91.36%	97.37%	86.05%
VGG16	86.26%	81.58%	93.94%	72.09%
ResNet101	57.78%	2.62%	100.00%	1.33%
ResNet50	42.22%	59.37%	42.22%	100.00%

As shown in the TABLE 3, ELA & CNN boasting an impressive accuracy of 93.13%, showcases distinct advantages over other models like VGG16 with 86.26% accuracy, ResNet50 with 47.22% accuracy, and ResNet101 with 57.78% accuracy. Its robust architecture and advanced techniques enable ELA & CNN to effectively capture intricate features in images, leading to higher accuracy rates. Additionally, ELA & CNN demonstrates superior performance in handling image transformations and complexities inherent in image forgery detection tasks.

The model's deep learning capabilities facilitate comprehensive understanding and classification of image content, contributing to its higher accuracy compared to other models. ELA & CNN's ability to

generalize well across diverse datasets and its adaptability to varying image characteristics further enhance its accuracy and reliability. Consequently, ELA & CNN emerges as the preferred choice for image forgery detection tasks [18], outperforming alternative models in accuracy and robustness.

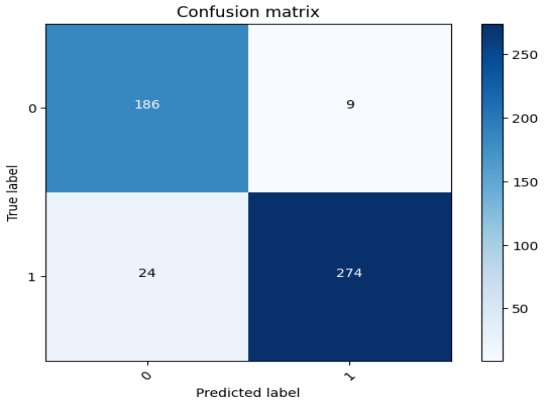

FIG. 8. Confusion matrix for ELA & CNN.

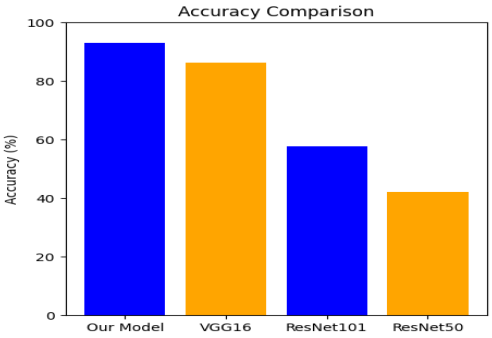

FIG. 9. Accuracy graph for the four models

All things considered, ELA & CNN are highly suited for detecting image forgeries, such as whether an image is real or fake, forged or unforged, and aid in achieving high detection accuracy rates. These factors include deep architecture, massive data set training, reliability to image transformations, and advanced techniques.

The F1 score, along with precision and recall, assesses how effectively a classification process distinguishes between two classes. These metrics are crucial for evaluating a model's performance in classification tasks. A higher F1 score, precision, and recall indicate better classification accuracy. Precision is high for ResNet101 and Recall is higher for ResNet50. Figures 10,11 and 12 highlights that the ELA & CNN model demonstrated superior performance across all three metrics. Thus, it indicates that ELA & CNN achieved optimal balance between precision, recall and resulting in a high F1 score.

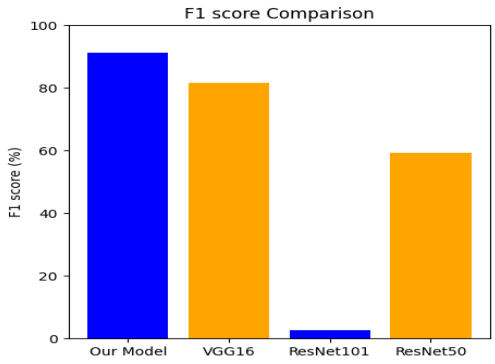

FIG. 10. F1 score graph for four models

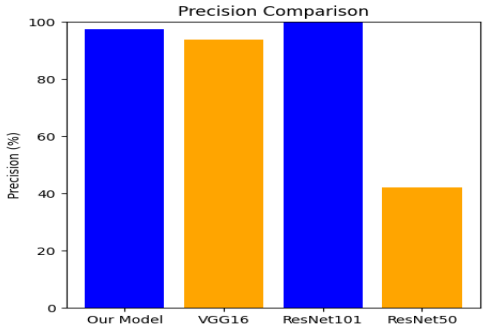

FIG. 11. Precision graph for four models

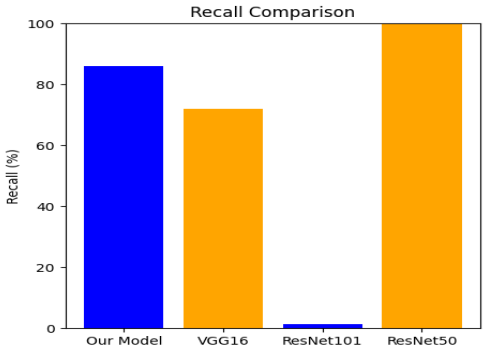

FIG. 12. Recall graph for four models

Percentage of real positive cases that a classification model accurately identifies is called the True Positive Rate (TPR) or sensitivity. It shows the degree to which the model correctly selects positive examples from among all real positives. Known by the name

specificity, True Negative Rate (TNR) is a measure of the percentage of real negative cases that the model properly identified. Out of all genuine negatives, it shows how well the model detects negative events.

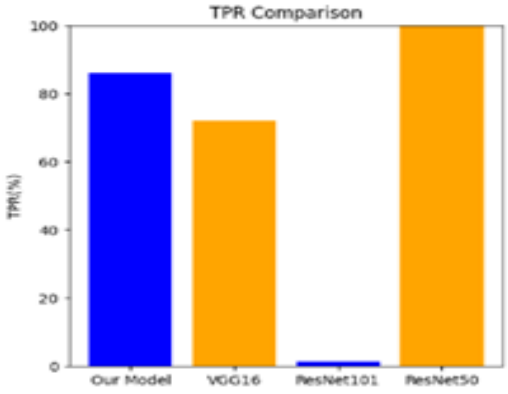

FIG. 13. TPR graph for four models

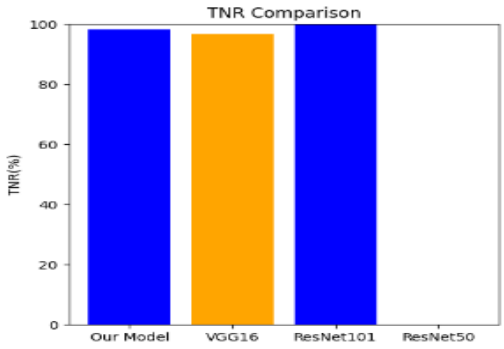

FIG. 14. TNR graph for four models

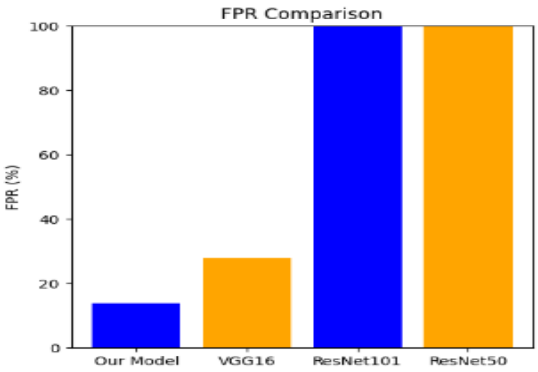

FIG. 15. FPR chart for the four experiments.

The percentage of real negative cases that the model mistakenly identified as positive is called the False Positive Rate, or FPR. The percentage of real positive examples that the model mistakenly identified as negative is known as the False Negative Rate, or FNR. When taken as a whole, TPR, TNR, FPR, and FNR offer insights into how well the model performs in various classification scenarios.

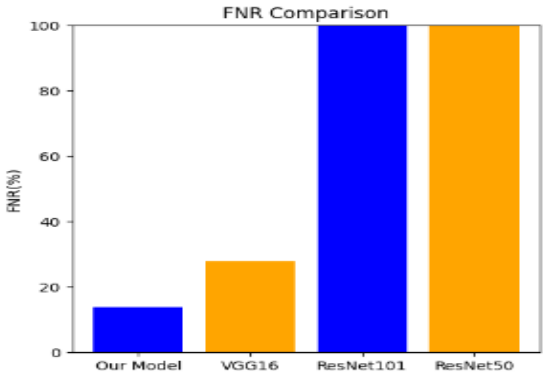

FIG. 16. FNR graph for four models

Figures 13 & 14 reveal that ELA & CNN boasts highest TPR and TNR, signifying its ability to accurately identify positive and negative cases, respectively. With an impressive detection accuracy rate of 93.15%, ELA & CNN emerges as the top performer across various metrics such as recall, precision, F1 score, TPR. Its balance between detection accuracy and computational efficiency, makes it the optimal one in image forgery detection systems, ensuring maximum accuracy while minimizing the time of training.

V. CONCLUSION AND FUTURE SCOPE

The implemented CNN model demonstrates the capability to classify images as real or fake, aiding in image forgery detection. A dataset is used to train and assess the model, its performance is visualized through training metrics and confusion matrix.

Based on the analysis of evaluation metrics and visual representations across four models, ELA & CNN emerges as the standout performer. With a detection accuracy rate hovering at approximately 93%, showcases superior performance compared to its counterparts.

What sets it apart is its ability to achieve such high accuracy while maintaining a smaller number of training parameters. This not only translates to faster training times but also significantly reduces computational costs and system complexity, all while keeping memory consumption low.

Given these compelling attributes, ELA & CNN is strongly recommended as the backbone for image processing tasks, particularly when detecting image splicing and copy-move operations concurrently. Its efficacy in this regard has yielded highly promising results, making it a preferred choice for applications requiring robust detection capabilities with efficient resource utilization.

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