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IMPROVED FORENSIC TECHNIQUE FOR EXPOSING REGION DUPLICATION FORGERY BY KEY BASED WITH GREY WOLF OPTIMIZATION

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Abstract - Copy-Move is done with the intention either to cover truth or to make some enhancement in the visual effects of the image. The copy-move tampering can be performed in a credible manner without much difficulty. But still copy-move tampering is practically difficult to detect. Therefore, it is likely that this kind of tampering can be often applied to forge an image. For example, courts of law, where images are presented as basic evidence, its verification plays a crucial role as images can be edited to change its meaning and thus influence the judgment. The basic challenge in copy-move forgery detection is the process of overlapping features, which come because of non-linearity of features. So, the reduction of overlapping uses grey wolf optimization layers which refine the non-linearity by means of sigmoid and TANH functions. The results obtained helps in presenting the grey wolf optimization by upgrading the sigmoid activation function, thus improving the results significantly. Within the last few years' because of existence of high resolution and cheap digital cameras, there is massive quantity of digital images worldwide. Likewise with help of super easy tools of photo editing, any kind of non-professional may change image. Any kind of image treatment may become a forgery, if it alters semantic (logic or language) of real image. There may be multiple reasons for any forgery to become occurred with a forger just like: to cover items within a picture to be able to possibly produce fake proof, to help make the image nicer for overall look, to cover something in picture, to give emphasis to a specific objects and so forth. There are numerous methods to categorize the digital graphic forgery, yet main types of digital photo forgery consists of splicing, enhancing, morphing, retouching, and copy move.

Key words: ***Grey wolf optimization, image forensic, forgery detection, algorithm***

1. INTRODUCTION

In the era of digital images, it is possible to have a tampering effect. Rapid advancement in various techniques helps attackers to modify the contents of digital images. The intelligent use of digital image editing software is continuously increasing the difficulty in distinguishing the authentic photograph from the tampered one. In copy-move tampering, the portion of an image region is copied and moved at a different location of the same image. Splicing is a particular case of copy-move tampering, where the copied part of one image is pasted on some location of different image. Copy-Move is done with the intention either to cover truth or to make some enhancement in the visual effects of the image. The copy-move tampering can be performed in a credible manner without much difficulty but the copy-move tampering can be practically difficult to detect. Therefore, it is likely that this kind of tampering can be often applied to forge an image. In courts of law, where images are presented as basic evidence, its verification plays a crucial role as images can be edited to change its meaning and thus influence the judgment. Many prominent personalities of film industry have also been victimized by image tampering. It has begun such an era where seeing is no longer believing. It is thus important to prove the authenticity of the image and bring the truth towards the world.

1.1 Copy-Move Forgery

The digital image forensics can be broadly classified into three branches as Image source identification, Computer generated image identification and Image forgery detection. The image forgery detection techniques can again be classified into many categories like, geometry-based technique, format-based technique, camera-based technique, physics-based technique and pixel-based technique. Many tools are available for doing the copy move in Photoshop, proliferation digital cameras, digital signatures, watermarking etc. Copied areas are usually textured regions Thus, it is very much important to have a detection system that automatically identifies the copied move forgery areas, because it may hide some important details and can even change the contents of the image.

1.2 Digital Image Forgery Attack

In this era due to presence of low-cost and high-resolution digital cameras, there is wide number of digital images all over the world. Digital images play a very important role in areas like forensic investigation, insurance processing, surveillance systems, intelligence services, medical imaging and journalism. But the basic requirement to believe what we see is that the images should be authentic With the availability of powerful image processing software's like Adobe Photoshop it is very easy to manipulate, alter or modify a digital image. Any image manipulation can become a forgery, if it changes semantic of original image. There can be many reasons for a forgery to be occurred by a forger like: To cover objects in an image in order to either produce false proof, to make the image more pleasant for appearance, to hide something in image, to emphasize particular objects etc..

1.3 Types of Digital Image forgery

There are many ways to categorize the digital image forgery, but main categories of Digital image Forgery are Enhancing, Retouching, Splicing, Morphing and Copy/Move. Following is brief description of different types of digital image forgery:

a. Image Enhancing

Image enhancing involves enhancing an image with the help of Photoshop such as saturation, blur and tone etc. These enhancements don't affect image meaning or appearance. But somehow effects the interpretation of an image. Enhancing involves changing the color of objects, changing time of day in which the image appears to have been taken, changing the weather conditions, Blurring out objects.

b. Image Retouching

It is basically used to reduce certain feature of an image and enhances the image quality to capture the reader's attention. In this method, image editors change the background, fill some attractive colors, and work with hue saturation for toning.

c. Image Splicing

In image splicing different elements from multiple images are pasted into a single image. At last, one image is obtained from content of different images.

d. Image Morphing

Image morphing is defined as a digital technique that gradually transforms one image into another. Transformations are done using smooth transition between two images.

e. Copy-Move

In copy-move forgery one region is copied from an image and pasted onto another region of the same image. Therefore, source and the destination both are same. Copy Move involves copying regions of the original image and pasting into other areas. This forgery can alter the meaning of the original image .Copied areas will likely mix with the background for the images with textured areas, such as grass, foliage with irregular patterns, it will make difficult for the human eye to detect dubious artifacts. Forgery detection methods that look for incompatibilities in different parts of the image cannot detect this copy-move forgery because of the copied portions come from the same image, most of its important properties will be compatible with the remaining part of the image. Feathered crop or the retouch tool can again mask any indication of the copy-moved segments and make the detection task even harder.

1.4 Copy Move Forgery Attack

Copy-Move is a type of forgery in which a part of image is copied and then pasted on to another portion of the same image. The main intention of Copy-Move forgery is to hide some information from the original image. Since the copied area belongs to the same image, the properties of copied area like the colour palette, noise components, dynamic range and the other properties too will be compatible with the rest of the image. So, the human eye usually has much more trouble detecting copy-move forgeries.

Also, forger may have used some sort of retouch or resample tools to the copied area so as it becomes even more difficult to detect copy-moved forgery Retouching involves compressing the copied area, adding the noise to the copied area etc. and re-sampling may include scaling or rotating the image. For example: An image from the crime scene is taken. Fig. 1 shows the original image and fig. 2 shows the forged image. Forgery is done to hide some important evidences.

Fig. 1.1 Original Source Image

Fig. 1.2 Output Forged Image

2. PROPOSED METHODOLOGY

2.1 Proposed Flowchart

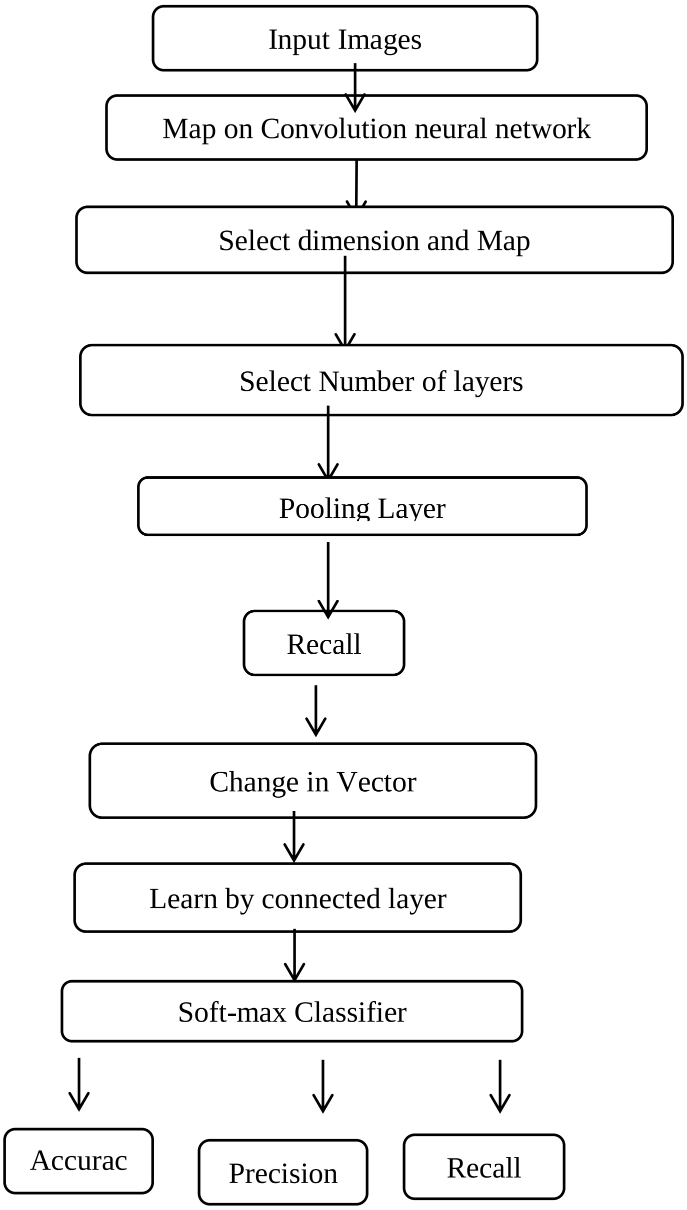


Fig 1 Flow Chart of Methodology

2.2 ALGORITHM

- Input the Images.
- Map the input images on the convolution neural network.
- Select the Dimension and map of the images.
- Select the layers in the CNN.
- If the large count <1 then go to step 6 otherwise go back to step 3.
- Pooling layer changes the values of the vector.
- Learn by the connected layer.
- The output of the connected layer is used by the SoftMax classifier for classification.
- Make the model for the analysis.
- Calculate the values of Accuracy, Precision, and Recall

2.3 Steps of Methodology

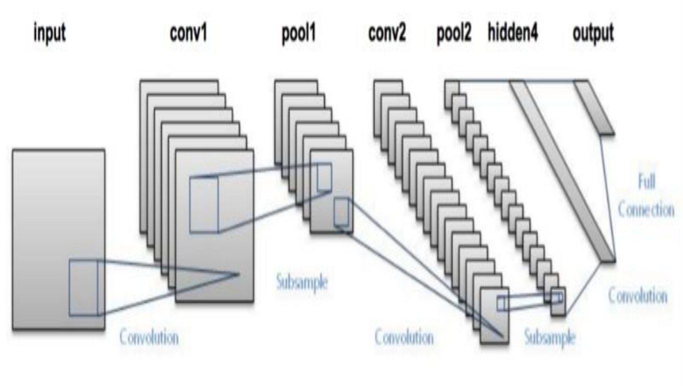
Step1: Input Dataset with static and fixed size. After inserting the image pre-process the image. After pre-processing the image provide input to the image matrix for segmentation. fig 4.1 shows the segmentation.

Step2: Initialize segmentation process randomly and apply clustering on it. After clustering process initialize the object in swarm intelligence and reduce the errors of overlapping boundaries by objective function.

Step3: After this fitness function will update the boundaries value iteratively till it converges the error of object boundary.

Step4: After segmentation segmented image is inserted in deep learning. In this process segmented image will change in data matrix. In data matrix apply convolution, activation function and pooling layers as show in fig

Convolutional Neural Networks (CNN), were first introduced by Yann LeCun's in 1998 for Optical Character Recognition (OCR), where they have shown impressive performance on character recognition. CNN is not just used for image related tasks, they are also commonly used for signals and language recognition, audio spectrograms, video, and volumetric images.



CNN uses multiple layers in its architecture. Following are the layers used to build convolutional neural network architectures.

Convolutional Layer

Activation Layer

Pooling Layer

Fully-Connected Layer or Densely Connected Layer

Output Layer or Softmax Layer for classification

CNN architecture is explained in detail in section 3.

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Convolutional Layer

Convolution Layer provides a convolution operation, in which a 2-D or 3-D filter of appropriate size sweeps over an image and apply the filters to each depth of an image. The convolutional layers are restricted version of the Multi-Layer Perceptron (MLP) adapted to take a 2D / 3D inputs instead of 1D. The idea behind convolutional layers is to detect elementary features such as edges, corners, and endpoints, and combine them using multiple layers to get high-level features that might describe an object completely.

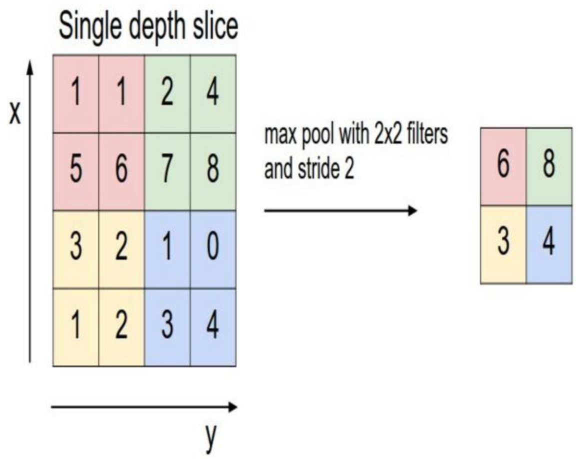
Moreover, this architecture is designed for high-level features extraction from an image at any given layer to describe an object like face, chair, or a car. In addition to this, convolution also provides an important and valuable feature attribute called shift invariance. That is, if the input to the first layer is shifted, then the output of the first layer is also shifted by the same amount. Convolution has 2 main parameters which can change the behavior of convolution, like stride and padding.
Output of the convolution layer is calculated as per the following formula.

$$W_{new} = \frac{(W_{old} - F_{width} + 2P)}{S} + 1[22]$$

F_{width}: Filter or Kernel size as in width and height parameter while using respective formula.
P: Padding
S: Stride window size for convolution
W_{new}: New width of the output image
W_{old}: Old width of the input image

Pooling Layer

Pooling is a method of reducing the feature size in width and height of an input. The pooling operation sweeps a rectangular window over the input feature and computes a size reduction operation for each window (average, max, or max with arg max). Each pooling operation uses rectangular windows of size k, separated by offset strides. For example, if strides are all ones every window is used, if strides are all twos every alternative window is used in each dimension. a simple way of reducing the precision for the position from where distinctive features are located in the feature map. Since the exact position of the feature is irrelevant, only its position in relation to the other features is of importance, especially for classification tasks.



Pooling layer output is calculated as per the following formula.

$$W_{new} = \frac{(W_{old} - F)}{S} + 1[22]$$

W_{new}: New Width for the output image

W_{old}: Input image width

F: Filter Width size

S: Stride size

This formula is used for the output image width calculation, and same can be used to calculate the resulting height of an output image from the pooling layer by changing width parameter with the height parameter.

Activation Function

The activation function is really important to the deep neural network, which is complicated and complex. They bring non-linearity property to neural networks. The main property of an activation functions is to convert an input signal to output signal. This is used in every node of the deep neural network for abstraction representation of action potential firing the node. If we don't use the activation function, the output mapping function will be, by default a linear function, which linearity is less effective towards learning of complex function boundaries of the input data. Following are some of the activation functions explained in detail.

Step5: After activation function collects the feature score this feature score is compared by query image by cosine similarity. After that cosine similarity selects top K images for output and analyzing precision and recall.

2.4 Algorithm Used

GWO: Grey wolf optimization: Grey wolf optimization is fundamentally roused by the genuine ant settlements conduct and called artificial framework. Through the charts the Grey wolf optimization calculation (GWO) is utilized for the taking care of computational problems and discovering great way. Like ant conduct, looking for way between food source and their colony to look through an ideal way comparative is the principle point of this calculation. To take care of the problem of traveling salesman problem (TSP) the principal GWO was created. Prior to the pheromones are refreshed along their food source trail on change probability bases a probability decision is made in the standard GWO. Before refreshing the pheromones along their trail to a food source in the standard GWO, which depends on the progress probability, ants settles on a probabilistic decision. For the kth ant the change probability at the time step t from city x to city y in the TSP problem:

$$PROB_{xy}^{k}(t) = \begin{cases} \frac{[\tau_{xy}(T)]^{\alpha}.[\eta_{xy}]^{\beta}}{\sum_{y \in I_x^k}[\tau_{xy}(T)]^{\alpha}.[\eta_{xy}]^{\beta}} \text{ if } j \epsilon I_x^k \\ 0 \quad\quad Otherwise \end{cases} \quad [24] \ldots\ldots (3)$$

Where

η_{xy} ← Priority heuristic information,

τ_{xy} ← Pheromones trail amount on the edge (x, y) at the time T,

The pheromone trail and heuristic information relative effects are identified by two factors i.e., α and β. And the city's neighborhood set that are reasonable is denoted by I_x^k.

After a visit is finished by every ant, a constant dissipation rate at first bringing down them which refreshed the pheromone trail. Inferable from which every ant is permitted effective pheromone affidavit on curves which is its visit part as appeared in the condition underneath:

$$\tau_{xy} = (1-\rho).\tau_{xy} + \sum_{k=1}^{N} \Delta\tau_{yx}^{k} \quad [24] \ldots\ldots (4)$$

Where

ρ ← Pheromones rate of trail evaporation,

N ← no. of ants,

The pheromone trail that is boundless aggregated is averted by the utilization of parameter ρ which empowers the awful choices to be overlooked by the calculation. The no. of cycles declining the pheromone quality related on circular segments which ants don't choose. $\Delta\tau_{yx}^{k}$, the trail substance quality per unit length which lays nervous (y,x) is given as takes after:

$$\Delta\tau_{yx}^{k} = \begin{cases} \frac{Q}{L_k} \; if \; ant \; k \; in \; its \; tour \; uses \; edge \; (y,x) \\ 0 \quad\quad Otherwise \end{cases} [24] \ldots\ldots (5)$$

Where

Q ← constant that is predefined,

L_k ← Length of the tour

3. RESULT AND DISCUSSION

3.1 Performance Metrics

The following quantitative metrics are used to evaluate the performance of the present work.

- ***Accuracy:*** Accuracy is the starting point for a predictive model quality analyzing, as well as for prediction obvious criterion. Accuracy measures the ratio of correct predictions to the total number of cases evaluated.

Accuracy = TP+TN / (TP+TN+FP+FN)[32]

Where,

TN is the number of true negative cases

FP is the number of false positive cases

FN is the number of false negative cases

TP is the number of true positive cases

- ***Precision:*** Precision (P) is defined as the number of true positives (T_p) over the number of true positives plus the number of false positives (F_p). Precision = TP / (TP+FP)
- ***Recall:*** Recall (R) is defined as the number of true positives (T_p) over the number of true positives plus the number of false negatives (F_n). Recall = TP / (TP+FN)
- ***True positive rate:*** TPR refers to the positive samples proportion which predicts correctly as shown below:

$$TPR=\frac{TP}{TP+FN}[32]$$

- **False Positive Rate:** FPR refers to the false positive rate expectancy. It is calculated as the ratio between wrongly categorized negative case numbers as positive (FP) and actual negative numbers in total.

$$FPR=\frac{FP}{FP+TN}[32]$$

3.2 Detection

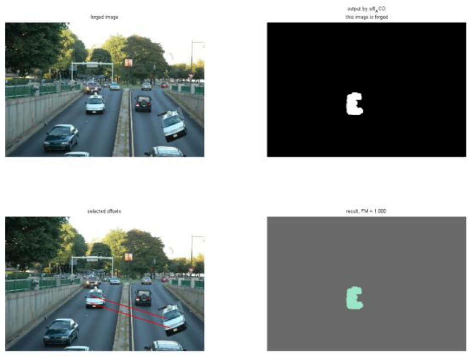


Fig5.1: Analysis of SIFT _CNN features Detection

In fig5.1 show, the detection of forgery part by SIFT feature convoluted by convolution process and then matching based on collected masking of features which show in fig 5.1. In fig 5.1 four subfigure first is original second and fourth is masking and third show detected part of image .its recognized because of copy-move detection algorithm that was developed a feature refinement by kernels in convolution layer then map on polling after that learning so overlapping of features will reduce

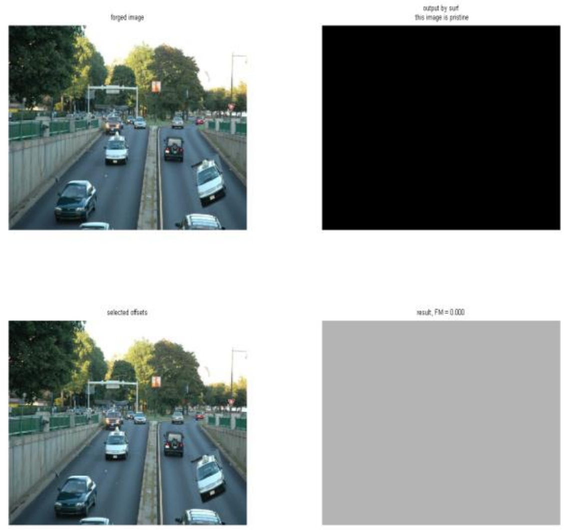


Fig 5.2: Analysis of SIFT _REGION features Detection

In fig5.2 show the detection of forgery part by SIFT feature region process and then matching based on collected masking of features which show in fig 5.2. In fig 5.2 four subfigure first is original second and fourth is masking, and third show detected part of image tested images used for the comparison with 512 × 512 size. The phase correlation values that are used (0.392617, 0.702759, and 0.659926) in three levels respectively. The number of rows "p" for phase correlation comparison is "4". The padding values "m" (2, and 4) for the tseiga two levels respectively.

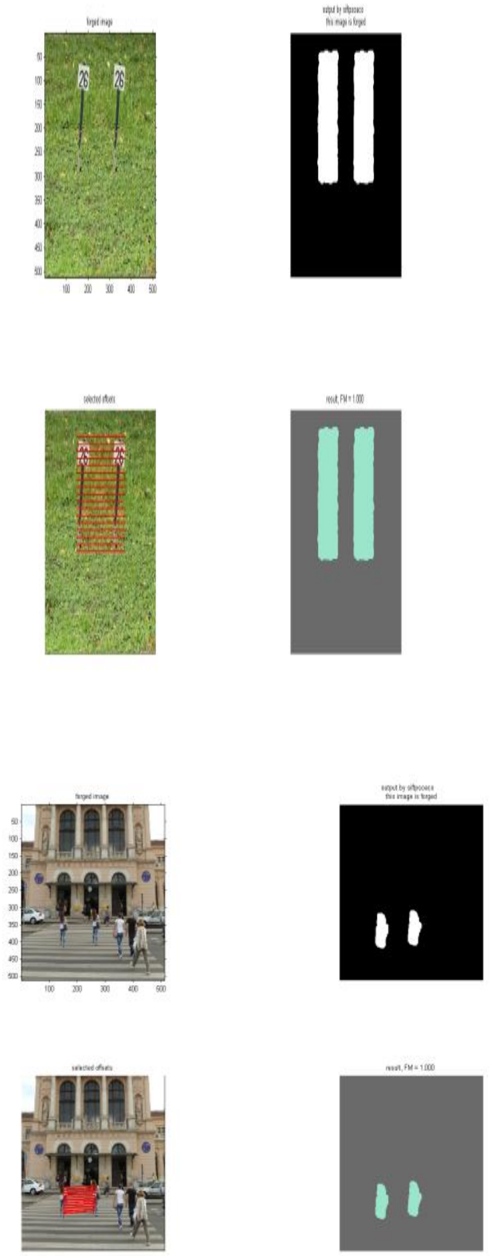


Fig 5.3:SIFT_Region

In fig5.3 show the detection of forgery part by SIFT feature region process and then matching based on collected masking of features which show in fig 5.3. In fig 5.3 four subfigure first is original second and fourth is masking, and third show detected part of image . Get all overlapped block in reference region by extracting the resulting pixel values by rows into a row of matrix "refReg", and store the topleft co-ordinates "indRef".. Get all overlapped block in matching region by extracting the resulting pixel values by rows into a row of matrix "matchReg" and store the top-left co-ordinates "indMatch".

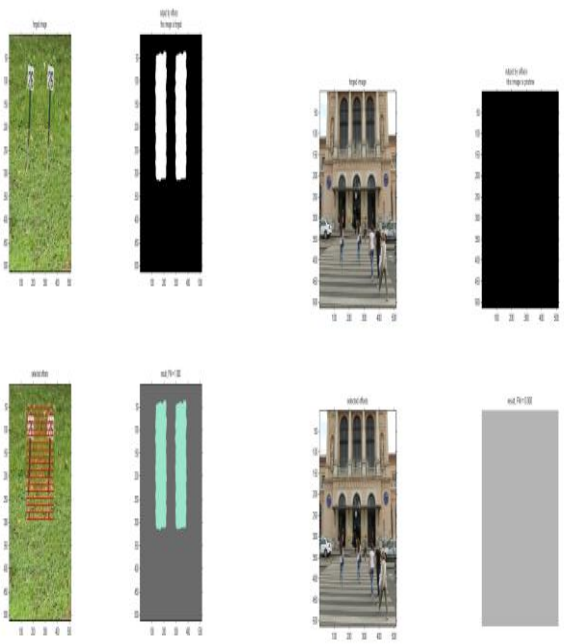


Fig 5.4 SIFT_CNN

In fig5.4 show, the detection of forgery part by SIFT feature convoluted by convolution process and then matching based on collected masking of features which show in fig 5.4. In fig 5.4 four subfigure first is original second and fourth is masking and third show detected part of image . Compare the current row with block corresponding to "p" rows below the current row. If the computed maximum phase correlation value exceeds a preset threshold value "t", then store the top left coordinates of the corresponding reference block and the matching block from the "index" matrix in a new row of a matrix

3.3 Results and Graphs

The following section shows the tales and graphs showing the results of implementation to calculate values of various parameters.

Table 2: Precision Value for Different Classifier

Classifier	Precision
SIFT with GWO(polynomial)	0.8917
Surf(Gaussian)	0.4714
SIFT_CNN (Gaussian)	0.9
Surf(polynomial)	0.4737

In table 2 depicts the precision of the four classifiers that are SIFT with GWO (polynomial), surf(Gaussian), SIFT with SIFT_CNN(Gaussian) and surf(polynomial). The graph show the maximum precision is on SIFT with SIFT_CNN (Gaussian) classifier and minimum is on surf(Gaussian).proposed approach improve precision up to 90%.its increase compare to others approach it nearby optimization of SIFT features. Reason of results near to indicate optimization improve at well but convolution more optimization then others

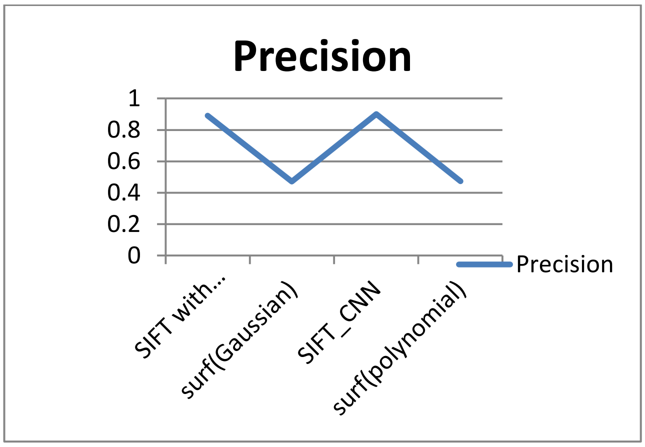


Fig 5.5 Graph showing the precision for different classifiers

Figure 5.5 depicts the precision of the four classifiers that are SIFT with GWO (polynomial), surf(Gaussian), SIFT with SIFT_CNN(Gaussian) and surf(polynomial). The graph show the maximum precision is on SIFT with SIFT_CNN (Gaussian) classifier and minimum is on surf(Gaussian).if analysis the SIFT _CNN its improve as much but surf base features not improve because not able to detect minute information.

Table 3: Accuracy Value for Different Classifier

Classifier	Accuracy
SIFT with GWO(polynomial)	0.8896
Surf(Gaussian)	0.6153
SIFT_CNN (Gaussian)	0.8979
Surf(polynomial)	0.6193

In table 3 depicts the accuracy of the four classifiers that are SIFT with GWO(polynomial), surf(Gaussian), SIFT with SIFT_CNN (Gaussian)and surf(polynomial).SIFT with SIFT_CNN (Gaussian) shows the maximum accuracy classifier and minimum is on surf(Gaussian).surf features accuracy 61% in same polynomial or Gaussian because it not improve its mapping also. But proposed approach much improve because of SIFT features and the layer wise optimization. In proposed approach approx. 89.79% but same or nearby accuracy by 88.96% by SIFT with GWO. its show SIFT features improve the results compare to surf features.

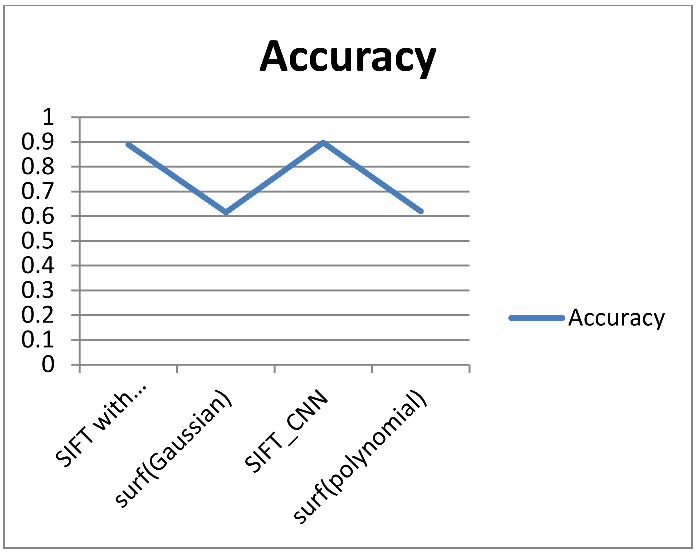


Fig 5.6 Graph showing the accuracy value for different classifiers

Figure 4.6 depicts the accuracy of the four classifiers that are SIFT with GWO(polynomial), surf(Gaussian), SIFT with SIFT_CNN (Gaussian)and surf(polynomial).SIFT with SIFT_CNN (Gaussian) shows the maximum accuracy classifier and minimum is on surf(Gaussian).its reason to improve block base and key based features and other reason is optimization base approach using GWO and gradient descent. Surf base features not improve more than 61-62% but key based features improve in convolution and other optimization

Table 4: Recall Value for Different Classifier

Classifier	Recall
SIFT with GWO (polynomial)	0.888
Surf(Gaussian)	0.4703
SIFT with SIFT_CNN (Gaussian)	0.8963
Surf(polynomial)	0.4726

In table 4 overlapped blocks are excluded. Since many overlapping blocks is confront when making comparisons between the candidate blocks that resulted from various steps in algorithm. The FFT is calculated for each block one time before processing (i.e. no need to calculate it at each comparison). improved method can accurately and quickly reveal the doubled regions of a tampered image. In addition, the processing time is greatly reduced compared with khan algorithm, while keeping accuracy at the same level.

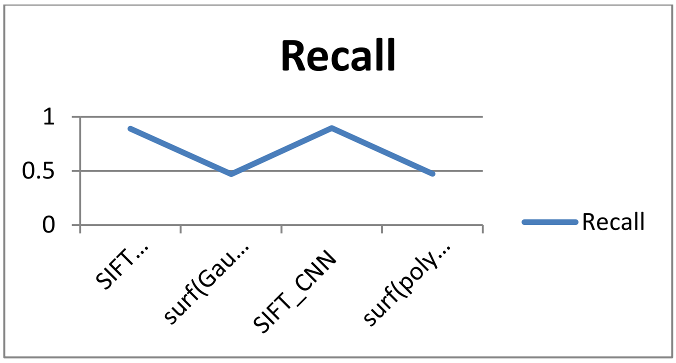


Fig 5.7 Graph showing the Recall value for different classifiers

Figure 5.7 depicts the recall of the four classifiers that are SIFT with PSO(polynomial), surf(Gaussian), SIFT with SIFT_CNN(Gaussian)surf(polynomial).SIFT with GWO(Gaussian) shows the maximum recall classifier and minimum is on surf(Gaussian). Methods does not work well with complex scene image(this type image have large number of key points and triangle.).In case of proposed method, number of circle is less than number key-points. therefore, Proposed method word well in case of complex image comparative reference method.

Table 5: Comparison between parameters (Precision, Accuracy, Recall) of different classifiers

Classifier	Precision	Accuracy	Recall
SIFT with GWO(polynomial)(SA)	0.8917	0.8896	0.888
Surf(Gaussian)	0.4714	0.6153	0.4703
SIFT_CNN	0.9	0.8979	0.8963
Surf(polynomial)	0.4737	0.6193	0.4726

In table 5 different types of techniques to detect copy-move image forgery. The analyzation of the studies still suffers from some drawbacks. There is need to investigate image region transformation so that copy-move attacks can be easily detected. The proposed study focuses on the detection of copy-move attack on digital images. The image region transformation includes rotation, rescale and reflection in copy-move forgery. The rotation invariant with block based copy-move forgery detection method is used which shows better results as compared to blur invariant copy-move forgery detection and provides accuracy rates between 90%

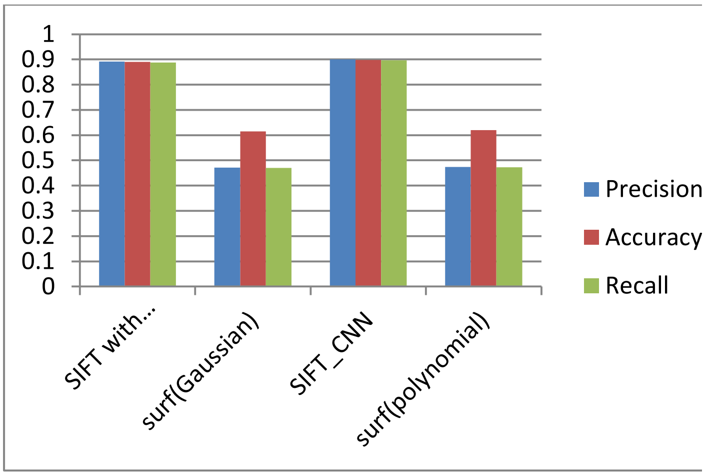


Fig 5.8 Graph showing the comparison of all the parameters

In fig 5.8 After uploading the tampered image, the object in the image rotated using rotation invariant method and a grayscale image is produced while clicking on grayscale button. When the image gets converted into grayscale it is signified into blocks and a CNN. The CNN transform is a portrayal of a picture of complex exponentials of fluctuating extents, frequencies, and stages. The Fourier transform assumes a basic part in an expansive scope of picture handling applications, including improvement, investigation, rebuilding, and pressure.

cross validation	Precision(SA)	Accuracy(SA)	Recall(SA)
1'	0.867	0.874	0.8744
2'	0.89003	0.8244	0.8424
3'	0.9023	0.8533	0.89242
4'	0.88	0.90233	0.9022
5'	0.9012	0.92344	0.89

In table 6 depicts the precision of the four classifiers that are SIFT with GWO(polynomial), surf(Gaussian), SIFT with SIFT_CNN (Gaussian)surf(polynomial). This figure shows the comparison of Precision, recall and accuracy on the different classifiers. The overall good result of the SIFT with SIFT_CNN(Gaussian) Classifier. Its improve the proposed approach compare to other existing approach because of different hidden layers using sigmoid function .sigmoid function non linear mapping. If analysis surf features precision not improve as much but deep learning base SIFT_CNN in different validation improve accuracy, precision and recall.

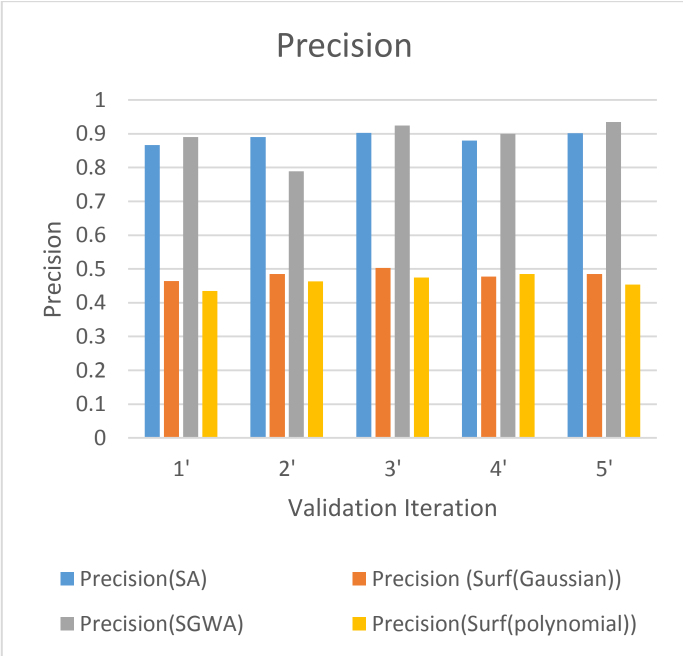


Figure 5.8 depicts the precision of the four classifiers that are SIFT with GWO (polynomial), surf(Gaussian), SIFT with SIFT_CNN (Gaussian)surf(polynomial). This figure shows the comparison of Precision. The overall good result of the SIFT with SIFT_CNN(Gaussian) Classifier. In proposed approach SGWA improve the precision in different validation iteration. If analysis the fig5.8 in starting analysis different approaches like sift base, surf base feature bu proposed approach use deep learning approach which convoluted features the mapping in different activation which abstract and optimize the features.so result will improve 93.44%.its indicate convolution more generalize the features compare to others.

4. CONCLUSION AND FUTURE SCOPE

4.1 conclusion

In this thesis authors have done analysis to evaluate the performance of previously proposed feature sets. They aim to answer which copy-move forgery detection algorithms and processing steps perform best in various post-processing scenarios. They achieve this by casting existing algorithms in a common pipeline. In this paper, the 15 most prominent feature sets are examined. Detection performance was analysed on a per-image basis and on a per-pixel basis. Authors created a challenging real-world copy-move dataset, and a software framework for systematic image manipulation. Experiments show, that the Key point-based features, as well as the block- based features perform very well. These feature sets exhibit the best robustness against various noise sources and down sampling, while reliably identifying the copied regions In present versatile over division calculation sections the host picture into no overlapping and sporadic blocks adaptively. Then, the element focuses are removed from each block as block elements, and the block components are coordinated with each other to find the named highlight focuses; this technique show the presumed forgery blocks in the images. In past few years, Copy-move forgery is a very common way to tamper an image. Many researchers have proposed various schemes to detect the tampered images. Sometimes the copied regions are rotated or flipped before being pasted. In this thesis, detection and classification methods are done by using the machine learning with optimization method. In the present work forgery detection and classification is done by using SIFT with GWO and SIFT _ABC with SVM Gaussian and polynomial kernel but Sift_ABC show significance high accuracy, precision and recall in case of classification.

4.2 Future Scope

In future, research work can be enhanced by following parts as,

- Improve the transformation by neighbourhood pixel mixing and use convolution base features.
- Enhance the optimization by hybrid optimization which improve block and key point features separately.

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