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MOBILE-BASED SPLICING IMAGE IDENTIFICATION BY DEPLOYING DEEP LEARNING

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Abstract— Image forgery is the practice of tampering with or changing an image. It could seem safe to manipulate images in this way. However, to preserve the credibility of the evidence, images used in court or forensic investigations must remain unmodified. Forgery detection can be carried out utilizing a variety of different ways, just like picture modification. For this goal, two distinct algorithms are proposed in this paper, and the superior approach is chosen. Choosing the most suitable deep-learning algorithm to utilize in the process of spotting image counterfeiting is the study's major goal. The CASIA Tampered Image Detection Evaluation dataset includes both unedited and modified photos. Denoising, scaling, and resizing are used in the initial preprocessing of the photos. The preprocessed dataset is then used to train the deep-learning models. Deep learning (DL) models are built using the UNet and ResNet-UNet, two separate methods. Both models showed similar outcomes during training. But even from the first epoch, the ResNet-UNet method produced better results. The models are examined to find the optimum algorithm after seeing the same results during training. This testing is based on a wide range of factors, including but not restricted to precision and accuracy. The model created using the UNet algorithm has an acceptable final accuracy of 94.6. But the ResNet-UNet method has a 96.3% accuracy rating, which is higher. The ResNet-UNet algorithm produces better outcomes in terms of all the other parameters, similar to how accurate it is. As a result, the ResNet-UNet model is determined to be the best method and is implemented into a software application's backend process where it successfully forecasted a fake image.
Keywords— Image Manipulation, Deep Learning, Image Preprocessing, Forgery Detection, Accuracy, Mobile App

I. INTRODUCTION

Image forging or splicing is the process of altering or changing the original image. This image alteration could look harmless. But to retain the veracity of the evidence, an image utilized in forensic investigations or judicial proceedings must be void of any manipulation. The veracity of the photos typically plays a significant role and is examined before a selection is made.

Image manipulation can be done in a variety of ways. The process of manipulating an image's pixels, adjusting its saturation and brightness levels, and changing its anomalies is all considered to be image forging. There are numerous ways to anticipate image falsification, much like with forgeries. But the issue with those techniques is that they are so cutting-edge that the average person cannot use them. Though these minute changes may not mean a lot in day-to-day lives, they can create a major difference when the image is used as a piece of legal evidence or forensics. Almost every image or other kind of media used for such proceedings is analyzed thoroughly before a decision. Just like image manipulation, forgery detection can also be done using various techniques. This study proposes two different algorithms for this purpose and identifies the best among the two. The use of DL methods as well as the development and workflow of the models are covered in detail in the following sections.

II. LITERATURE SURVEY

Many techniques were constructed to identify image forgery. Image classification is used in research [1] to identify fake images. According to this study, using a convolutional neural network to construct the ground truth makes it difficult to recognize copies of moves accurately. So, in the realm of picture forensics, an efficient technique is needed. Multiple levels of segmentation and classification are used in this investigation. As a result, it can offer improved accuracy and an F1 score. The SURF and PCET approaches are used in another study by researchers in the area of image forgery detection [2]. Polar Complex Exponential Transform, or PCET, is an acronym meaning Speeded Up Robust Feature. The study uses four steps to identify forgeries. Superpixel segmentation is used to separate the images into blocks in the first stage, ensuring no pixels overlap. The primary features of the photos are extracted in the next phase. The final phase involves using the SURF and the PCET to remove undesirable characteristics from the image. The model is mathematically transformed as the last stage to guarantee consistent performance each time.

To identify image counterfeiting, a pair of Indian researchers combined many distinct algorithms [3]. They claim that adding and subtracting elements from photographs that result in image interference makes it easy to prove image fraud. The picture forensic unit is now researching copy-move forgeries. Different techniques have been used to identify fake digital images. Time complexity, fraudulent content, and blurry images are some of the problems that still need to be solved. The SIFT and RANSAC algorithms were employed in existing research to eliminate a forged area from images utilizing a block and feature-based method. The 80 photos used in the fake dataset were gathered to attain an accuracy of up to 95%. They enhanced the accuracy rate and image resolution metric by employing the simulation setup with MATLAB 2016 version. The author used K-Means clustering and Gabor descriptors in image forgery detection [4]. Their research suggests a successful region-duplication forgery detection method. This investigation falls within the category of segment-based region duplicate forgery detection techniques. The algorithm was created utilizing Gabor descriptors, K-Means clustering, and image segmentation. The suggested technique outperforms existing image forgery detection algorithms, according to a comparison.

Forgery localization is a crucial subset of forgery detection that, like forgery detection, can pinpoint the area of an image that has been altered. The article has out the concept of forgery localization based on PRNUs. For this objective, picture segmentation is also used in this work [5]. Photo-Response Non-Uniformity, or PRNU, is a term. The multi-orientation strategy is the foundation of the localization approach. Because of this, although if two or much more sections of the images are changed, our model can still successfully detect the manipulated portions. The journal used parallel convolutional networks in the detection of image splicing [6]. In contrast to the conventional DL, methods utilized in image fraud detection, a system for detecting image forgeries is proposed in this paper by merging three deep neural network topologies simultaneously. Three different datasets were used to evaluate the suggested method, and the results indicate its effectiveness with a promising level of classification accuracy.

III. MATERIALS AND METHODS

A database consisting of authentic images and edited versions of the same images is collected from the CASIA Tampered Image Detection Evaluation dataset. The images are then used to manipulate the deep-learning models. The best DL model that can be used in the detection of image forgery is found by the procedures that are shown in figure 1.

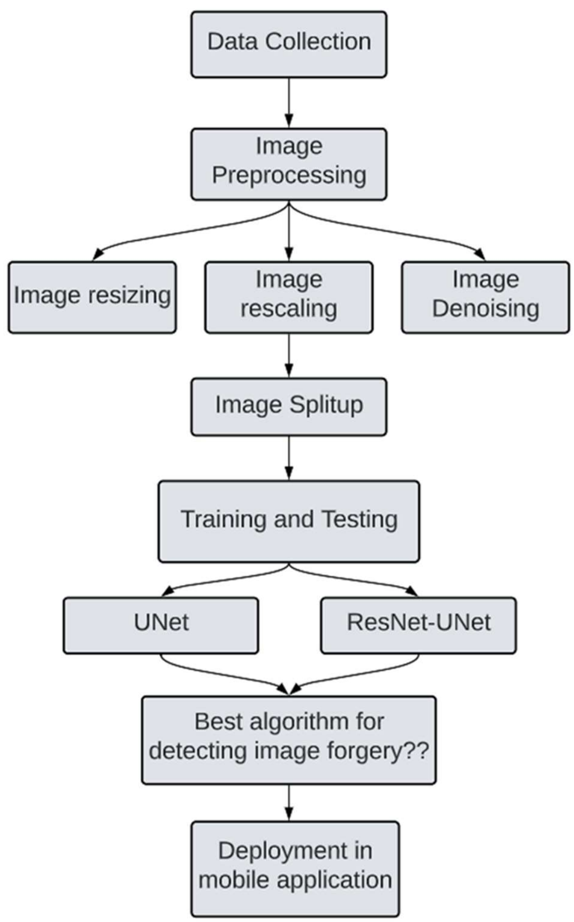

Figure 1. Workflow of the study

Figure 1 shows that picture resizing, image rescaling, and denoising are used as the first steps in the preprocessing of the images. The deep-learning models are subsequently trained using the preprocessed dataset. Two distinct algorithms, the UNet and ResNet-UNet, are used to create the DL models. The optimal image forgery detection technique is then discovered by analysis of the models' performance.

IV. DATA COLLECTION AND PREPROCESSING

The images that are used to train the DL models have a great impact on the performance of the models. Thus, it is always important to choose a dataset with versatile images to increase the performance range of the final algorithm. In this study, a dataset was collected from the CASIA Tampered Image Detection Evaluation database [7]. This database consists of over 12,000 images and has both authentic images and edited images. The split-up of the images in the database and the images which are used for training and testing is shown in table 1.

CASIA V2.0	Total	Train	Test
Original	7492	5994	1498
Forge	5124	4099	1025

Table 1. Image split-up

It can be inferred that an almost equal number of images are taken from each category and that step ensures that the DL model is not biased. The sample from the dataset chosen to train and test DL models is shown in figure 2.

Figure 2. Sample images from the database

From figure 2, it can be seen that both the authentic and spliced images are more or less similar making it tough for the deep-learning models to predict forgery. This way it was made sure that the model can perform properly with real-time images. The images have to be preprocessed to ensure uniformity and greater efficiency. Three preprocessing techniques are used in this study and they are image resizing, image rescaling, and image denoising. The preprocessing techniques are explained below.

A. Image Resizing

Image scaling is a crucial preprocessing step in computer vision. . Every image processing generally acquires new skills more quickly on smaller images. The photographs must also be the same and small in both DL and machine learning models to perform properly [8]. However, the raw pictures can be found in a variety of formats, including unique sizes. Every available image was therefore deleted and reduced to a specific size.

B. Image Rescaling

The method used to produce a new representation of an image with either a different dimension is known as rescaling or resampling. Rescaling is the process of physically altering the image's pixel count. Image quality is less affected when scaled down from its original size [9]. Image resampling comes in two different types. Up-sampling and down-sampling are what they are. Up-sampling and down-sampling are two terms used to describe how an image's size is changed. Rescaling enhances the model by putting all characteristics on an identical scale, which increases the likelihood that the model will identify the proper patterns.

C. Image Denoising

Images pulled from the database occasionally have contamination from poor camera quality. Other sources of visual noise include the environment's temperature, which in some circumstances is unchangeable. Noise is the name given to these contaminants. The computer vision model's effectiveness may be hampered by the image's noise [10]. Image denoising is the technique of removing or lessening the effects of the noise from the photographs. When computer vision uses DL, one of the required preprocessing processes is this one.

V. CONSTRUCTION OF THE DL MODEL

The DL models can be referred to as the brain of the study. The images are collected and preprocessed to train and test the DL model. Thus, it is safe to say that DL models play a crucial role in the detection of forgery from images [11]. Two distinct algorithms are chosen and examined to determine the best DL algorithm that may be applied for this purpose. The UNet and ResNet-UNet algorithms are used.

A. UNet

The UNet algorithm is a modified version of the convolutional neural network algorithm. The name of the algorithm is because the model consists of encoder and decoder layers arranged in the form of an English alphabet "U". The network includes 23 convolutional layers in total. Greater picture segmentation and prediction procedures are aided by the additional layers. It belongs to the group of algorithms for supervised DL [12]. To function with fewer training images and generate more precise segmentation, the network's architecture was enlarged and modified from a complete convolutional network's initial design. Semantic segmentation necessitates not only pixel-level discriminatory behavior but also a method for superimposing the feature representations that were trained at different stages of certain encoders on the space between both the pixels, in comparison to classification, at which deep network's final output can be the only factor that matters. [13].

B. ResNet-UNet

A DL model called Residual Network (ResNet) is applied in computer vision applications. The encoder/down sampling portion of the U-Net can utilize a ResNet. It is an architecture for a convolutional neural network (CNN) that can accommodate hundreds or even thousands of convolutional layers [14]. This many layers ensure great analysis of images. ResNets is one of the most efficient neural network architectures, which helps the network maintain low error rates much further into the network. ResNet is another supervised DL model. The ResNet model also has nearly a million trainable parameters, indicating a deep architecture that improves picture identification [15]. In this work the ResNet-UNet is employed which is the combination of ResNet and UNet. The outcome of ResNet is given to the UNet for classification.

VI. RESULT AND DISCUSSION

The CASIA Tampered Image Detection Evaluation database is successfully used to produce a dataset made up of genuine and modified photos. The training and testing of the DL models are made more efficient by the dataset's more than 12,000 photos. Next, three alternative preprocessing methods are used on the DL models. Picture resizing, image rescaling, and image denoising are some of the ways. The UNet and the ResNet-UNet algorithms are used to create two DL models. The DL model is then trained using the previously processed photos. For simpler analysis, the models' performance during training is noted and plotted into a graph. The accuracy of the model created using the UNet during training is shown in Figure 3.

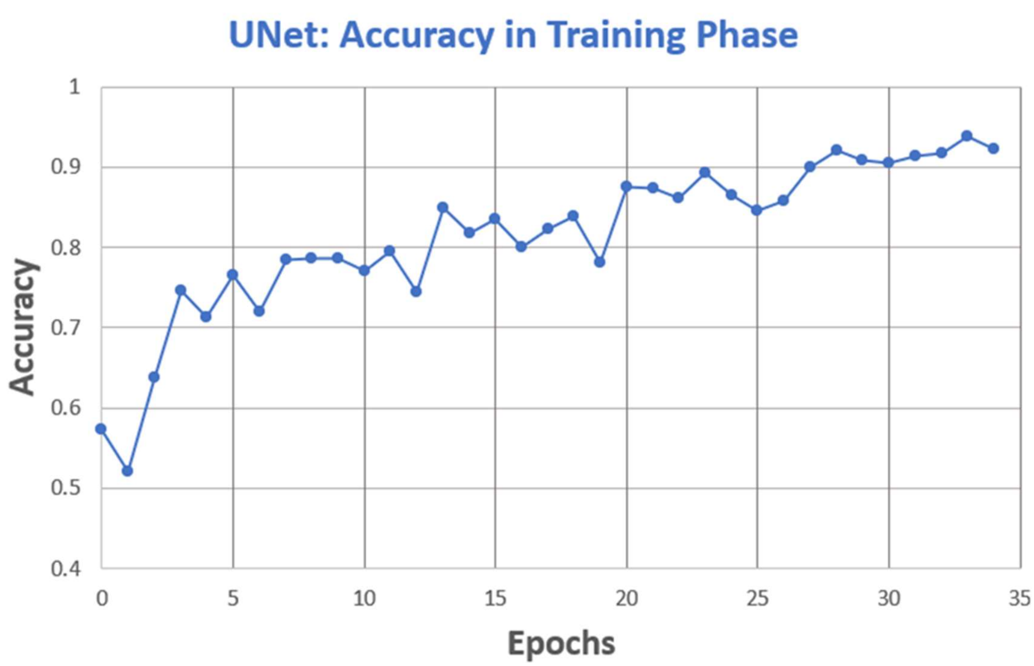

Figure 3. Accuracy plot of the UNet algorithm

Figure 3 shows that for the first five epochs, the model's accuracy is quite low. But as the number of epochs rises, it gets higher and higher until it even exceeds 90%. Figure 4 displays the model's loss analysis during training.

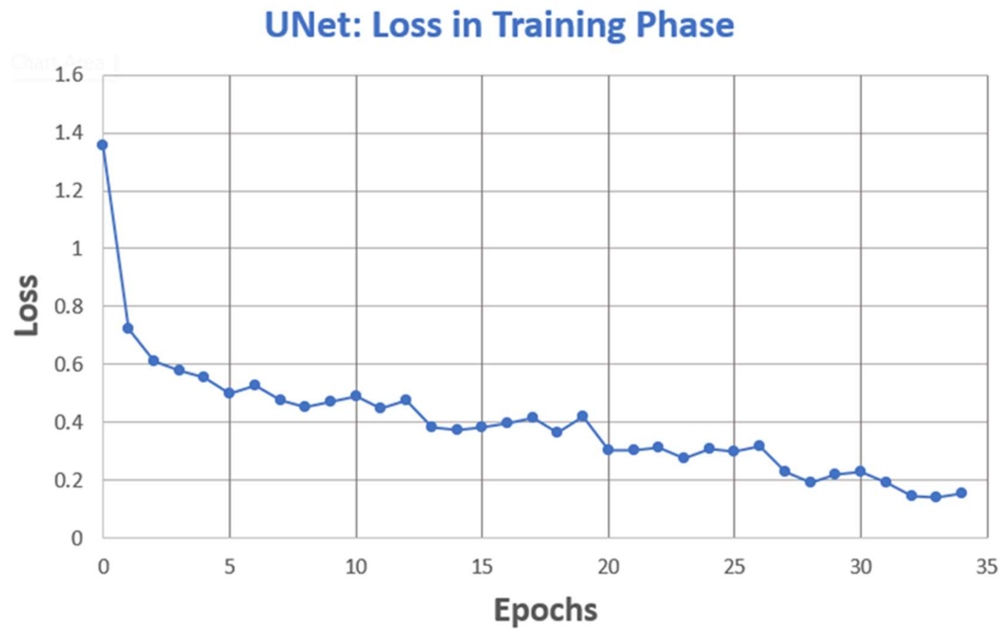

Figure 4. Loss plot of the UNet algorithm

Unlike the accuracy of the model, the loss value of the model is inversely proportional to the number of epochs. As the number of epochs increases, the loss value decreases and it reaches a point where it is so small that it can be neglected. Figure 5 explains the performance of the ResNet-UNet model when it comes to accuracy.

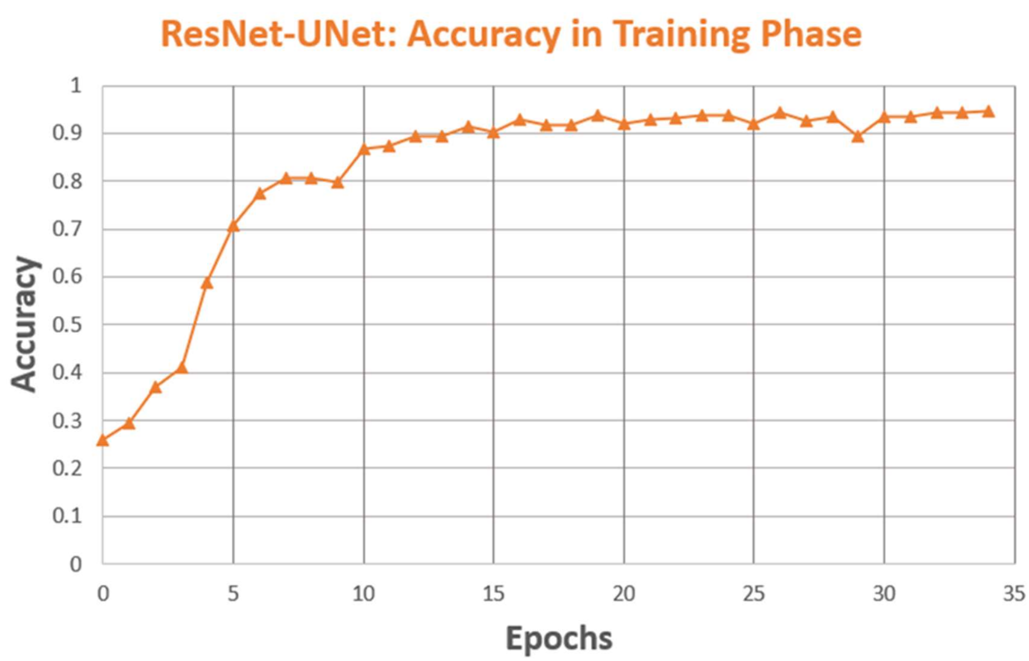

Figure 5. Accuracy plot of the ResNet-UNet algorithm

Figure 5 shows that for the first five epochs, the model's accuracy is fairly poor. But as the number of epochs rises, it gets higher and higher until it even exceeds 90%. But the main difference between the accuracy graphs is that the initial accuracy of the ResNet-UNet is better than that of the UNet algorithm. Figure 6 displays the model's loss analysis during training of the ResNet-UNet model.

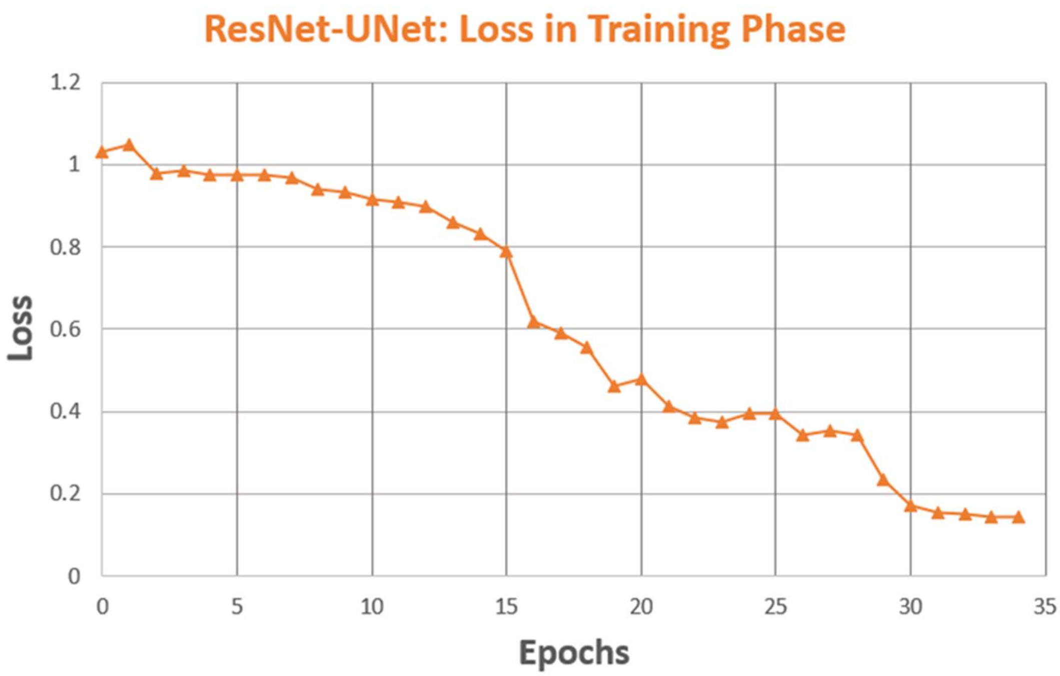

Figure 6. Loss plot of the ResNet-UNet algorithm

Just like the UNet algorithm, the loss value of the model also decreases as the number of epochs increases. So, to find the best DL algorithm among the two, the models are tested. This test contains various performance metrics, not only accuracy, and loss. The performance metrics are accuracy, True Positive Rate (TPR), True Negative Rate (TNR), False Positive Rate (FPR), False Negative Rate (FNR), precision, and F1-score. Out of all the metrics, the FPR and FNR should have the least value to make the model better, unlike the other metrics. The final results of the testing are shown in table 2.

Model	UNET	RESNET-UNET
ACCURACY	94.6096	96.3932
TNR	94.5283	96.7464
TPR	94.6685	96.1434
FNR	5.33151	3.85656
FPR	5.4717	3.25359
PRECISION	95.9806	97.6632

F1-SCORE	0.9532	0.96897

Table 2. Final test results

Table 2, clearly depicts the fact that the ResNet-UNet algorithm has better performance in terms of all metrics. Also, the accuracy of the model is 96.39 which is great for an image-processing model. Thus, the model is deployed as a backend process for a mobile application. The homepage of the application when no image is uploaded for detection is shown in figure 7.

Figure 7. Homepage of the application

It can be seen that the homepage consists of a header that explains the purpose of the application. It also consists of a need for proper unadulterated images and forgery detection. This part is followed by an uploaded image that allows the user to browse through the images to upload the image which has to be analyzed. At the bottom, it consists of a submit button that is used to submit the uploaded image. Figure 8, represents the look of the application when the user uploads an edited image.

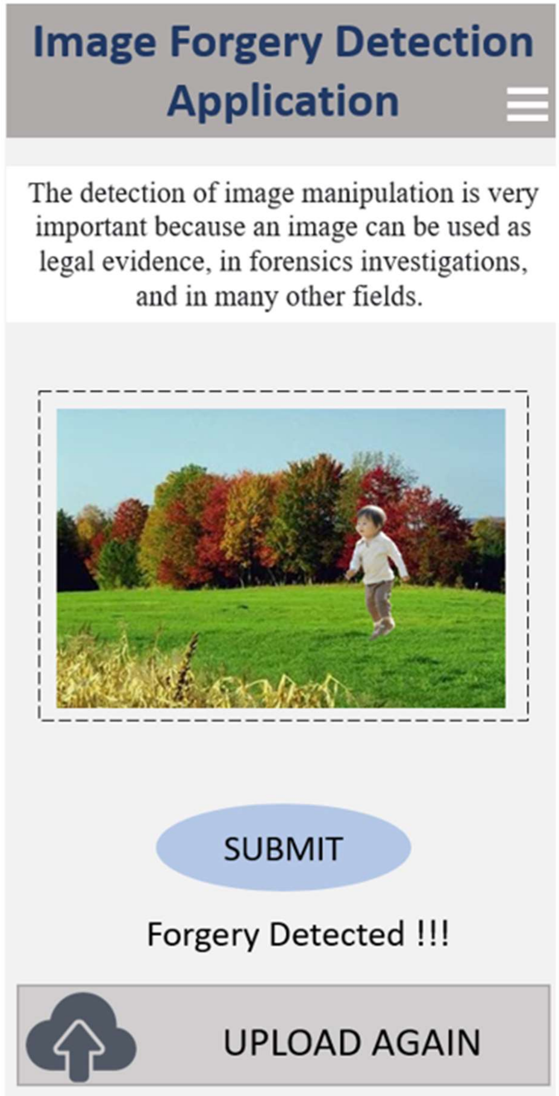

Figure 8. Results of the application

After the analysis, it is found by the model that the image is forged. Thus, it displays the result as “Forgery Detected !!!”. It also allows the user to upload another image with a different message saying “UPLOAD AGAIN”.

VII. CONCLUSION

The main aim of the study is to find the best deep-learning algorithm which can be used in the process of identifying image forgery. Both unaltered and edited images are collected from the CASIA Tampered Image Detection Evaluation dataset. The images are initially preprocessed utilizing denoising, scaling, and resizing of the photographs. The deep-learning models are subsequently trained using the preprocessed dataset. Two distinct algorithms, the UNet and ResNet-UNet, are used to create deep learning models. During training, both models depicted similar results. However, the ResNet-UNet algorithm showed better results even from the initial epoch. After observing similar results during training, the models are tested to determine the best algorithm. This testing is based on many other parameters including but not limited to accuracy and precision. The final accuracy of the model developed using the UNet algorithm is 94.6 which is satisfactory. But the ResNet-UNet algorithm has a greater accuracy value of 96.3%. Just like the accuracy, the ResNet-UNet algorithm has better results in terms of all the other parameters, Thus, the ResNet-UNet model is chosen to be the best algorithm and deployed into a backend process of a software application where it predicted a forged image correctly.

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