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Automated Image Forensics Based on Deep Learning for Discriminating Photorealistic Computer Graphic and Photographic Images

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Abstract

Intrinsic The rapid advancement in the field of digital image forensics from the recent few years is becoming very crucial nowadays. As it become easier to generate computer graphic images and forge the whole of the image or just part of image to perform illegal activities. Distinguishing Computer generated stuff with the Natural images is quite difficult task with naked human eye. In this research thesis we proposed the CNN-based Neural Network model for the identification of images. For the classification of images Columbia image dataset is used which includes Photorealistic Computer Generated (PRCG) images and Photographic Images (PIs). Original, resized, filtered and patched images with different modification are used to feed in Convolutional Neural Network (CNN) before training and testing phase. The proposed method used five convolutional layers. All of the experimental results and analysis shows that proposed method achieved 99% training accuracy and 98.5% validation accuracy on different types of images which is although sufficient enough for this proposed method with adequate amount of dataset.

Keywords: CNN, Photographic Images, PRCG, computer graphic, Generated

INTRODUCTION

The authenticity of digital content has become an essential criteria to evaluate the validity and quality of artifacts found on various types of digital sources. With the advent of technology in this innovative world it is extremely easy to alter Computer Generated (CGs) or Photographic images (PIs), Gifs and videos with the help of advance editing software's e.g. Adobe Photoshop, GIMP, Canva and Adobe Premiere etc[1].Digital forensics is the modern version of forensic science and it has played an important role in the domain of forensic analysis as well as in forensic investigation, journalism, intelligence services and medical imaging. It is a crucial facet in the information system to investigate and recognize any malicious activity performed on the digital information and ensure that obtained data is not corrupted. When piece of information is spread in the form of videos, Gifs and images there is hard to distinguish Computer Generated (CGs) images and Photographic images (PIs) whether it is exactly required data or may be fraud. To overcome computer crimes forensic analysis is widely use in different spheres of life as in law enforcement, cyber security and national defense. Law enforcement agencies, intelligence services, financial institutions and investment firms are comprising digital forensics into their infrastructure inevitably[2]. One of the vast field of digital forensics is digital image forensics which comprises various types of digital images and validation in order to investigate whether these images are genuine or may be altered by using some tools. The role of image forensics is really important in every sphere because fictitious images could bring severe problem pertaining to authenticity, when forged or tempered images are employed in the area of intelligence, justice, crime and defense[3].

A visual data which is represented on multimedia is considered to be actual and authenticate apparently such that when an image is printed in the newspaper it is usually assumed as a certificate of genuineness of the news. With the excessive growth of innovative technology it is very easy to use digital devices which are highly capable of acquisition of visual data. In this progressive age almost everyone has probability of capturing, storing and sharing images over multimedia[4]. CG technology is getting more effective nowadays and CG images becoming photographic images. Therefore recognition of CG images from Photographic images (PIs) is becoming crucial because those images can hardly be recognized by naked human eye from Photographic images (PIs). An example of PRCG image and PI Images is given below:

Figure 1:
Pair of images, on the Left is PRCG Image and on the Right PI Image

There is an image forensics technology which is most realistic technique to identify this essential issue[5]. With the help of innovative software tools falsification of digital images have become easier. The work was started to analyze the difference between Photorealistic Computer Generated (PRCGs) Image and Photographic Images (PIs) in the early 1970s and 1980s. The federal agents of United States first began to investigate the digital evidences in the 1980s. In 1984 the United States work started in the FBI Computer Analysis and Response Team (CART) and the following year computer crime department was establish within the British Metropolitan Police fraud squad[6].

Later on, in 1990s the academia researchers observed that the digital forensics can speed up the process of investigation to the great extent.The chain of Conferences originally convoked by the Serious Fraud office and the Inland Revenue took place at the Police Staff Collage at Bram-shill in 1994 and 1995, in the duration of these years advance British digital forensic approach was demonstrate. The very first definition of digital forensic was given in the first Digital Forensic Research Workshop (DFRWS) in 2001[7]. Working on digital image forensics has been rapidly increasing with the advancement of new technologies in deep learning techniques. For digital images validity and originality are the major problems and the most important matter to be focused on. Computational complications are the leading issues as well due to the advance operations required in images processing to distinguish Photorealistic Computer Generated (PRCG) images from Photographic Images (PIs). Digitally altered images are ethically permitted as long as they are not intended to violate some legal rules. But there are still certain types of tampering operations that are not allowed under the federal law. As technology is growing rapidly so there are many advance image editing applications that are enable to alter images very quickly and easily. These altered images are making life easy in some cases when there is alteration is required to recover some part of the images.

This is rapidly growing field in recent years because the authenticity of images is really important in almost every sphere of life, essentially where images are used as evidence for legal purposes. In this research work has been done using the deep learning techniques to derive best possible accuracy rate. The purpose of the research is to render novel techniques based on deep learning classification that would be efficient to distinguish between Photorealistic Computer Generated (PRCG) Images and Photographic Images (PIs). This research thesis addresses the problem of distinguishing Photorealistic Computer Generated (PRCGs) Images from Photographic images (PIs) using deep learning techniques based on Convolutional Neural Networks (CNNs). This research got significantly better results by using simple CNN based model than that of earlier used techniques.

The rest of the sections of this paper is organized as follows. Section 2 represents relevant related work in the field of image forensics. In Section 3 proposed methodology of this research and detail of dataset is discourses. Section 4 describes experimental setup and results of this proposed model. Lastly section 5 delineates the conclusions of this research.

Related Work

Literature review provide the all related work which is being proposed by using different Machine Learning (ML) and Deep Learning (DL) algorithms are being developed to discriminate Photorealistic Computer Graphics (PRCGs) and Photographic Images(PIs). In this chapter both of machine learning and deep learning methods of related work from the previous years have been discussed.

Methods Based on Machine Learning Techniques

Morinaga, Atsushi, et al.[8] Presented a novel method for distinguishing computer generated images and natural images based on Multiresolution Wavelet Analysis and Generalized Gaussian Distribution (GGD). The LIBSVM[9] package is used for the Support Vector Machine (SVM) classifier. Moreover a grid search is used to select the best parameters for the Radial Basis Function RBF kernel. This approach achieved 87% average accuracy. Birajdar, G.K. and Mankar, V.H.[10] Introduced Discrete Wavelet Transform (DWT) based binary statistical image feature to differentiate images using Support Vector Machine (SVM) as Classifier. Fuzzy entropy supported feature selection approach is used to extract the relevant image features. Accuracy rate was 87.72% by using this approach. Shaojing Fan et al.[11] Introduced a new approach to discriminate photographic images from computer generated images based on image contour information and got 90% identification accuracy by using SVM classifier. Feng Pan and Jiwu Huang[12] has used

Hidden Markov Tree (HMT) technique for image discrimination. From HMT model a set of features were derived and its effect were verified. Different experimental results were concluded by Hue Saturation Value (HSV) color space and Red Green Blue (RGB) color space. This experiment is based on Support Vector Machine (SVM) of the LIBSVM. Results has showed up to 84% average accuracy. CHEN Jiong Bin et al.[13] presented a method using fractal geometry in which a part of features were derived from fractal dimensions and several generalized dimensions were used. SVM is used as classifier, Radial Basis Function (RBF) kernel is used in Support Vector Machine (SVM). All experiments are tested by optimal parameters using grid search are selected in the joint parameters space. The average accuracy was 91%.

Methods Based on Deep Learning Techniques

Weize Quan and Kai Wang et al.[14] Introduced generic framework base on Convolutional Neural Networks (CNNs) and the so-called local-to-global strategy to classify the images. Two cascaded convolutional layers were used at the bottom of CNN and this model was adjusted to accommodate different size of image patches to see the different results. This novel method derives forensics decision on local patches of images and global decision on full size images. The model obtained 80.65% of accuracy on the RAISE[15] and Columbia dataset. In the work of Ming He[16] transfer learning techniques and fine-tune strategy were used to classify images. They adopted VGG19 and ResNet50 as two CNN Networks and it has been observed that ResNet50 is more powerful than VGG19, the model is competitive among state- of-art models and achieved 96% accuracy.Gabriel Mukob et al.[17] Proposed a CNN based method for the classification of images and achieved 96% accuracy.

The Proposed Methodology

The proposed method comprised two main steps, image pre-processing and CNN based model training and testing on the available image dataset. In the very first original images are used for classification. Then both of PRCGs and PIs images either RGB or Gray-Scaled are resized to form equal image dimensions and these resized images are trained and tested through CNNs algorithm.

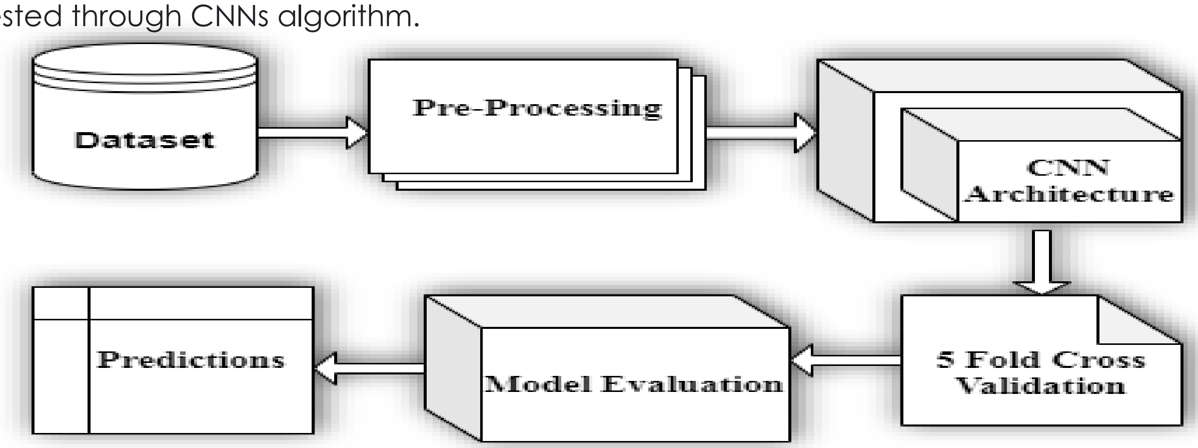


Figure 2:
Schema of Proposed Methodology

A High Pass Filter (HPF) is used on RGB and Gray-Scaled images to see the different results. The proposed CNN based model used five layers of CNN for classification. A step by step procedure is discussed in this section. In this proposed method different modifications were applied on original images which are taken from both of PRCGs and PI images. For the classification of images, firstly original RGB images, Original Gray-Scaled images are used as they have different resolution and they are not same in size. Then Resized RGB and Gray-Scaled images were used and lastly HPF is applied on both of RGB and Gray-Scaled Images. CNN based model is used on all of the image datasets and results are concluded.

Figure 3:
Some of sample images from Dataset. Images on the left (a) are PRCGs and images on the Right (b) are PIs.

We have used 2D Convolutional Neural Network to extract conclusions of proposed methodology. In this proposed methodology 5 Convolutional layers and Maxpooling layers are used. In each of convolutional layer ReLU activation function is used. Furthermore Batch normalization and dropout layers are used to better understanding of images. In the end of training model fully-connected (FC) layers are applied and in the very last there is softmax function as output layer.

Cross Validation Technique

Cross validation is used for the purpose of splitting the data into training set and testing set randomly. Dataset division is performed through cross validation data splitting. In cross validation whole dataset is divided into two parts i.e. training and testing sets with the particular range which is decided for both of datasets. In our experiments both PRCGs and PIs images are randomly split into training and testing datasets i.e. 20% of the whole data is selected for Testing Purpose and remaining 80% of data is selected for Training purpose as in training there is more data is required than Test purpose.

For the classification 2D CNN based model is used with 5 convolutional (Conv) Layers and Max-Pooling layers, regularization layers, dense layers and in the last Softmax layer is applied for activation function. For training and testing samples there are automatic split of training and testing datasets. After training the model through CNN based architecture, model evaluation and predictions are concluded and the final results of existing experiments are finalized.

Image Pre-Processing

Photographic Images (PIs) taken from cameras and Photorealistic Computer Generated (PRCG) images generated from advance software often have large resolution. Images with large resolution need large amount of memory for their processing, so due to the limited hardware memory we needed to resize and clip images into smaller size so that they can easily be used to feed into neural network for the training purpose. This technique is data augmentation technique used in deep learning[18]. In data augmentation amount of training samples is increased and it helps to improve the maximum capability of the trained model[19]. In data augmentation new data is not collected rather it increase the diversity of that data which is already available for training the model. Original images are also resized into the resolution of 128×128.

As Photographic images taken from cameras have larger resolution than PRCG images. Both of PRCGs and PIs are not in equal because of larger size of Photographic Images (PIs) so PIs are needed to be clipped and resize more to meet the requirements of same size images. Image pre-processing is done with both RGB and Gray-Scaled Images.

Filtering Images with High Pass Filter

Since PRCGs and PIs are created from different ways so it is expected that they are different in features. High pass filters have the ability to dilute low frequency noise by attenuating some of frequencies and letting high frequency signal pass through. In this proposed method we used a 3×3 High Pass Filter (HPF) on RGB and Gray-Scaled Images. High pass filter which is used for filtering the dataset is filter of size 3×3. This filter was applied to images to obtain image residuals. This filter is used on both of RGB and Gray-Scaled images.

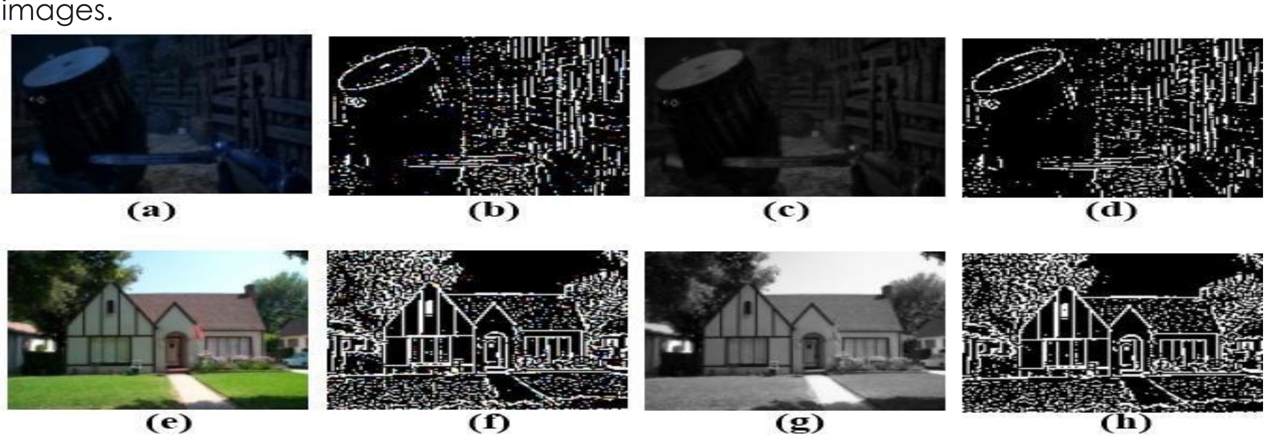


Figure 4:
This Figure illustrate the in the above row PRCGs images, Original RGB (a),RGB Filtered(b), Gray-Scaled Original (c) and Gray-Scaled Filtered (d). In the second row PIs images are shown, Original RGB (e), RGB Filtered (f), Gray-Scaled Original (g) and Gray-Scaled-Filter (h).

Programing Language and Tools

Anaconda[20] is free and open source Python distribution with the collection of hundreds of package and libraries related to data science, citify programming, development and much more. It is used in many applications of image processing, machine learning and deep learning. Anaconda is widely used platform for data processing purposes. This platform is appropriate for different operating system such as windows operating system, Mac OS and Linux. The Jupyter notebook[21] is Integrated Development Environment (IDE) which is one of open source web-based applications for programing. In Jupyter notebook all of the work or coding is comprises in gradual coding block, which makes works more precise and efficient. It allows user to create and share their data and documents which contain live codes, narrative text, visualization, equation.

Furthermore it also includes data cleaning, numerical simulation, statistical modeling, transformation, machine learning, deep learning and much more. Python is used as programming language for distinguishing between Photorealistic Computer Generated (PRCGs) and Photographic Images (PIs). Python is inferred, object-oriented language used for writing code with vibrant syntactic[22]. Python has high-level built-in data constructions which is collective with lively typing and vibrant binding as well and it makes this language more attractive for programming purposes. It supports modules and packages which promotes program standards and reusing of codes.

Table 1:
Detail of Coding Platform

Integrated Development Environment (IDE)	Jupyter Notebook
Programming Language	Python 3.7
System Specifications	Laptop Intel Core i5 2520M CPU @ 2.50 GHz 12 GB of RAM
Installed Python Libraries	Tensorflow, Scikit-Learn, Keras, Theano
Keras Version	2.0.0
Tensorflow Version	2.3.1
Matplotlib Version	3.0.3
NumPy Version	1.17.3
Scikit-Learn Version	0.23.1
Model	Sequential
Optimizer	RMSprop
Testing Set	20%
Training Set	80%
Batch Size	64
Number of Epochs	50
Training/Testing Method	Via Cross Validation

Proposed Network Architecture

CNNs Architecture vary with respect to layers, its parameters and types of layers used in specific purpose. Our proposed network architecture is explained in detail in this section. The proposed CNN- based architecture consist of five Convolutional Layers. Each convolutional layer have Batch Normalization Layer[23], a Rectified Linear Units (ReLUs) Layers [24] and Max-Pooling Layer (MaxPooling2D)[25]. In end of the proposed model, a Fully-Connected (FC) Layer [26]and a Softmax layer[27] are employed to convert the image symmetrical features directions to the real classification possibilities. The kernel size in each convolutional layer of this CNN based model is (7×7), (7×7), (5×5), (5×5), (3×3) respectively. The quantities of feature maps from each of the previous layer are 16, 32, 64, 127 and 256 respectively. The Pool size in Max Pooling Layer is 2×2.

CNN-Based Model Training

The proposed architecture of CNN based model is shown in the figure. The image dataset is used to feed into the neural network as an input. Different images are used to train and test the dataset. In our model by using cross validation out of 3400 images 80% of images are randomly selected for training while 20% of images are used for testing. Following figure shows dataset splitting over training and testing data. In the given CNN-based model diagram 1 represent Gray-Scaled images while 3 represent RGB images. Names and factors of each of the layers are shown in the containers. Filter size in each of the layer are represented as amount of *feature maps (kernel size.* Max pooling layers have pool size is equal to 2×2. Furthermore ReLU and Batch Normalization used in each layer or Convolutional Neural Network for better performance.

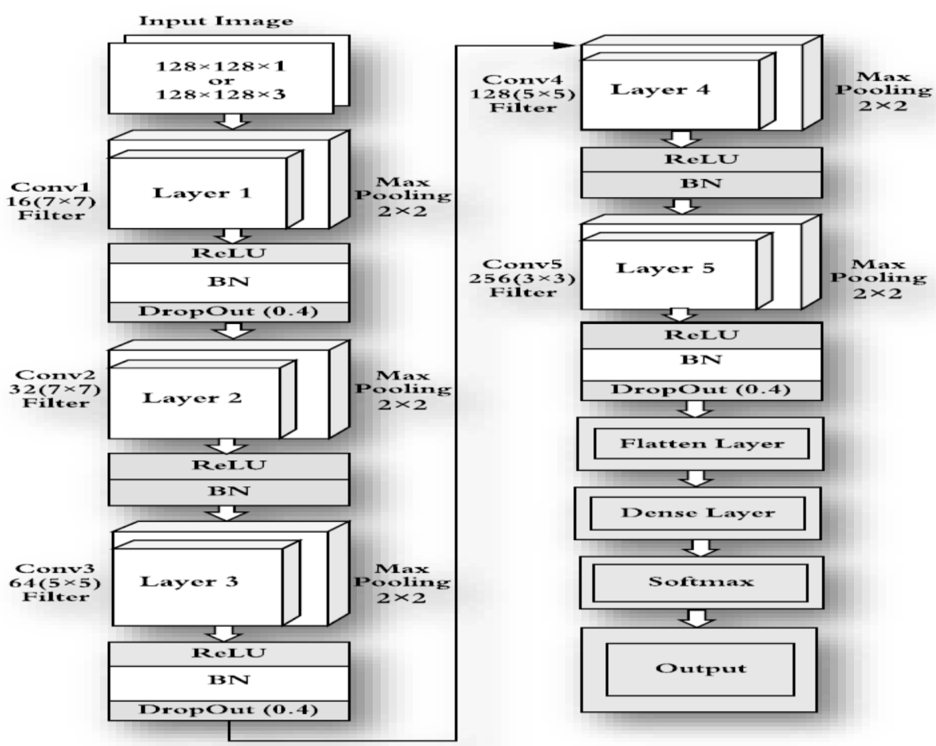


Figure 5:
Block Diagram of Convolutional Neural Network in our Proposed Methodology

EXPERIMENTAL RESULTS

K-Fold Cross Validation

For the purpose of training and testing whole dataset is divided into two sets, one of them is training set and other one is Testing test. Dataset division is performed through cross validation data splitting which is known as K-fold cross validation (KCV)[28]. In cross validation whole dataset is divided into training and testing sets with the particular range which is decided for both of datasets. In our experiments both PRCGs and PIs images are randomly split into training and testing datasets i.e. 20% of the whole data is selected for Testing Purpose and remaining 80% of data is selected for Training purpose as in training there is more data is required than Test purpose. In K-fold cross validation dataset is split into K number of folds in which each fold is used for testing at some specific point. In the proposed methodology K=5, so for 20% of test data we have applied 5-fold Cross validation technique. As in the figure below in the 1st iteration very 1st fold is used for testing and rest are used for training. In the 2nd iteration 2nd fold is used for testing the model and rest of them are used for training the model. The process is proceeded until each of the fold from 5 folds are used for testing the model. Each time one of the fold is used as testing dataset and remaining are used for training dataset and so on.

Evaluation Parameters of Experiments

Result is conducted through different evaluation parameters such as Precision, Recall, F1-Score etc.[29]. Following is explanation about terms of evaluation parameters[30].

Precision

Precision is called positive predictions as it is consist of positive predicted values of the results. It is calculated as the number of True Positive (TP) over True Positive plus False Positive. Precision Formula = TP/ (TP+FP)

Recall (Sensitivity)

Recall which is sensitivity in other words. It is calculated as the number of True Positive over True Positive plus False Negative. Recall Formula = TP/ (TP+FN)

F1 Score

F1 Score is the value that is concluded by taking the weighted average of Precision and Recall. F1-Score Formula = 2× (Recall × Precision) / (Recall + Precision.

Table 2:
Classification Result of Both Classes

	Method	Image Set	CG	NI	CG	NI	CG	NI	CG	NI
Exp-1	5 Fold Cross Validation	Original RGB Images	93	92	93	92	93	92	358	322
Exp-2	〃	Original Gray-Scaled Images	94	93	94	93	94	94	〃	〃
Exp-3	〃	RGB-Resized Images	95	96	95	96	95	96	〃	〃
Exp-4	〃	Gray-Scaled-Resized Images	96	97	96	97	96	97	〃	〃
Exp-5	〃	RGB-Resized-Filtered Images	97	98	97	98	97	98	〃	〃
Exp-6	〃	Gray-Scaled-Resized-Filtered Images	98	99	98	99	98	99	〃	〃

Design Adopted for Experiments

Classification between 2 image classes is performed through 6 different experiments for image forensics analysis and all results have been analyzed to discover the different outcomes of images. Training and testing loss and accuracy graphs have been designed to investigate their true accuracy values. Both of RGB and Gray-Scale images have been used using different variations such as RGB and Gray-Scaled Original Images, Resized Images and Filtered Images.

Original RGB Images

In the first experiment from both of classes Original RGB images were used with the resolution of 384× 512 to 1760×1168. These images were fed into to neural network without early resizing of images. CNN model achieved 99.52% Training accuracy and 92.5% validation Accuracy which is shown in Graph.

Original Gray Scaled Images

In the second experiment from both of classes Original Gray Scale Images were used with the resolution of 384× 512 to 1760×1168. All of images converted to gray scale before experiment and got 99.71% training accuracy and 93.52% validation accuracy.

RGB Resized Images

In the 3rd Experiment RGB images were used from both of the dataset classes and image were resized before getting fed into the neural network. These all images have resolution of 128×128 and got classification accuracy as 99.19% training accuracy and 95.59% testing accuracy.

Gray-Scaled Resize Images

In the 4th Experiment Gray Scaled images were used from both of the dataset classes and image were resized before getting fed into the neural network. These all images have resolution of 128×128 and got classification accuracy as 99.45% training accuracy and 96.53 % validation accuracy.

RGB Filtered Images

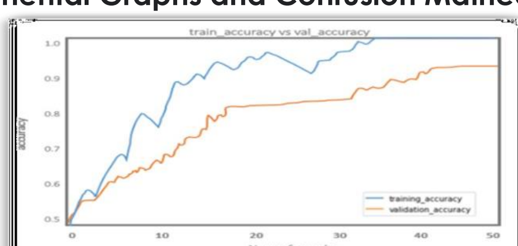
In this experiment RGB images were taken from both of the image classes. All images have been filtered with HPF of size 3×3. After filtering images were fed into CNN model for training. This experiment achieved 99.49% training accuracy and 97.51% validation accuracy.

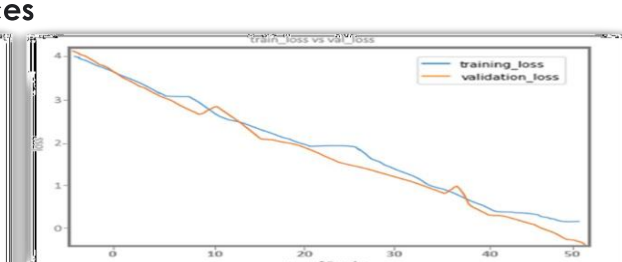
Gray Scaled Filtered Images

In this experiment Gray-Scaled images were taken from both of the image classes. All images have been filtered with HPF of size 3×3. After filtering images were fed into CNN model for training. This experiment achieved 99.12% training accuracy and 98.56% validation accuracy.

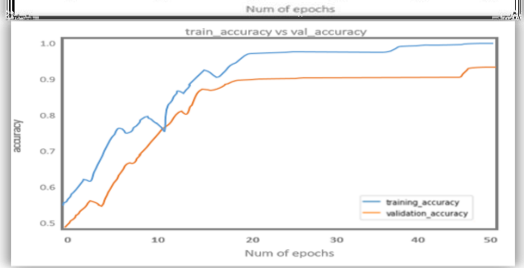
Experimental Graphs and Confusion Matrices

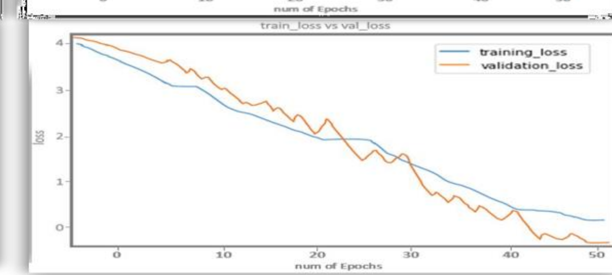
Exp-1



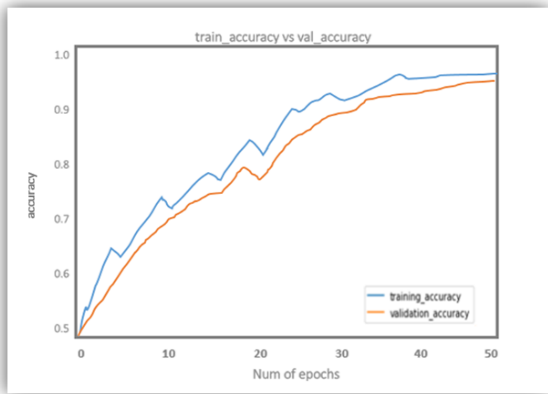


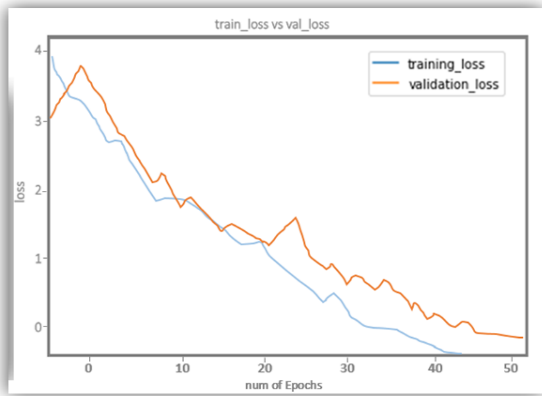
Exp-2



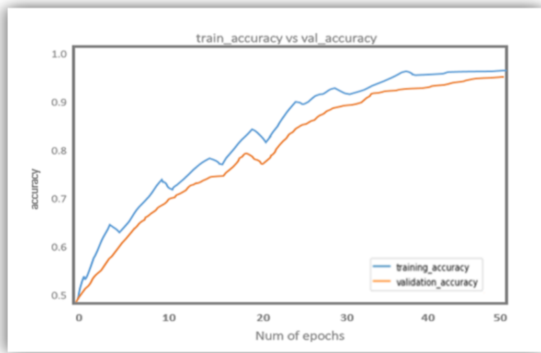


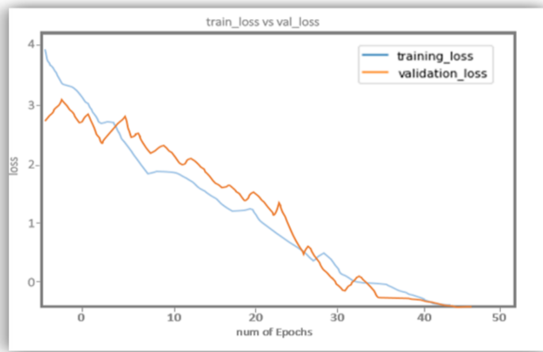
Exp-3



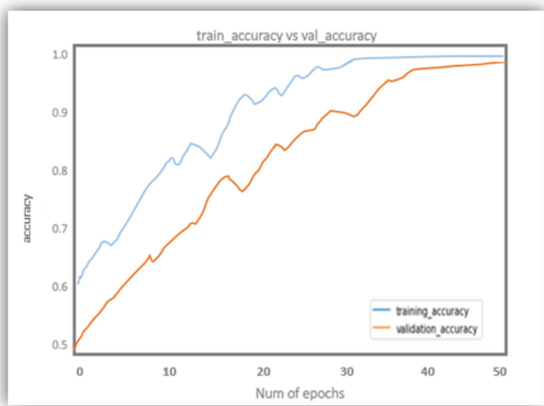


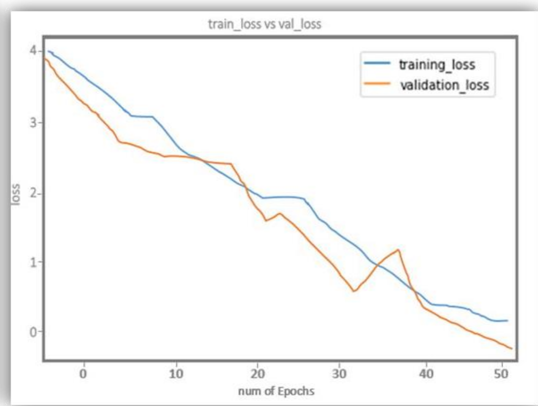
Exp-4



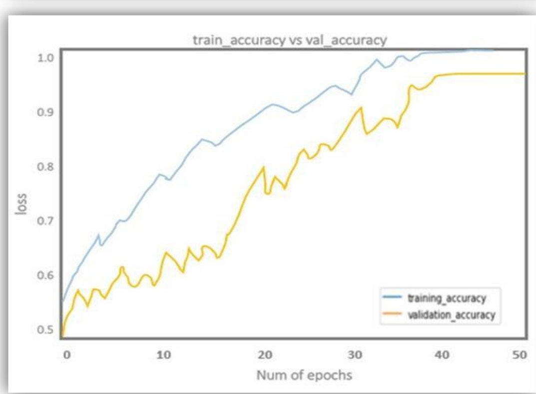


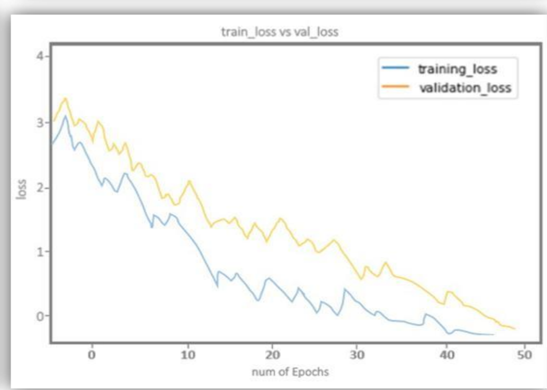
Exp-5





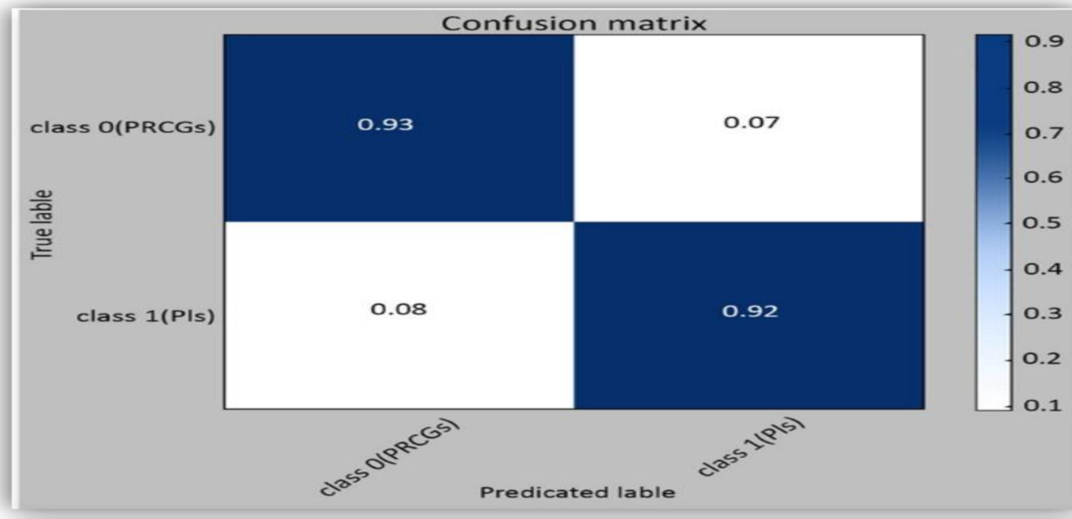
Exp-6



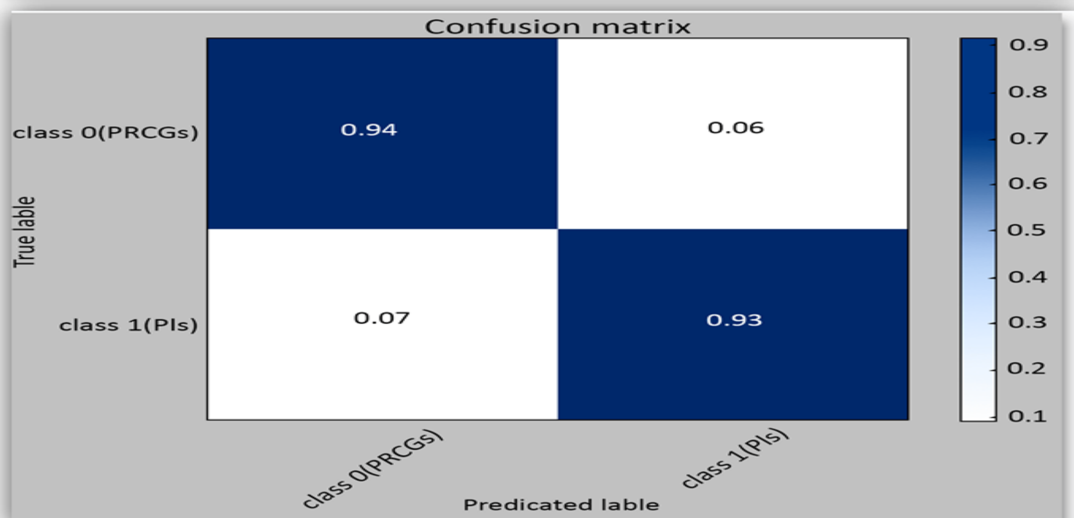


Confusion Matrix

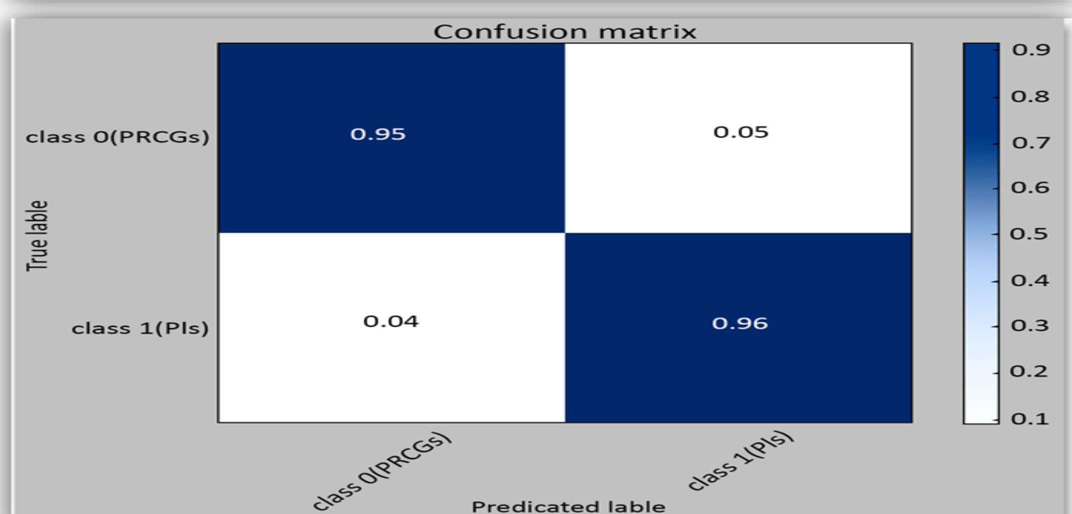
Exp-1



Exp-2



Exp-3



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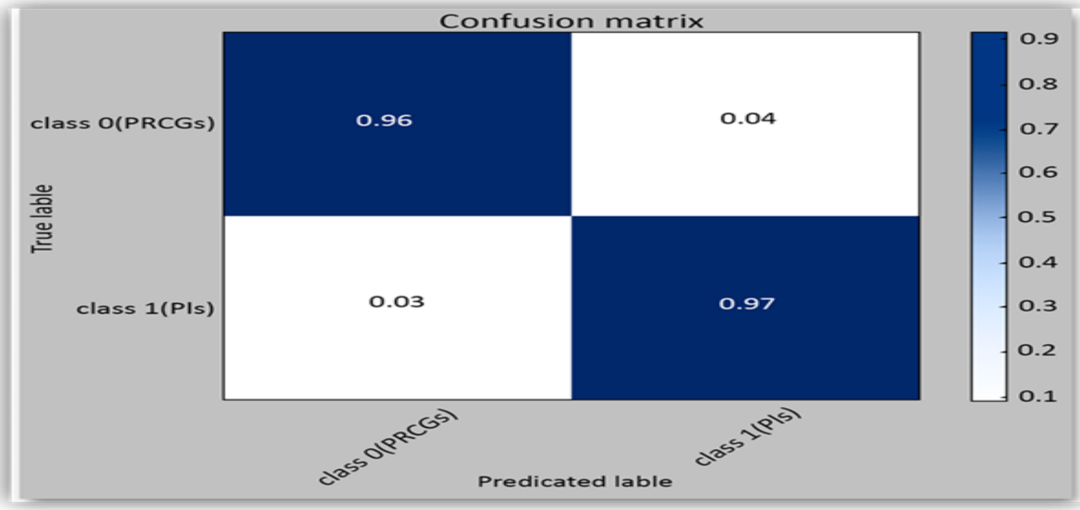
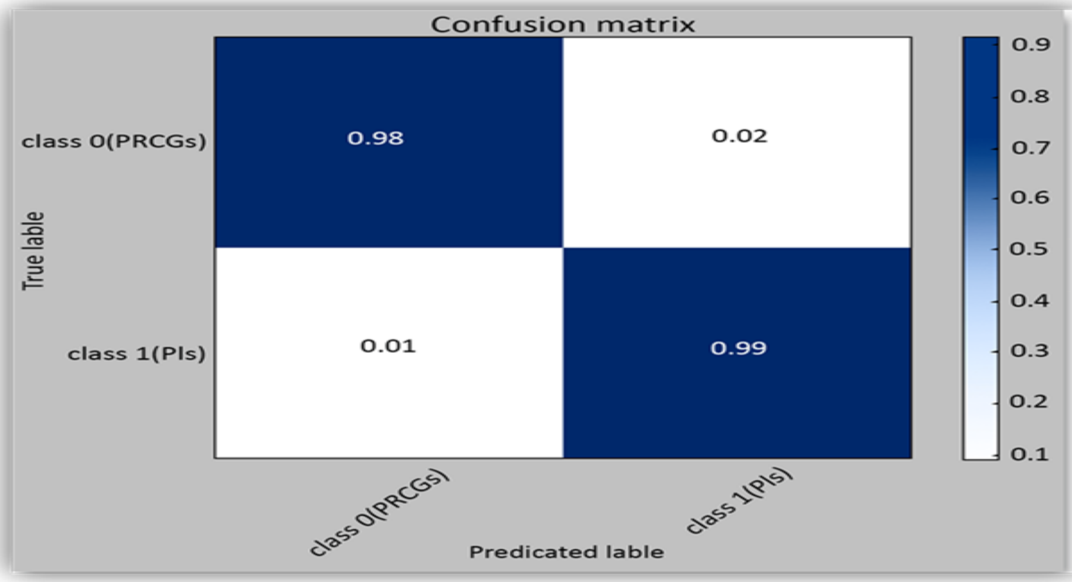


Exp-5



Exp-6

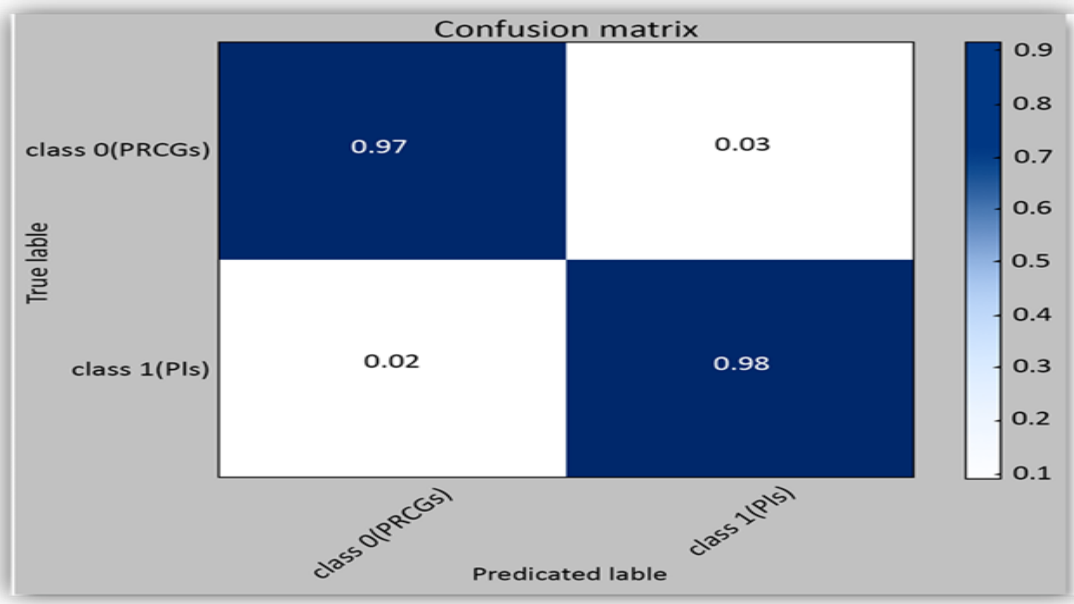


Table 3:
Training and Testing Accuracy of Proposed Method

Image Set		Training Accuracy	Testing Accuracy	
Exp-1	5 Fold Cross- Validation	Original RGB Images	99.52%	92.50%
Exp-2	〃 〃	Original Gray-Scaled Images	99.71%	93.52%
Exp-3	〃 〃	RGB-Resized Images	99.19%	95.59%
Exp-4	〃 〃	Gray-Scaled-Resized Images	99.45%	96.53 %
Exp-5	〃 〃	RGB-Resized-Filtered Images	99.49%	97.51%
Exp-6	〃 〃	Gray-Scaled-Resized-Filtered Images	99.12%	98.56%

Table 4:
Configuration Summary of CNN Model

Name	Layer Type	Number of Filters	Filter/Pool Size	Padding	Activation Shape	Activation Size
Input Image	Input Layer	-	-	-	128×128×1/3	16,384/49,152
Group 1	Conv2D Layer-1	16	7×7	Same	122,122,16	238,144
	ReLU Layer-1	-	-	-	122,122,16	238,144
	Batch Normalization-1	-	-	-	122,122,16	238,144
	Maxpooling2D-1	-	2×2	-	61,61,16	59,536
	Dropout Layer-1		-		61,61,16	59,536
Group 2	Conv2D Layer-2	32	7×7	Same	61,61,32	110,072
	ReLU Layer-2	-	-	-	61,61,32	110,072
	Batch Normalization-2	-	-	-	61,61,32	110,072
	Maxpooling2D-2	-	2×2	-	30, 30,32	28,800
Group 3	Conv2D Layer-3	64	5×5	Same	30,30,64	57,600
	ReLU Layer-3	-	-	-	30,30,64	57,600
	Batch Normalization	-	-	-	30,30,64	57,600
	Maxpooling2D-3	-	2×2	-	15,15,64	14,400
	Dropout Layer-2	-	-	-	15,15,64	14,400
Group 4	Conv2D Layer-4	128	5×5	-	15,15,128	28,800
	ReLU Layer-4	-	-	-	15,15,128	28,800
	Batch Normalization	-	-	-	15,15,128	28,800
	Maxpooling2D-4	-	2×2	-	7,7,128	6,272
Group 5	Conv2D Layer-5	256	3×3	-	7,7,256	12,544
	ReLU Layer-5	-	-	-	7,7,256	12,544
	Batch Normalization	-	-	-	7,7,256	12,544
	Maxpooling2D-5	-	2×2	-	3,3,256	2,304
	Dropout Layer-3	-	-	-	3,3,256	2,304
	Flatten	-	-	-	2304	2,304
	Dense	-	-	-	512	512
	ReLU Layer	-	-	-	512	512
	Batch Normalization	-	-	-	512	512
	Dropout Layer-4	-	-	-	512	512
	Dense Layer	-	-	-	256	256
	ReLU	-	-	-	256	256
	Batch Normalization	-	-	-	256	256

Dropout Layer-5	-	-	-	256	256
Dense Layer	-	-	-	2	2
Softmax layer	-	-	-	2	2

CONCLUSIONS

In this research thesis we worked on the digital image forensics technique using by using CNN-Based Classification Model. 2 classes of images were taken one of the image class is Photorealistic Computer Generated (PRCG) and other one is Photographic Images (PI). The average test accuracy on Columbia image dataset is 98.5%.So by this research it is found that CNN-based architecture can immensely improve the classification problem of digital images. The performance of our proposed model is better than earlier complicated designed model yet it is simple and comprehensive in its terminology. For future work we will continue this work on dynamic images to capture the malicious attacks on both of the static and dynamic images.

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