**DFT Coefficient Method Based Copy Move Forgery Detection Technique Using Faster R-CNN**

**Abstract**

*The internet has made it possible for humans to retrieve and modify any content that is available online. Copy-Move Forgery (CMF) imaging includes copying and pasting image parts. Digital image forensics detects frauds in digital photographs. Digital image forensics uses active or passive (blind) approaches to identify image frauds. The computational cost has risen due to more needed regions. The provided technique can be utilized to identify the area to solve this issue and reduce regions. The current work uses a faster Region-based Convolutional Neural Network (R-CNN) to recognize and categorize counterfeit images. A Discrete Fourier Transform (DFT) coefficient for each block improves categorization. According to the results, the suggested method is more accurate in detecting forgeries in images than the standard method. Future studies could involve modifying the Convolutional Neural Network (CNN) to speed up the process. More difficult datasets can be used to test the technique. Deep learning can identify other digital image frauds.*

**Keywords** Copy Move Forgery Detection (CMFD), DFT coefficient, R-CNN, Digital image encryption, Discrete Cosine Transform (DCT) transform, Feature extraction

# **Introduction**

The internet has made it possible for anyone to get information in whatever form or shape it chooses and then modify or alter it to suit their purposes. Forgery imaging based on CMF is a type of forgery that includes copying and pasting pieces of an image back into the actual image. As a result, the networked world of image forensics related to CMFD has become increasingly significant manner. Passive detection and Active detection are the two types of visual forensics technology. As compared to active detection methods, passive detection methods do not need prior knowledge of an image's content to determine its validity. The passive detection approaches can make use of the detective strategy's burkeites to locate the tampering locations. As a direct consequence of this, the vast proportion of photo fraud detection algorithms makes usage of a method that is based on passivity to recognize the type of tampering which is described in further depth in this study. There are two different kinds of passive detection technologies such as block-based techniques and key point-based approaches [1].

An interesting field in current time called digital image forensics has appeared that looks for signs of forgeries in digital photos. The main purpose of digital image forensics is to detect forgeries in images using active or passive (blind) methods. Digital signatures and watermarking are effective methods that depend on the information stored in the images. The lack of knowledge can restrict the use of active approaches in practice. Image splicing and area duplication by copy-move forgeries are two common methods of image manipulation. The image splicing uses parts from numerous photographs to generate a forged image. In copy-move forgeries, image regions are replicated and pasted onto the identical image to suppress or enhance certain crucial information in the image. It is difficult to analyze the difference between tempered and actual regions for compatible components (such as noise and color) to appear to be the same in reproduced areas. A counterfeiter can utilize postprocessing techniques such as edge smoothing, blurring, and noise to obscure the visual evidence of photo forgeries [2]. Some important qualities of CMFD are as follows [2]:

* Consumption of the shorter length of feature vectors.
* Smaller computational cost.
* Toughness against several postprocessing operations over the forged regions.
* Capability to identify several copy-move forgeries

Authentication solutions have been created to safeguard the image transmission process. Active and passive authentication are the two types of authentications [3]. Active validation is accomplished through the use of methods like digital image encryption, digital signatures, and the insertion of a logo in the image's initial matter before use. The actual content of the image should be accessible for comparison with the test image in effective verification [4]. Active validation is utilized in the protection of color image steganography which is linked to several payload partitioning strategies and data-embedding algorithms [5][6]. In active authentication, compressive sensing and the DFT are used to ensure recovery and provide a customizable payload by concealing separable data in encrypted images [7]. The prior substance of the image is not available in passive authentication. the test image is inspected devoid of any prior knowledge of the initial matter. This sort of authentication is commonly employed to detect digital image forgeries due to the initial matter of the analyzed image being inaccessible [8]. Forgery detection in digital photographs is a critical subject. As scraps of evidence, forgery detection is performed by looking for odd traits, qualities, or abnormalities. The homogeneity of the original image's statistical, geometrical, or physical features is used to identify forgery, however, this homogeneity is not preserved in altered images. Image morphing, image merging and resampling, image retouching, and eventually CMF are all examples of digital image forgery. Image splicing is the process of combining more than two photographs to produce the latest image that contains pieces from the original images. Morphing of an image is a type of image fraud in which two distinct forms from different photographs are combined to make a new shape [9].

In coloring, lighting, contrast augmentation, erasing noticeable imperfections on skin or background alteration, image retouching is done to enhance an image to show or hide particular elements [10]. Image resampling is the process of modifying the proportions of an object or many objects in an image to give the beneficiaries a different interpretation. CMF is accomplished by duplicating an area by one spot in an image and inserting it in a different place in a similar image to duplicate an item or several objects to create a fictitious perspective [11]. The DCT, Gaussian Radial Basis Function (GRBF) kernel, and Principal Component Analysis (PCA) are utilized to evaluate the comparison of copied regions in the current study to identify copy-move forgeries [12].

## **Splicing image**

Image splicing is a method of manipulating images that involves copying a portion of one image and pasting it onto another image. After image splicing, postprocessing operations like local/global blurring, compaction, and scaling are often performed on the images. The image-rich models, which are feature set that has been successfully employed in steganalysis, are first assessed on the spliced image dataset, and the dominant sub-model is chosen to serve as the first sort of feature [13].

## **Morphing image**

The transformation from one picture to another can be accomplished by morphing using an image computing technique known as morphing.  The goal is to get a series of intermediate images when combined with the initial images, that would accurately portray the transition from one image to the next. Interpolation is used in this approach to determine the color of each pixel by comparing the first picture value to the matching second image value and then adjusting for time [14].

## **Retouching image**

The term image retouching refers to the process of removing all of the flaws that are present in an image. This process often involves the adjustment of color and brightness, the removal of blemishes and under-eye circles, and adjustments to the image brightness, contrast, and saturation. Aside from that, the process of image retouching often sometimes comprises an additional step known as airbrushing, which entails erasing specific components from the background of the image or adding things that were absent from the original version of the image [15].

## **Resembling image**

Resembling refers to the process of altering the size of an image's pixels. Resembling can reduce image quality. A picture is downsampled when the number of pixels it contains is reduced, and when it is upsampled, the number of pixels it contains is increased.

## **Tempered image**

Image tempering is a form of digital art that requires a strong visual imagination as well as a grasp of how images work. Image tampering can serve several purposes, including the production of fabricated evidence or the pursuit of artistic fulfillment through the process of digitally generating stunning images [16]. Figure 1 shows an illustration of CMF as given below:

A collage of a person

Description automatically generated with medium confidence

1. **Splicing image**

A picture containing posing, person, person, suit

Description automatically generated

**(b) Morphing image**

A collage of a person

Description automatically generated with medium confidence

**(c) Retouching image**

A butterfly on a leaf

Description automatically generated with medium confidence

**(d) Resembling image**

**,**A picture containing text

Description automatically generated

**(e) Tampered image**

**Figure 1. All types of Digital image forgery [12]**

# **Literature Review**

In this section some related work based on copy move forgery detection technique using faster R-CNN are discussed below:

**Gan et al., (2022) [17]** demonstrated that CMFs have used the massive assault to emphasize or cover the target items in an image by using a homogenous area in the image, which is easy to construct but hard to detect. The currently available CMFD algorithms are incapable of detecting forgeries of such a nature. For this reason, a novel Feature Label Matching (FLM) approach is presented to break down the enormous key points into a variety of distinct little label groups, each of which comprises just a small number of feature points, to considerably improve the matching efficacy and efficiency. Extensive testing findings show that the suggested strategy obtains the greatest F1 scores while incurring the least amount of computing cost.

**Ye et al., (2022) [18]** illustrated that the CMF alludes to the process of copying and pasting a region from the real image into the aim area of the identical image. This represents a typical method of image tampering that has the quality to manipulate and produce high-quality results. Existing single-feature-based approaches to detecting forgeries have several drawbacks, such as a high false alarm rate, limited resilience, and poor detection accuracy.  This work provides an advanced two-stage detection technique that is based on parallel feature fusion and an adaptive threshold creation algorithm. The goal of this method is to overcome the deficiencies that have been identified. According to the findings of the experiments, the suggested technique is superior to the one that is already in use, as it was able to achieve an accuracy of 99.01 percent on the MICC-F220 dataset and 98.5 percent on the MICCF2000 dataset, respectively.

**Zheng and Zhang (2022) [19]** emphasized that to address the high time complexity of the attribute matching stage in the existing CMFD algorithm, a new image CMFD algorithm that clusters feature points using structure tensors and the Hue Saturation Value (HSV) color model has been proposed. In the end, it was determined that the findings demonstrate that the suggested method is capable of efficiently detecting tampered regions, possesses a better advantage in matching time, and possesses strong resilience.

**Krishnaraj et al., (2022) [20]** remarked that it is essential to build reliable forgery detection techniques as there has been an explosion in the number of high-quality images that have been posted on social media platforms and the internet in recent years. The conventional image processing techniques involve the physical search for patterns that are related to the copied material. This severely limits their application in the classification of vast amounts of data. An automated Deep Learning-based Fusion Model (DLFM) is presented in this paper to recognize and localize CMFs. The results of the experiments demonstrated that the suggested model is superior to the techniques that have just recently been devised.

**Babu and Rao (2022) [21]** found that the use of CMFD to search for copied and pasted sections in a single image is helpful. It is extremely important in a variety of contexts, including legal proof, forensic inquiry, defense, and many more. Forgery can be identified in a two-step process, which is detailed in the CMFD approach that has been suggested. The OSVM classifier is performing much better than its competitors, the Optimized Naive Bayes Classifier (ONBC), and the Extreme Learning Machine (ELM).

**Elaskily et al. (2020) [12]** suggested a new model for automatic recognition of copy-move fraud. In this suggested paper, copy-move fraud is dependent on Deep Learning (DL) methodologies. A CNN is a kind of neural network that is specially intended for CMFD. The CNN is used to understand classified feature descriptions from input images that are utilized to distinguish between tampered and untampered images. The three publicly available datasets are mineral-insulated copper-clad cables. With the help of these datasets suggested study shows that the deep CMFD method outperforms typical CMFD systems by a significant margin.

**Agarwal et al. (2020) [22]** suggested a DL technique that provides an effective approach for identifying the copy-move forged image. The suggested approach uses the tampered image as the starting point for detecting the tampered region in our system. This proposed method includes segmentation, the extraction of features, dense depth reconstruction, and, finally, the identification of tampered areas. The suggested deep learning-based method can reduce computing time and improve the accuracy of duplicated region detection.

**Wu, Y et al. (2018) [23]** suggested a novel Deep Neural Network (DNN) named as BusterNet for image CMFD. Unlike other DNNs, BusterNet is a fully trainable architecture from start to finish. The fusion module sits amid a two-branch arrangement. Graphical artefacts and visual commonalities are used by both branches to discover probable manipulation spots and copy-move areas. First of its kind in the CMFD field, this algorithm is capable of separating the sources from the targets. BusterNet training can be accomplished in stages, and methods for producing huge numbers of out-of-field CMFD examples are also offered. BusterNet surpasses state-of-the-art CMFD processes by a significant edge on the 2 widely comprehensible datasets. The Institute of Automation, Chinese Academy of Science (CASIA) is resistant to many common assaults, according to suggested comprehensive research.

**W, Natarajan, et al. (2018) [24]** used the contribution to extending the existing CMFD approach to an extreme level of functionality. The approach can explicitly utilize a CNN to retrieve the block's characteristic from the image and determine the relationship of the several blocks by comparing the region in the fraudulent extraction's convincing feature. This can be incorporated into the existing technique. In addition to being an efficient way to blur, modify, and extract photographs, the approach that has been offered uses this technique. The recommended method has the potential to produce the best possible forgery detection, which in turn can maximize the effectiveness of the outcomes when contrasted to the current level of efficiency in the same area.

**Warif et al. (2016) [25]** suggested CMFD approaches in depth and compare them using block and keypoint-based techniques. The new method was created by the researchers in this suggested study, based on its recent implementation in CMFD. The features and varied tendencies of the CMFD are also discussed. The authors also intended to enhance this strategy by avoiding fresh attacks on their future efforts.

**Nanda et al. (2013) [26]** suggested that non-block-based and block-based algorithms are the two types of traditional CMFD algorithms. The images are separated into corresponding rectangular blocks in block-based algorithms, which differ from method to algorithm. Following that, multiple feature extraction approaches are used to extract features from each block. Block-based algorithms use several feature extraction approaches incorporating frequency transformations, image intensity, consistency, and invariant moments. Ultimately, a matching technique is used to identify related blocks based on their characteristics.

**Muhammad et al. (2013) [27]** employed Zernike moments to identify copy move frauds, for distinguishing image forms. An undecimated wavelet transform is used to find an estimated image. The estimated image is then split into overlapping chunks. Each block's Zernike moments are subsequently retrieved. Finally, the Euclidean distance is preferred to compute the similarity among the blocks. A fast approach has been given to speed up moment computations.

This section contains the comparative study of the literature review shown in table 1.

Table 1 Comparative analysis of literature review

|  |  |  |
| --- | --- | --- |
| **Author Name** | **Technique Used** | **Outcomes** |
| **Gan et al., (2022) [17]** | FLM | It shows that the suggested strategy obtains the greatest F1 scores while incurring the least amount of computing cost |
| **Ye et al., (2022) [18]** | 2- stage detection method | The suggested technique is superior to the ones that are already in use, as it was able to achieve an accuracy of 99.01 percent on the MICC-F220 dataset and 98.5 percent on the MICCF2000 dataset, respectively |
| **Zheng and Zhang (2022) [19]** | HSV color model | The suggested method is capable of efficiently detecting tampered regions, possesses a better advantage in matching time, and possesses strong resilience |
| **Krishnaraj et al., (2022) [20]** | DLFM | The results of the experiments demonstrated that the suggested model is superior to the techniques that have just recently been devised |
| **Babu and Rao (2022) [21]** | OSVM | The OSVM classifier is performing much better than its competitors, the ONBC, and the ELM. |
| **Elaskily et al. (2020) [12]** | CNN | It shows that the deep CMFD method outperforms typical CMFD systems by a significant margin. |
| **Agarwal et al. (2020) [22]** | DL | It can reduce computing time and improve the accuracy of duplicated region detection. |
| **Wu, Y et al. (2018) [23]** | BusterNet | BusterNet surpasses state-of-the-art CMFD processes by a significant edge on the 2 widely comprehensible datasets. |
| **W, Natarajan, et al. (2018) [24]** | CNN | It has the potential to produce the best possible forgery detection, which in turn can maximize the effectiveness of the outcomes when contrasted to the current level of efficiency in the same area. |
| **Warif et al. (2016) [25]** | Keypoint-based technique | The new method was created by the researchers in this suggested study, based on its recent implementation in CMFD. |
| **Nanda et al. (2013) [26]** | Block-based algorithms | It can generate the best forgery detection, which can maximize results compared to current efficiency. |
| **Muhammad et al. (2013) [27]** | Undecimated wavelets transform | It finds 98.26% copy-move blocks with 3.34% false positives, while the other two approaches have less than 92% accuracy and over 9% false positives. |

# **Background Study**

It is suggested a new structure for automatically finding CMF based on DL technology that CNN is precisely intended for CMFD. The CNN is utilized to classify feature descriptions by incoming images, which are utilized for detection of the interfered and exact images. The extensive research shows that the suggested deep CMFD algorithm outperforms the conventional CMFD systems by a significant margin on the 3 datasets: MICC-F2000, MICC-F220, and MICC-F600. Also, these 3 datasets are incorporated and affiliated to the SATs-130 dataset to form the latest groupings of datasets. The precision of one hundred percent has been attained for the 4 datasets applying fifty epochs. This illustrates the robustness of the proposed approach when compared against several different known assaults, and to provide a more accurate estimation, comparative results are combined [12].

# **Research Objective**

Following are the research objective of the proposed methodology:

* To study and evaluate the state-of-art Literature for CMFD.
* To propose novel image forgery detection techniques using fast Region-Based CNN.
* To assess the effectiveness of the research approach using efficiency evaluation metrics established in the scientific literature.
* To validate the research outcome via comparison with state-of-art Literature techniques.

# **Problem formulation**

Image alteration techniques such as area duplication CMF are becoming more popular as strong editing software and sophisticated digital cameras become available. The majority of available methods for detecting this kind of temper are hampered by their inability to deal with large amounts of data. DL algorithms like CNN are often employed for learning and tempered/original categorization in autonomous processes in general. With CNN, various issues have an impact on the overall results and also vary, dependent on the application. For example, the item can cover a large portion of the image in some circumstances but just a tiny portion of the image in others. The computational cost has gone up for the increasing number of areas needed. As a result, the suggested approach can be used to pick the area to address this issue and minimize the number of regions. As a computing approach, quicker R-CNN is employed in the present study to identify and classify the forged image. A DFT coefficient for each block adds a parameter to improve the classification's performance, as well. A pixel is also used in the works as a forgery detecting element.

# **Important Techniques used in Proposed Methodology**

Following are the important techniques used in the proposed methodology:

* 1. **CNN**

CNN is also known as ConvNet and it is a category of Artificial Neural Network (ANN) with a deep feed-forward construction and incredible simplifying capability when associated with more networks with fully connected (FC) layers [28].

This can grasp highly conceived elements of things, especially spatial data, and can identify them efficiently. A deep CNN architecture consists of a constrained number of computational layers, each of which is capable of learning many tiers of abstractions from the image it is fed as input. The initiatory stages are responsible for learning and extracting the higher-level traits, whereas the deeper layers are responsible for learning and extracting the lower-level characteristics [28] Figure 2 depicts CNN's core conceptual paradigm.

Input

Convolution Layer

Pooling Layer

Convolution Layer

Pooling Layer

Convolution Layer

Pooling Layer

Fully Connected Layer

Output

**Figure 2. CNN [28]**

* 1. **Region of Interest** (**ROI)**

ROI detection has been used to identify the item in an image in a variety of applications which include security surveillance, medical imaging, database, and remote sensing imaging. The categorization of the ROI of an image can be done manually or automatically. Most research has been conducted to create automatic ROI identification utilizing image segmentation techniques; the amount of image segmentation used relies on the application's ultimate solution. Many alternative strategies for detecting ROI have been suggested [29].

* 1. **Discrete Cosine Transform (DCT)**

It decomposes a signal into a succession of harmonic (cosine) functions, the DCT is analogous to the DFT. The DFT is a cut-down variant of the DCT. The major reason is image compression, which has turned out to be useful in various applications [30.

### Feature extraction

It is required to reduce the number of resources without losing any important or relevant information. It removes all the redundant data from the data set. Image-based characteristics such as form, texture, and statistical data have been extracted using a feature extraction approach [30].

# **Research Methodology**

This section shows the proposed methodology. The following steps are as follows:

* **Step1 (Input Image):**

An image is used as an input to the CNN model. CNN allocates significance to different objects in the image and is capable to distinguish one from the other.

* **Step 2 (Region detection Function):**

In step 2, the region detection Function is used for feature extraction of the given dataset of the image which is an important step in the process of the proposed methodology because extracting the features from the input data, improves the accuracy of learned models.

* **Step 3 (Feature ROI Pool):**

Feature ROI pool is a combination of CNN and region detection Function input. A feature ROI pool is also called a node at which two inputs are met for further process.

* **Step 4 (Classification Layers):**

After running the input picture through the ROI pool in step 4, the next step is to categorize the input image. This is done by using the classification layer, which is used for categorizing the output at separate layers.

* **Step 5 (Final Outcomes):**

In this last step, finally, the desired results are reached by classifying the output at each layer. The input picture is exactly identified as faked or not in this method. Figure 3 shows the pictorial representation of the planned methodology.

Diagram

Description automatically generated

**Figure 3. Pictorial representation of the proposed methodology**

Figure 4 shows the detailed process of the region detection function. In this image, a suspect image is used as an input for block dividing. The Block dividing system divides the image into blocks. The resultant image now follows the DCT transform. DCT transform and Dimension reduction are used for getting feature extraction. Finally, the extracted feature reaches the ROI pool.

Diagram

Description automatically generated

**Figure 4. Detailed diagram for Region Detection Function**

# **Result and discussion**

In this part, a detailed description of the findings achieved using the proposed DFT Coefficient method-based CMF detection technique using faster R-CNN is presented. Overall system performance is significantly influenced by how many training sessions have been completed. Models that employ several epochs take longer to develop their most accurate feature maps, and this is because of the connection between the two variables.

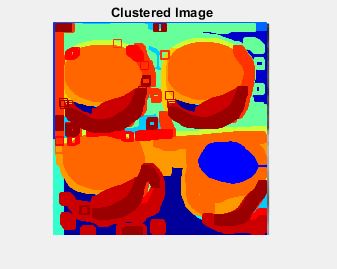
* **Result 1**

The proposed algorithm is tested with both a real and a fake image to detect whether the image is forged or not. During the color fastness testing, it is utilized for the evaluation of color change as well as staining. Figure 5 shows the original image that is taken to convert it into a grey scale.

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**Figure 5 Original image**

* **Result 2**

![A group of toilet paper rolls

Description automatically generated with medium confidence](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEAYABgAAD/4RDQRXhpZgAATU0AKgAAAAgABAE7AAIAAAADSFAAAIdpAAQAAAABAAAISpydAAEAAAAGAAAQwuocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFkAMAAgAAABQAABCYkAQAAgAAABQAABCskpEAAgAAAAM1MgAAkpIAAgAAAAM1MgAA6hwABwAACAwAAAiMAAAAABzqAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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amount of training periods is a crucial variable that has a significant impact on the outcome of the suggested algorithm. After getting a grey image it is converted into a clustered image with the help of the clustering technique Figure 6 (a) shows a greyscale image of the original image that is taken initially to conduct the test and figure 6 (b) shows the clustered image.

**Figure 6 (a) Greyscale image and (b) clustered image**

* **Result 3**

Finally, it classified the outcome of the image. Based on the extracted features the proposed algorithm detected that the original image that is taken initially is forged which means the image initially taken is a fake image. Figure 8 shows the resulted image.

![Chart, bubble chart

Description automatically generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEAYABgAAD/4RDQRXhpZgAATU0AKgAAAAgABAE7AAIAAAADSFAAAIdpAAQAAAABAAAISpydAAEAAAAGAAAQwuocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFkAMAAgAAABQAABCYkAQAAgAAABQAABCskpEAAgAAAAMyMwAAkpIAAgAAAAMyMwAA6hwABwAACAwAAAiMAAAAABzqAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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**Figure 7 Result image**

* **Result 4**

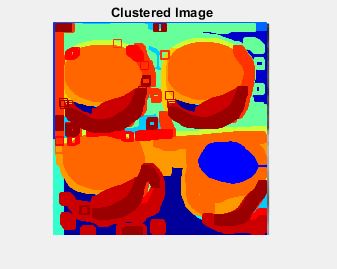
Now this time a real image is tested in the proposed model to check the accuracy of the proposed system. Initially, a real image is taken as a test case to convert it into a greyscale image. Figure 8 shows the original image.



**Figure 8 Original image**

* **Result 5**

The number of training periods is a key factor that has a big effect on how well the suggested algorithm works. After getting a grey image it is converted into a clustered image with the help of the clustering technique Figure 9 (a) shows a greyscale image of the original image that is taken initially to conduct the test and figure 9 (b) shows the clustered image.

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**Figure 9 (a) Greyscale image and (b) clustered image**

* **Result 6**

Finally, it classified the outcome of the image. Based on the extracted features the proposed algorithm detected that the original image that is taken initially is not a forged image which means the image initially taken is a real image. Figure 10 shows the resulted image as given below:

![Application

Description automatically generated with low confidence](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEAYABgAAD/4RDQRXhpZgAATU0AKgAAAAgABAE7AAIAAAADSFAAAIdpAAQAAAABAAAISpydAAEAAAAGAAAQwuocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFkAMAAgAAABQAABCYkAQAAgAAABQAABCskpEAAgAAAAM2MAAAkpIAAgAAAAM2MAAA6hwABwAACAwAAAiMAAAAABzqAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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**Figure 10 Resulted image**

# **Conclusion and future scope**

As editing software and digital cameras improve, area duplication and copy-move forgeries grow increasingly prevalent. Most approaches for detecting temper can't handle big volumes of data. CNN is commonly used for autonomous learning and tempered/original classification. CNN's overall outcomes depend on the application and several factors. In some cases, the object can cover a considerable section of the image, but in others, only a little piece. The computational cost has risen due to more needed regions. The provided technique can be utilized to identify the area to solve this issue and reduce regions. The current work uses faster R-CNN to recognize and categorize counterfeit images. The suggested method has been tested on a variety of datasets and puts through its paces under a wide range of copy-move scenarios, which include solo or sequential cloning with a variety of cloning regions. The result revealed that the suggested method shows a high accuracy rate in detecting the forgery in images than other traditional methods. In future work, CNN modification could be carried out to further accelerate the suggested algorithm. In addition, more difficult datasets could be studied as a means of putting the proposed algorithm through its paces. In addition, methods from the field of DL can be utilized to identify various kinds of digital image fraud.