SRI, C.G., BANO, S., DEEPIKA, T., KOLA, N. and PRANATHI, Y.L. 2021. Deep neural networks based error level analysis for lossless image compression based forgery detection. In *Proceedings of the 2021 International conference on intelligent technologies (CONIT 2021)*, 25-27 June 2021, Hubli, India. Piscataway: IEEE [online]. Available from: https://doi.org/10.1109/CONIT51480.2021.9498357

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2021

Deep Neural Networks Based Error Level Analysis for Lossless Image Compression Based Forgery Detection

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Abstract **- The proposed model is implemented in deep learning based on counterfeit feature extraction and Error Level Analysis (ELA) techniques. Error level analysis is used to improve the efficiency of distinguishing copy-move images produced by Deep Fake from the real ones. Error Level Analysis is used on images in-depth for identifying whether the photograph has long passed through changing. This Model uses CNN on the dataset of images for training and to test the dataset for identifying the forged image. Convolution neural network (CNN) can extract the counterfeit attribute and detect if images are false. In the proposed approach after the tests were carried out, it is displayed with the pie chart representation based on percentage the image is detected. It also detects different image compression ratios using the ELA process. The results of the assessments display the effectiveness of the proposed method.**

Keywords: Error level analysis (ELA), Convolution neural network (CNN), Deep Learning.

I. INTRODUCTION

The rapid improvement of advances in automatic imaging has empowered the imaging devices with excessive goals to utilize computerized pictures for distinct functions. But the superior photograph often managed to distort(twist) the substance of the primary photo. Subsequently, the automated picture is not always, trusted by most people at this point. Image crime scene research is a region of studies that distinguish the inception and confirm a picture's realness.

The photo of a crime scene investigation contemplates over organized types which are dynamic affirmation and uninvolved verification. The dynamic verification calls for more records about the first photo carries the manner in the direction of implanting a watermarking into a picture or extricating an incredible detail as a mark of the photograph. The uninvolved validation is a visually impaired region that requires no additional information about the primary image. There is training in uninvolved verification that is identifying the picture altering. Identifying the image changing is alluded for the utilization of examination and measurable techniques to recognize the manufactured locales.

This paper introduces and speaks about an ELA process for the independent confirmation in felony sciences of photography, including JPEG strain, photograph grafting, circulate photo fabrication, and picture correcting. The commitments of this paper are Firstly, we process the pressure and resizing method to incorporate the fact in the three most common image altering types. Secondly, the ELA method is applied to the records, and the consequences appeared are clarified completely. As a result, the recognized proof of the methodology on prison sciences of photograph may be further advanced.

IMAGE FORENSICS

Image forensic is the quick and simple approach for identifying the photograph content material. When it comes to evaluating the message, pictures are an important and popular correspondence media for humans. Legitimately there has been agreement within the respectability of visual records to such a volume that a photo imprinted in a paper is generally stated as an affirmation for the news of honesty or video statement chronicles.

With the short dispersion of reasonable price and easy to utilize devices that empower the obtaining of visual statistics. Anyone has the chance of recording, putting away, and sharing numerous automatic photos. Simultaneously, the enormous accessibility of image altering, programming gadgets makes it amazingly smooth to control the pictures' substance or make new ones. Hence, the hazard of altering and forging visible substance is not always any more limited to professionals. Finally, cutting-edge programming permits the development of photorealistic PC diagrams that viewers can distinguish from photographic images [12,5] or the processing of half and half of the generated visual content.

In summary, a noticeable superior article now-a-days may match at any point during its lifetime, from acquisition to success, by dealing with ranges, aimed at improving quality, creating new content by mixing old material, or in any case, messing with the substance. As a result of every single past truth, adjusted snapshots are displaying up with a growing recurrence in diverse application fields. Along those strains, the existing computerized innovation has begun to dissolve the accept as true with on visible substance. So that clearly "Accepting is done while examining" [14,10,17]. This kind of troubles will deteriorate as getting ready methods to come to be increasingly more modern.

The current situation requires the development of techniques that enable the ancient background of an automated photograph to be checked for accuracy. Two questions about the collection of reports and the authenticity of a photograph may be raised: Is it true that the snapshot obtained with the machine's assistance can be found in the picture depicting the specific stuck scene. The primary inquiry seems to be of a vast hobby, while the documents on which the photo is based to discuss the actual evidence. Because it allows the user or device that produced the image to be identified; the following inquiry is of a greater vast hobby. When the primary image is being considered, providing proof to certain questions is usually easy. In reasonable circumstances, but almost no data can be deduced from the first photograph. As a result, experts must confirm the image documents are in a visually impaired manner.

To discover a response to the beyond issues, a research group focused on mixed media content material security has suggested some economic models that can be further divided into dynamic and inactive advances, as addressed.

The use of "dynamic" means that some information from the source side has been documented for the purpose of assessing reliability. It is exploited at some stage during the acquisition process, while with the term "indifferent," a solution that seeks to render an appraisal, by removing automated content.

The alter programming techniques made it easy for a character to govern the first photograph without leaving any obvious symptoms. The photo altering may be taken care of into three types as follows:

A. Image grafting

It is a cycle of consolidating as minimum picture to make some other picture. A special district is duplicated from one image and fixed into another to frame an exchange image. The area of expertise within the grafted region can be coordinated [5].

B. Copy-move imitation

It is an average sort of image changing. It consists of a cycle of reordered inside a similar picture. The duplicated district is normally modified using sports like scaling, revolution, and including commotion to mix the managed locale with the encircling region [14]. Subsequently, the altering is along those traces which is hard to understand by way of the herbal eyes.

C. Image enhancing

An image correcting is a cycle of editing replicated pixels to coordinate the surrounding pixels [10]. It may enhance or decrease a few highlights of the first photo without converting its actual significance. This kind of altering is normally achieved through the magazine editors to make the photograph extra attractive [17].

II. RELATED WORK

The new generative adversary networks (GANs) were first introduced by Goodfellow et al. [13], and usually consist of two networks: a generator and a discriminator. Thies et al. [16] proposed Face2Face, an innovative real-time facial re-enactment technology that can alter facial expressions in video sources, such as movie trailers. Recently, several deep learning-based methods for facial image synthesis have been suggested. The majority of these techniques suffer from a lack of image resolution. To improve image quality, Karras et al [18] use an increasingly growing GAN. High-quality facial synthesis is one of their outcomes.

Digital image verification technology has made a number of breakthroughs in the field of image tampering detection as a secure form of judicial identification. Previous approaches, such as CFA pattern analysis, local noise estimation, and double JPEG localization, can be categorized based on the image features they strive to achieve. A probability model for estimating DCT coefficients and quantization factors was proposed by Bianchi et al [7]. FUD et al [1] used an estimation consistency factor to see if the picture had been tampered with.

Ferrara et al [9] proposed a model for estimating the camera filter mode based on the variance of prediction error between CFA current (genuine) and CFA absent (false) areas (tampered areas). The tampered regions can be located after the Gaussian Mixture Model (GMM) classification.

Using EXIF image tag information and ELA, Cpatel et al. [15] proposed a method to distinguish forgery area frames from a given input video. Jeronymo et al. [19] proposed an ELA-based approach for detecting image forgery in lossy compressed digital images, with the noisy components filtered using automatic wavelet soft-thresholding. To solve the problem of separating real images from forged images, Sudiatmika et al. [21] suggested a new method based on a combination of ELA and CNN.

Zhang Weiguo [20] proposed a method for simulating the process of creating faces in Deepfake to generate a face-swap image dataset, as well as a novel counterfeit feature extraction technique based on deep learning and ELA.

III. METHODOLOGY

This proposed method unites unique methodologies and picture getting ready systems to find picture adjusting, to find fake Copy Move and Splicing on lossy and lossless pictures. To get adjusted pictures magnificent procedures are executed. The model works with ELA pre-processing and changes in various pre-arranged Models (MICC-F2000, CASIA v2), which can be coordinated using Keras and TensorFlow. An image Forgery places utility grants to check pictures with the application coordinated designs or train the product with the new dataset and test picture with this new arranged model.

A. Error Level Analysis

Error Level Analysis (ELA) perceiving regions inside a photograph at different strain stages. With JPEG pictures, the total photo ought to be at typically a tantamount(equivalent) stage. On the off danger that a period of the image is at an explicit error level, by then, it most likely shows an electronic change.

ELA function differs within the JPEG compression rate. The region with uniform disguising, comparing with the blue sky or a white divider, they are most likely having a diminishing ELA result (hazier tone) than high-examination edges. While searching for an Edges in an image similar edges need to be combined, which is close to magnificence inside the ELA result. All high-assessment edges appear to take off one by one, and all low-assessment edges appear to be relative. With a wonderful picture, low-assessment edges ought to be especially just about as super as high-evaluation edges.

In Surfaces, Similar surfaces should have close to hiding underneath ELA. Areas with more surface parts, for instance, a nearby ball, will most likely have a favoured ELA result over an ideal floor. Irrespective of the surface's genuine shade of image, all stage surfaces ought to have around a tantamount disguising under ELA.

Take a gander(glance) at the picture and perceive(recognize) the remarkable outrageous(excessive) assessment edges, low-evaluation edges, and surfaces. Separation of those zones and the ELA results. On the off threat that there are principal contrasts, it sees problematic zones that may have been intentionally changed. Resaving a JPEG clears out high-frequencies and results in a lot fewer contrasts among high-examination edges, and surfaces. An unacceptable phenomenal JPEG will seem moronic(idiotic). Scaling a photograph extra inconspicuous(unnoticeable) can help high-isolate edges, making them extra unimaginable under ELA. Besides, saving a JPEG with an Adobe thing will most likely hone(sharpen) superfluous distinction edges and surfaces, demanding them to uncover up altogether more unmistakable staggering than low-floor surfaces.

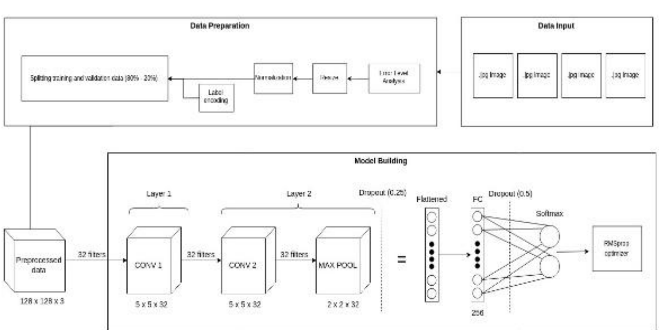


Fig. 1. Block Diagram for ELA based CNN

There is a wide collection of image report plans. A couple of setups are lossy, at the same time as others are lossless.

Lossless: Lossless record plans shield specific pixel concealing information. On the occasion which stacks a photograph, shops it, and weighs it some other time, every pixel should have a similar worth. In truth, even an exchange among lossless arrangements will hold exactly the indistinguishable concealing regards. For example, PNG and BMP are numerous lossless preparations. The off hazard, which adjustments an image from a BMP over to a PNG, will maintain indistinguishable pixel regards, regardless of whether the record design is altered.

Lossy: A lossy report configuration would not guarantee that the tones will keep on being equal. With JPEG, saving requires showing a brilliant level. The 5-star degree changes the stress entire (decline quality makes greater noteworthy humble files). Notwithstanding, it packs via removing more than one concealing fact. With JPEG, saving a photo makes the shadings alternative a lump. The resaved record may likewise ostensibly appear equal to the source image, yet the specific pixel will vary.

Applying ELA to Lossy Images

JPEG previews use a lossy dire part contraption. Every re-encoding (resave) of the picture gives a severely beguiling issue to the photograph. In stunning, the JPEG calculation manages an 8x8 pixel enterprise challenge. Each 8x8 rectangular is squeezed self-overseeing. On the occasion that the picture is unmodified, all 8x8 squares ought to have tantamount mishandle openings on the off threat that the image is unmodified and resaved, every rectangular need to destroy at cycle an almost indistinguishable charge.

ELA saves the photograph at a predefined JPEG splendid degree. This resave offers an apparent part of stumble throughout the entire picture.

The resaved photograph is then checked out towards the simple photograph. On the off peril that an image is adjusted, every 8x8 rectangular that became moved to utilize the trade needs to be an excellent screw-up potential relaxation of the image. Changed zones will show up with an advanced potential blend-up diploma.

JPEG Encoding Blocks

JPEG shops tone the use of the YUV disguising an area. 'Y' is the luminance or sensitive scale pressure of the photograph, 'U' and 'V' are the chrominance-blue and chrominance-purple hiding packs. For the show, the JPEG decoder adjustments the photograph from YUV over to RGB. JPEG usually encodes luminance with an 8x8 go section. Regardless, chrominance may be encoded with the utilization of 8x8, 8x16, 16x8, or 16x16. The chrominance subsampling is a JPEG encoding preference. Subordinate upon the picked chrominance subsampling. Each 8x8, 8x16, 16x8, 16x16 bypass degree is probably transparently encoded.

A report is altered over from a lossy file dating to a lossless leisure plan, resave collectibles are held. Here offers ELA to contain changes made to a JPEG photo that changed over to a PNG. Not all lossy file plans are practical. For example, the lossy WebP, HEIC, and HD Photo (JPEG XR) plan uses stand-apart strain tallies than JPEG. Regardless of whether or no longer, at this point a JPEG photo has been more vital than once stored, it might at any fee bring about first time-set apart important rarities at the off hazard that it has ways altered over to the ones assorted report plans takes place insensitive that the WebP, HEIC, and HD Photo odds and ends are actualized inquisitively.

FotoForensics can notice ELA to all saved up document plans. Regardless, ELA expects that non-JPEG documents have been changed over from JPEG pic. (This is a beneficial uncertainty considering that there are not any frequently close by cameras that generally get pics in PNG, WebP, HD Photo) consequently, all ELA appraisals are analyzed in competition to JPEG lossy dire aspect.

Applying ELA to Lossless Images

Lossless file plans do not cope with the tones in a photograph. While a lossy photo is changed over to a lossless connection, the amount of the appropriate lossy rarities is held. These licenses are spotting explicit groupings of modifications, for example, Document configuration changes. Changing over from JPEG to PNG will preserve up the beyond JPEG relics. Since a local vicinity PNG ought no longer to consolidate JPEG relics, the change is detectable.

Neighbourhood lossless. An image that in no way has gifted JPEG encoding (e.g., changing over a programmed camera RAW photograph direct to PNG - without using an Adobe factor) will have no JPEG relics. ELA wishes to file a well-known photo amazingly great, and no 8x8 or 16x16 shape-primarily based impeding in gentle that it offers the zones which intend to trade for the span of the actual JPEG encoding.

Convolutional Neural Network (CNN) CNN is a sort of Feedforward totally based organization, Which the development of records is just a single heading, specifically from contribution to yield. While there are some CNN structure styles, all in all, CNN has some convolutional layer and pooling layer. Then, trailed with the aid of one or More associated layers. In picture grouping, put on CNN is a picture so that every pixel can be prepared. It appears that evidently, a convolutional layer is applied as Extracting highlights that review the portrayal of those highlights from images that are contribution on CNN. In the interim, Pooling Layer is entrusted with diminishing spatial aim from highlight maps. For the most part, earlier than the related layer, there are a few stacks of Convolutional and Pooling layer that capacities for Extract Representation more particular highlights. From that point onward, the related layer will decipher These highlights and carry out capacities that require a significant degree of questioning.

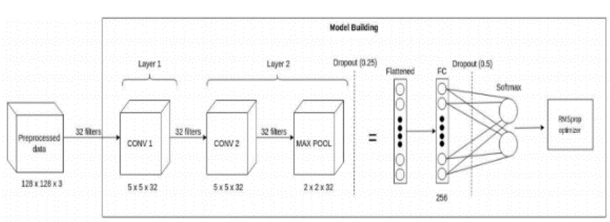


Fig. 2. The trained architecture of Convolutional Neural Network

B. CNN architecture

Changing simple facts over to ELA results is a course used to amplify the CNN version's preparation talent. This productiveness may be carried out in mild that ELA photos contain records that are not always needless as its specific picture. The highlights introduced with ELA snapshots' aid have been targeted around the photo area with a degree blunder above the breaking point. Other than that, the pixels of an ELA image will in fashionable have colorations that might be like or in sharp differentiation to Pixel-pixel close by, so preparing the CNN version seems extra talented.

IV. RESULTS

A. Experiment Setup:

Here, in this process the ELA (Error Level Analysis) method is used for pre-processing and two different pre-trained Models are used for fine tuning and the erroneous results are occurred in the pie-chart format by saying that the image is with what percent forged and unforged. This proposed model is combination of Copy-Move and Splicing dataset they are MICC-F2000 copy-move dataset contains 2000 images (1300 authentic-700 tampered) color images, 2048x1536 pixels. CASIA v2 splicing dataset contains 12,614 images (7491 authentic -5123 tampered) color images, 384x265 pixels. Forged images are used in the datasets to detect whether they are masked or unmasked, and a model is taken here which is trained first and later we will do testing. Training efficiency is improved with our proposed model even though the forged image seems to be that it does not contain more information to the human eye than the source image. The forged image function concentrates on the area of source image where the error level exceeds the parameter values. Furthermore, the pixels in the forged image are often very different from the nearby pixels, and the distinction is quite clear, so the image processed by ELA improves the effectiveness of the training model. As we have discussed we firstly, train the model to extract information of the forged image, then determine whether or not the pixel data is forged. Since the forged images produced during the conversion process will highlight the characteristics of the original image where the error level is higher than the parameter value, only convolution layers are needed in framework we use.

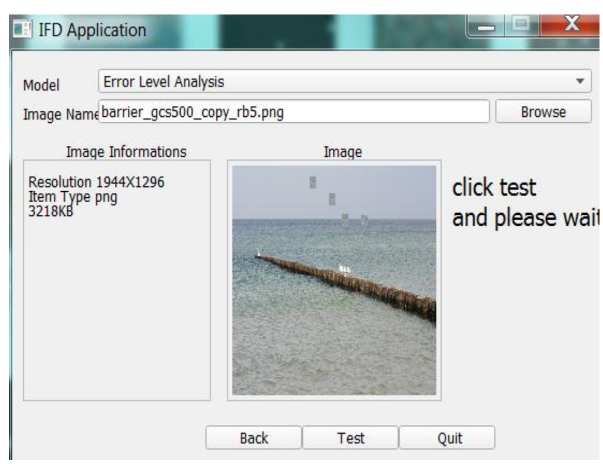


Fig. 3. The Final result showing the patches of forgery

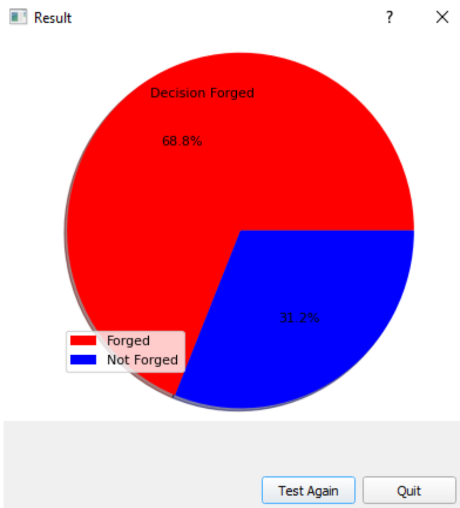


Fig. 4. The Overall Percent of image forgery area

As a result, determining whether or not the picture is fake is much simpler. The findings obtained by our proposed method have a maximum accuracy of 98 percent. Figure shows an example of accuracy and loss function pie-chart. This is also a concluding method of training in advance during training, i.e., when the confirmation prediction accuracy begins to decline or the testing percentage error begins to rise, the training would be terminated.

B. Comparison with Other Methods:

To demonstrate the feasibility of our approach, we have compared with another version. As a direct detection tool, it is not trained using the CNN and is done with ELA processing without the datasets. The images of positive and negative examples are directly fed into the network model for training in our process. We train the CNN model as explained in experiment setup.

The below existing procedure explains us that any alteration to the image can cause stable areas (with no additional error) to become unstable. Figure 6 depicts a photoshop picture that has been altered. The updated image was created using the first 60% resave. The adjustments are identified by the 95 percent ELA because they are places where the minimum error level has been exceeded. Since Photoshop combined information from different layers, it effectively modified several of the pixels, additional areas of the image display slightly more volatility.

In the investigation, we utilized the ELA procedure provided by Krawetz [11], which is on-hands from the website (http://fotoforensics.Com/). The trial climate as follows, the working framework depends on the Windows 7, 64 bits with Google Chrome program variation. Because of no popular dataset at the JPEG strain and resizing manner, we make our image consolidates with the strategy for every form of photograph changing. Then take a look at pic which are taken through the digital camera from iPad Mini 2 and altered utilizing Adobe Photoshop CS5 programming. The exams are completed with numerous types of photo changing along with:

Unique photo with numerous pressure:

1. Re-sizing the primary image.
2. Image joining with 60% JPEG strain.
3. A spliced image in photograph re-sizes.
4. Copy-circulate image fabrication with 60% JPEG stress.
5. Copy-circulate picture fabrication in photograph re-size.
6. Image correcting.

Re-sizing the primary image:

From the examination, the ELA can discover the unaltered district despite manage it. A high-quality JPEG image will produce clean white ELA effects, while a lower exceptional will result in more difficult-to-understand results. Fig.5 indicates the results for various nature of JPEG pressure in the first photograph.

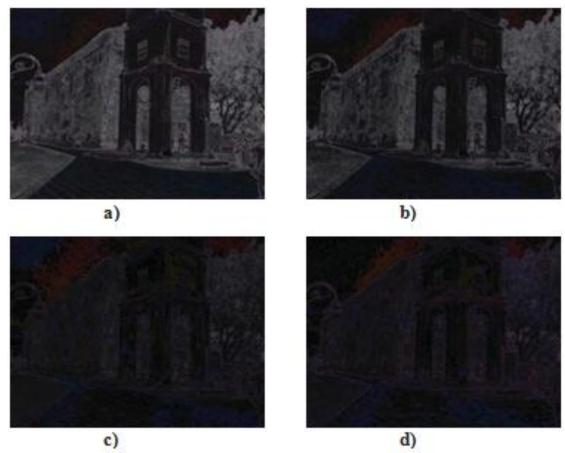


Fig. 5. ELA results for a) Original image b) Image with JPEG quality 90% c) Image with JPEG quality 70% d) Image with JPEG quality 50%

Re-sizing the original image:

Fig.6 offers extra commotion consequences while the image has been resized rather than compacted. Besides, the particularly blue aspect addresses that the photo has been altered via Adobe Photoshop programming.

Fig. 6. ELA results when the image is resized to 600×400

Image splicing with 60% JPEG compression:

For this case, ELA has been assessed through the brink and smooth varieties. The diploma of whiteness and splendour between the rims have to be indistinguishable for the first photograph. In like way, similar smooth areas must have a comparative blunder degree for every variety. For example, A picture should deliver final results that showed the difference at the rims or clean varieties. Fig. 7 offers the distinction of the white vicinity on the sleeves of an individual within the photo. In this manner, the sleeves are the conceivable managed locales of the photo.

a)

b)

Fig. 7. a) Sample of image splicing b) ELA results for the sample with 60% JPEG compression

The spliced image in image re-size:

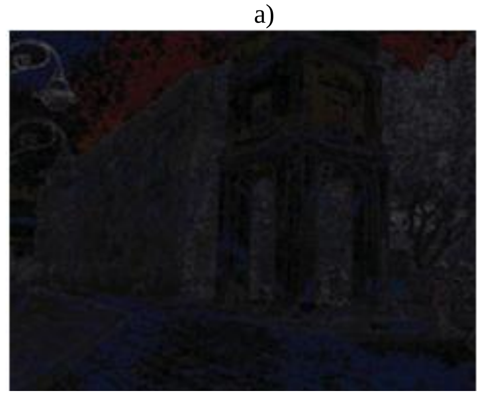
ELA has been evaluated in this case using the edge and flat varieties. For the first photograph, the degree of whiteness and magnificence between the rims must be visible. Similarly, for each variety, similar smooth areas must have a comparative blunder degree. For instance, as previously mentioned, photo member. A should have final results that demonstrated the difference between the rims and the clean varieties. Figure 8 shows how the white and blue-edges area on the sleeves of a person in the picture can be distinguished. As a result, the sleeves are the photo's potentially controlled locations.

Fig. 8. ELA results for image splicing with image re-sized

Copy-move image forgery with 60% JPEG compression

Contrasts from photograph becoming a member of photograph imitation which are hard to apprehend, because the manageable replicated areas have a comparable best degree. From all matters considered; ELA can help with distinguishing the controlled locales if the primary image has a great degree of similarity with the replicated districts. Fig.9 indicates that the top light is a lot extra high-quality in white contrasted with the base light. In this way, the workable reproduction pass locales could be the top mild.

a)



b)

Fig. 9. a) Sample of copy-move image forgery b) ELA results for the sample with 60% JPEG compression

Copy-move image forgery in image re-size:

Dissimilar to photograph grafting, ELA gives helpless outcomes in replica circulate photograph fabrication with photograph resize. The replicated areas are believed to be difficult to distinguish as shown in Fig. 10.

Fig. 10. ELA results for copy-move image forgery with image re-sized

Image retouching

Despite what is probably predicted, Fig. 11 gives numerous ELA effects like the first picture (see Fig. 11a) with the editing image (see Fig. 11b). It is proven that the substance of the character has some commotion with more than one white zone contrasted with the first photo. All are considered, including the possibility of altering the face by photo manipulation.

a) b)

Fig. 11. ELA results for a) Original image b) Image retouching

We can see that the procedure provided by Krawetz is proved in picture portrayal based on the results. As a result, the investigation is highly reliant on human translation, which may lead to erroneous results. We expected that the procedure will be improved specifically to provide quantitative results to the ELA strategy demonstration.

The following are some of the benefits of our model: the number of training cycles needed to achieve convergence is substantially reduced because the image features processed by ELA make training more effective and speed up CNN model convergence. In addition, the accuracy of our classification findings was significantly higher. This, combined with experiments showing that using the ELA method improves the training performance of the CNN model, means that our method is feasible in terms of simplicity and efficiency.

TABLE I. I

Model	Composition	Images Size	Performance & Accuracy
ELA using (MICC-F2000, CASIA v2) dataset	Contains 2000 images (1300 authentic-700 tampered) colour images for MICC-F2000, Contains 12,614 images (7491 authentic -5123 tampered) colour images for CASIA v2.	2048x1536 pixels for MICC-F2000, 384x265 pixels for CASIA v2.	99.51% for both datasets with 100 epochs.
ELA with no dataset (FotoForensic tool)	As this deal with no dataset tool every time takes single image as input.	Varies on images.	95%

V. CONCLUSION

We can see that the procedure can be enhanced in picture criminal fields in light of the various states of photo alteration attempted with the ELA process. ELA recommends critical outcomes for JPEG compression, image recognition, and image editing. Furthermore, ELA can also be useful for estimating the picture in cases where no previous re-size has been completed. For future bearing, the arranging concentrates on the unique way to increase the outcomes for duplicate circulate image fabrication and photo resize.

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