NITTE MEENAKSHI INSTITUTE OF TECHNOLOGY

(AN AUTONOMOUS INSTITUTION, AFFILIATED TO VISVESVARAYA TECHNOLOGICAL UNIVERSITY,

BELGAUM, APPROVED BY AICTE & GOVT.OF KARNATAKA

PROJECT REPORT

on

IMAGE TAMPER DETECTION

Submitted in partial fulfilment of the requirement for the award of Degree of

Bachelor of Engineering

in

Computer Science and Engineering

Submitted by:

AMITH KUMAR R	1NT18CS009
JAYA SHANKAR G S	1NT18CS062
MONISH K	1NT18CS100
RITHIK G	1NT18CS132

Under the Guidance of

Dr. SREENIVASA N
Associate Professor, Dept. of CS&E, NMIT

Department of Computer Science and Engineering
(Accredited by NBA Tier-1)

2021-22

NITTE MEENAKSHI INSTITUTE OF TECHNOLOGY

(AN AUTONOMOUS INSTITUTION, AFFILIATED TO VISVESVARAYA TECHNOLOGICAL UNIVERSITY, BELGAUM
, APPROVED BY AICTE & GOVT.OF KARNATAKA)

Department of Computer Science and Engineering
(Accredited by NBA Tier-1)

CERTIFICATE

This is to certify that the report on **Image Tamper Detection** is an authentic work carried out by **Amith Kumar R (1NT18CS009)**, **Jaya Shankar G S (1NT18CS062), Monish K (1NT18CS100)** and **Rithik G (1NT18CS132)** bonafide students of **Nitte Meenakshi Institute of Technology**, Bangalore in partial fulfillment for the award of the degree of ***Bachelor of Engineering*** in COMPUTER SCIENCE AND ENGINEERING of Visvesvaraya Technological University, Belagavi during the academic year ***2021-2022.*** It is certified that all corrections and suggestions indicated during the internal assessment have been incorporated in the report.

Internal Guide	**Signature of the HOD**	**Signature of Principal**
Dr. Sreenivasa N Associate Professor, Dept. CSE, NMIT, Bangalore.	Dr Saroja Devi Professor, Head of Dept. CSE, NMIT, Bangalore.	Dr. H. C. Nagaraj Principal, NMIT, Bangalore

Signature of Examiners

1.
2.

DECLARATION

We hereby declare that

(i) The project work is our original work

(ii) This Project work has not been submitted for the award of any degree or examination at any other university/college/Institute.

(iii) This Project Work does not contain other persons' data, pictures, graphs, or other information unless specifically acknowledged as being sourced from other persons.

(iv) This Project Work does not contain other persons' writing unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:

a) their words have been rewritten but the general information attributed to them has been referenced.

b) where their exact words have been used, their writing has been placed inside quotation marks and referenced.

(v) This Project Work does not contain text, graphics or tables copied and pasted from the Internet, unless specifically acknowledged, and the source is detailed in the thesis and in the References sections.

NAME	USN	Signature
Amith Kumar R	1NT18CS009	Amith
Jaya Shankar G S	1NT18CS062	
Monish K	1NT18CS100	Monish.K.
Rithik G	1NT18CS132	Rithik

Date: 12/07/2022

ACKNOWLEDGEMENT

The satisfaction and euphoria that accompany the successful completion of any task would be incomplete without the mention of the people who made it possible, whose constant guidance and encouragement crowned our effort with success. I express my sincere gratitude to our Principal **Dr. H. C. Nagaraj**, Nitte Meenakshi Institute of Technology for providing facilities.

We wish to thank our HoD**, Dr. Saroja Devi.** for the excellent environment created to further educational growth in our college. We also thank him for the invaluable guidance provided which has helped in the creation of a better project.

I hereby like to thank our **Dr. Sreenivasa N**, Associate Professor, Department of Computer Science & Engineering on her periodic inspection, time to time evaluation of the project and help to bring the project to the present form.

Thanks to our Departmental Project coordinators. We also thank all our friends, teaching and non-teaching staff at NMIT, Bangalore, for all the direct and indirect help provided in the completion of the project.

NAME	USN	Signature
Amith Kumar R	1NT18CS009	Amith
Jaya Shankar G S	1NT18CS062	
Monish K	1NT18CS100	Monish ·K.
Rithik G	1NT18CS132	Rithik

Date: 12/07/2022

ABSTRACT

Image manipulation is becoming a serious concern in many fields nowadays as the available software to manipulate images is increasing, at the same time it is becoming increasingly hard to authenticate between original and duplicate images. To address this problem, we discuss a few of the famous transfer learning architectures in image classification and how they can be used to authenticate between original and manipulated images in the JPEG format, with the use of lossy double compression for preprocessing. The classification is further improved by the new Deep learning architecture, a similar combination of AlexNet and InceptionNet. The paper mainly focuses on detecting passive image tampering with the help of the CASIA V2 dataset. And have provided good results both on test and validation data.

TABLE OF CONTENTS

SL No	Title	Page No
1	Introduction	7
2	Literature Survey	9
3	System Requirements	13
4	Design	14
5	Implementation and Results	17
6	Conclusion And Future Scope	25
7	Reference	26

LIST OF FIGURES

Fig No	Diagram	Page No
1	Data flow	14
2	Use case	15
3	Sequence	16
4	Flowchart of Error level analysis	17
5	ELA Test Image	18
6	ELA Output	18
7	Experimental Model	20
8	Original Image	23
9	Tampered Image	23
10	ELA Of Tampered Image	24
11	Model Output	24

CHAPTER 1: INTRODUCTION

1.1 Background

Digital media nowadays which includes images has become an important medium of communication because of its ability to express, acquire, distribute, and store easily. The significance of digital images in describing data has made them preferable to text information as a means of transmission. Image forgery implies the manipulation of the digital image to camouflage some significant or valuable data about the image. [1] JPEG can play a significant role in the field of digital image forensics by understanding inherited features of the JPEG format image. Advanced computers and image editing software have helped to manipulate images very easily. So, with the increase in tampering, several techniques and models are being developed for image tampering detection.

A convolutional neural network (CNN) is an artificial neural network that is used to recognize images and process the pixel data of the image.The program can be used to detect tampered images by making use of the convolution neural network. It can be used by the users to verify whether a forgery is made or not on a particular image.Image tampering detection has had the latest trend in recent times with an increase in the forgery of images. Many different algorithms were proposed and many Architectures were proposed for image classifications some of which were referred to as LeNet, AlexNet, VGG, and Inception network.

1.2 Brief history of Technology/concept

[2] Deep learning-based convolutional neural network(CNN) with error level analysis of JPEG is one such that is proposed in this project. There are various types of file formats; some formats can be lossless while few are lossy. If lossy formats are used then there is a chance of data loss.Adjusting the quality level happens in JPEG formats, by removing some colors it can be compressed. That is the reason why the color of the image changes whenever saved in an image format, like JPEG. It is hard to identify the damaged part of the image by human vision. The Error Level Analysis is performed on the JPEG images to find the modified sections of the images. The JPEG image is inserted onto a different JPEG image that is of high quality, it checks whether a part of the image is of lower quality compared to other parts of the same image. Error level analysis analyzes compression artifacts in lossy

compressed data, like JPEG image format. Normally, compression artifacts stay at a stable level in one image. Therefore, if a certain part of the image undergoes deformation or other kind of lossy compression, the data in those regions may occur differently from other data in the image. If all of the data are at the same rate then the image is not modified. If the part of the image data value is different from other parts then the image is altered. The error level analysis (ELA) technique is for passive authentication in image forensics which involves copy-move image forgery, JPEG compression, and image retouching. [3]The accuracy of the Lossy Image compression is analyzed. The investigation is done via several techniques which are Target Registration Error (TRE), Mean Square Error (MSE), and Mutual Information (MS). The outcome of this investigation exhibited MS performs well in lossless compression, but does not perform well in lossy compression.

1.3 Applications

The program can be used to detect tampered images by making use of the convolution neural network. It can be used by the users to verify whether a forgery is made or not on a particular image.

1.4 Research motivation and Problem statement

1.4.1 Research Motivation

The development of image editing software has made tampering with digital images very easy. So, with the increase in tampering, there are several techniques and models being developed for image tampering detection. Deep learning-based convolutional neural network(CNN) with error level analysis of JPEG is one such that is proposed in this project.

1.4.2 Statement of the Problem

With recent advancements in the field of image processing, it has become easier to modify images in the JPEG format, due to this it is nearly impossible to distinguish between original and tampered images with the naked eye.

1.5 Research objectives and contributions

1.5.1 Primary objectives

1. To classify between a modified and unmodified image.
2. To improve the accuracy of classification near the boundaries.
3. Compare different transfer learning architectures.
4. To build a generic approach to classify different passive tampering techniques like cut-copy-move, splicing, compression and resampling over a small image..

1.5.2 Main contributions

It has been designed to distinguish between original and tampered images, and so to find out whether an image is genuine, or a forgery has taken place.

1.6 Summary

Image tampering detection has had the latest trend in recent times with an increase in forgery of images. Many different algorithms were proposed, and many have been proved to be remarkable. The limitation of this approach is that it requires an image in higher dimensions like 240x240 or above. Thereupon it is needed to develop methods capable of distinguishing between tampered and original over small scaled images i.e 60x60. To achieve this, we have experimented on a few of the famous transfer learning architectures in image classification. The classification is further improved by the new Deep learning architecture, a similar combination of AlexNet and InceptionNet.

CHAPTER 2: LITERATURE SURVEY

As we know, there were many image classification architectures, and LeNet-5 a CNN architecture was the first of the architectures to become famous, developed by LeCun et al. (1998), for the recognition of handwritten digits. The LeNet model was developed especially to determine handwritten symbols.[1]The classic LeNet-5 model is enhanced by removing the 1*1 convolutional layer and adding the moving average model. [4] The base LeNet-5 CNN architecture was modified by changing the neurons in each layer of a CNN and also modifying the way that connects across various layers. The CNN outputs are set to error-correcting codes, therefore CNN can deny recognition results. To train the CNN, a reinforcement learning strategy with error-samples-based is developed, and they choose the model which gives good robustness and better performance. For traditional Competitive Learning, outputs for LeNet are placed with place code. By using these place codes it's not able to reject the recognition results. LeNet-5 could reject illegal samples in the printed character recognition. Compared with other methods, CNN has provided an encouraging solution for offline HECR.

[5]Mentioned problems that arise while classifying images in a cloud computing environment to achieve good stability of image classification and good effectiveness and robustness and improved AlexNet architecture was proposed and designed. To obtain stability of algorithm structure, the convolutional nerve is introduced and a brand new image training model is designed in combination with the AlexNet network model. The AlexNet network model firstly simplifies the image processing and describes the image features in a simple geometric form, and then by introducing the convolution nerve, the image obtained from the front layer of the convolution nucleus is trained by convolution training. The improved AlexNet network model is implemented which reduces the training time for the image classification process. [6] Transfer learning with AlexNet Convolutional Neural Network (AlexNet CNN) for the recognition established on human ear images. Transfer learning is an effective way to solve classification problems that will contain a very small amount of details. The Rectified linear unit(ReLU) can be added to enhance the non-linearity in the problem-solving capacity of the network. AlexNet is tuned to determine 10 classes only using 250 training images and 50 testing images, and the model performed 100% accuracy.

[7] A modified VGG-16 Network was designed which was able to automatically classify the three types of corneal ulcers.Data preprocessing steps normalization, masking, and data augmentation to find ulcer images were done before changing into the VGG-16 model. For the loss function of the training model, the weighted categorical cross-entropy can be added, and experimentations show that a modified VGG-16 network will have fewer parameters and promising performance than the classical CNN network.Compared with the classic VGG-16 network, the altered VGG-16 network with CCM layers addition of GAP, and added feature fusion layers. The experimentations show that the altered VGG-16 network achieved better than the AlexNet and VGG-16 networks. [8] Evaluates the VGG-19 and VGG-16 architecture and identify four different classes of dementia by adding a densely connected layer to the end of the network. The classic architecture is changed by the addition of a densely connected layer at the rear of the earlier un-trained network. With the change in the loss function, categorical cross-entropy can be used because of its capability to categorize into multi classes.Using VGG-16 and VGG-19 architecture 4 classes of Deep Convolutional Neural Network methods used to predict and classify dementia have been improved by adding a fully connected layer at the conclusion. [9] Implementation of a neural style transfer model consisting of VGG-19 and AlexNet architectures. Neural style transfer is used to generate an output hybrid image which is a mixture of both styled and the original image.By using VGG-19 and AlexNet the neural style transfer model is executed, and the major aim is to generate an output-styled image with high accuracy. In both models, 1000 iterations were performed. In VGG-19, Relu is used for the activation function, which helped to produce more accurate output-styled images than Alexnet's Relu-activated architecture.After comparing both architectures for 1000 iterations, the quality of the output image for VGG-19 is high than Alexnet architecture.

[10] A novel image is an image forgery detection scheme that will detect the copy-move by making use of the DenseInceptionNet. DenseInceptionNet is a multi-dimensional densely featured connection, DeepNeuralNetwork. Regardless, Inception Net and VGG-16 are the classical feed-forward network in which each layer will receive a previous layer's state and writes over the current layer. By keeping high detection performance the Dense-InceptionNet model can aim to get better efficiency. [11]Here architecture is designed by combining the Inception-like blocks into DenseNet, which is called Inception-DenseNet architecture. A new activation called hybrid activation was introduced, which is different from previous inception blocks. Visualization experimentations showed hybrid activation modes are giving more

flexible responses to object semantic regions. The experimentation results suggested that InceptionDenseNet can get the same or more acceptable classification results while using a smaller number of trainable parameters.

[12] To detect the tampered regions in a JPEG format image a convolutional neural network-based solution was developed. Here, DCT-coefficients will be input to CNN. The output will be in the form of a binary-segmented image that contains white and black pixels that depict tampered and original regions.While Corresponding with the previous MDBD approach, in which features value is established through know-how, a new approach is given which optimizes by using the CNN and reaches a more increased detection accurateness.

[13] Convolutional Neural Networks establish optimistic results when detecting faked images that emerge from the exact type of manipulation they are trained on. It is determined that not all techniques fetch good accuracy for all kinds of image tampering such as splicing, compression, etc. It is required to develop an effective deep learning-based architecture for noticing manipulations efficiently. It is also important to design architecture based on a characteristic extraction mechanism that comprehends correlation better among pixels. The conventional approach can classify a particular type of manipulation by identifying a definite feature in that image. In image formatting, various techniques like copy-move, splicing, etc., are the most known manipulation techniques that are found. Photocopying a part of the image, giving any distortion into this fragment, and infiltrating the altered piece into another area of the same image. [14] The image in the format of JPEG is a famous one. Because its higher compression rate is higher than that compared with the other formats. A novel method with DCT-Coefficient is used to find the tampered images. This method will decompose an input image by saving the image again with other JPEG formats. The tampered regions can be found by making use of the contrast image acquired by an input image and the image saved again in the DCTdomain. The significance of the presented technique was proved by testing results.

[15]The copy-paste effect on JPEG images can be found using these methods. The technique to detect will be executed by removing and examining blocking-artifact grids, presented through block-processing during compression of JPEG. The investigation is based upon the actuality that BAGs generally do not match after achieving copy-paste processes. The method is displayed on two faked images. This process allows adequate finding of impersonated

regions on faked images. [16]With the help of singular value decomposition, the hash generation method is used to detect image tampering. To detect and localize image tampering an efficient hash vector need to be designed.This technique is powerful against content preserving but too liable to even minute structural tampering. [17] Few details regarding image, image forensics, image features, and the way they're stored in devices, can be deleted and recovered can be observed. also emphasized a few components in forensic digital images, digital forensics, and some benefits for digital forensic pictures. [18]To detect the presence of non-aligned double JPEG compression (NA-JPEG) in compressed images a simple dedicated algorithm is developed. This model is based on the integer periodicity of the blockwise discrete cosine transform (DCT) coefficients which considers a single feature when the DCT is calculated according to the grid of the last JPEG compression. [19] The model with regular effects in dual quantize is diagnosed, and a possibility of quantization of DCT coefficients in every block is estimated on the whole image. The considerable rear chance of individual blocks is calculated pertaining to Bayesian theory and of the effects cited in the initial position. Afterward, the variance and mean rear possibility are utilized for evaluating if the target block has meddled. Exploratory results indicate that the process can precisely indicate the altered part, and via experimentation, it is also found that for detecting the meddled parts, the better the two contraction grades are the more different the detected efficiency.

CHAPTER 3: SYSTEM REQUIREMENTS SPECIFICATIONS

3.1 System Requirements

The following are the hardware and software requirements, which are necessary to run the application smoothly.

3.1.1 Hardware Requirements

1. A processor of intel I5 core or above with a cycle speed of at least 1.5GHz.
2. RAM space equal to 4GB or above.
3. Hard Disk space with at least 10GB of free space.
4. Preferable with GPU support of Intel HD 6000 or above but not necessary.

3.1.2 Software Requirements

1. Operating System of Windows 7 or later version, Mac OSX or later version, and Linux with Ubuntu 19.5 or later versions.
2. With python interpreter support of version 3.x (preferable 3.6).
3. Developer Environment of Jupyter notebook with Conda package management (preferably anaconda).
4. Library requirements: Numpy, Pandas, Matplotlib, Scikit-learn, Keras, Tensorflow, PIL, and pylab.

CHAPTER 4: DESIGN

This system works on methods presented in [8] with the input of Error Level Analysis (ELA) of Image Dataset.

4.1 Data Flow Diagram

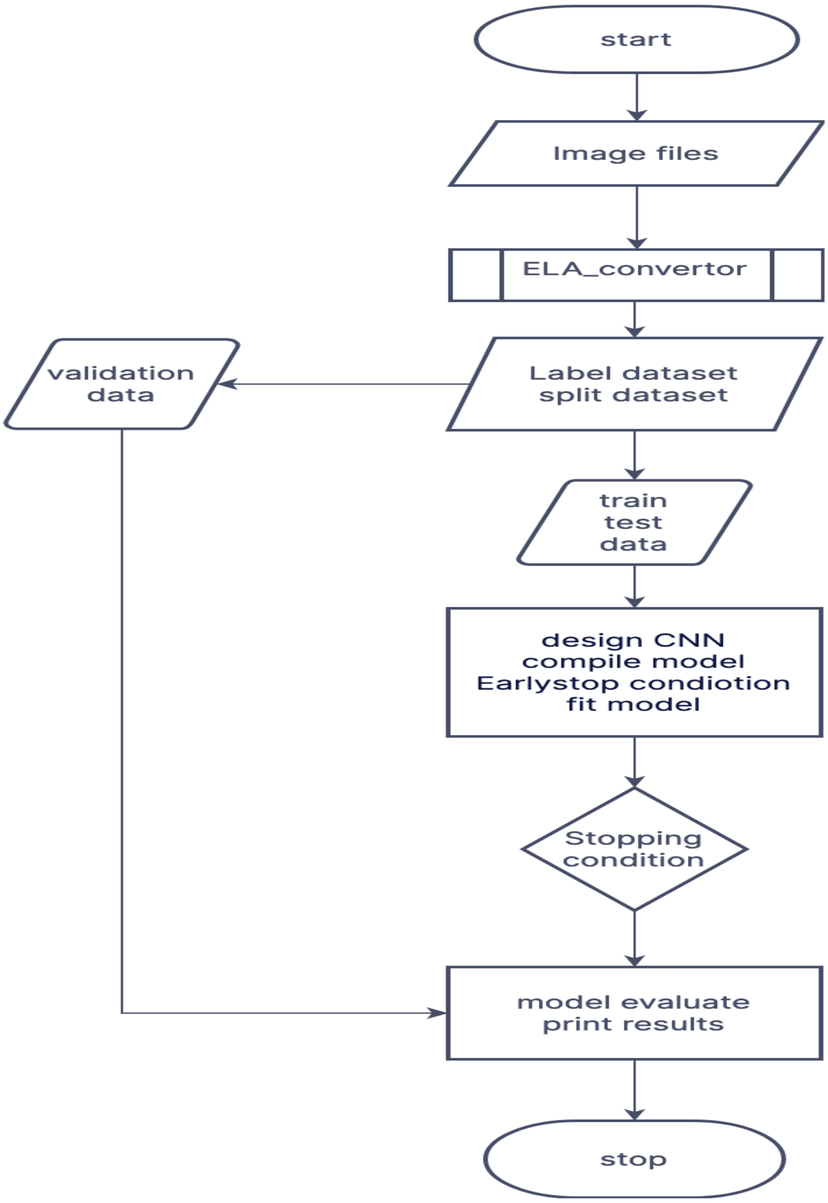

start
Image files
ELA_convertor
validation data
Label dataset split dataset
train test data
design CNN compile model Earlystop condiotion fit model
Stopping condition
model evaluate print results
stop

Fig.1 Data flow diagram

The above diagram shows how the data is being used and saved in our machine while executing the program. Gray color rectangular boxes and circles signify the data flow and black double-bar boxes signify how data is being converted.

4.2 Use case Diagram

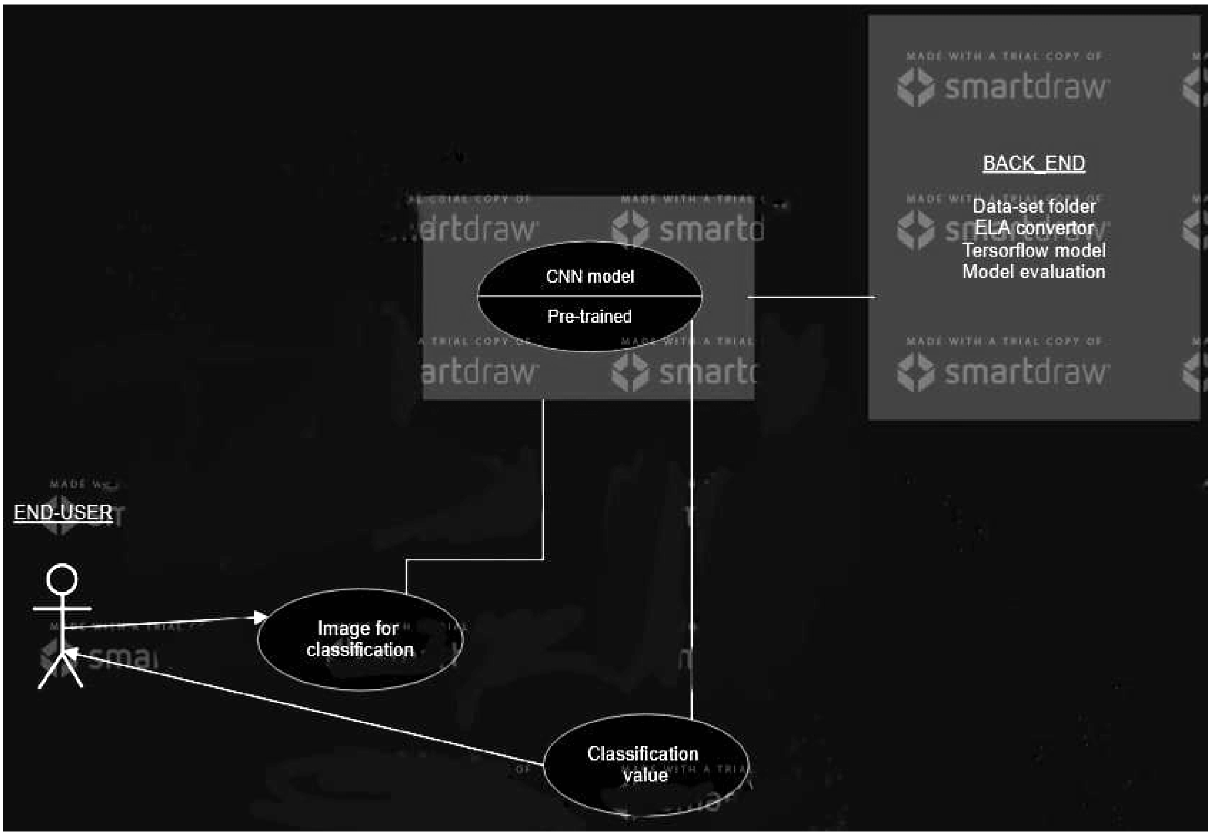


Fig.2 Use case diagram

Above is the single-use case diagram of our product, here the end-user is considered as someone who can directly access the program to classify whether the given image is tampered with or not. Use-case without Front-End application as follows:

1. End user gets access to the class model object where the class model is already trained with a training set.
2. The end-user inputs an image to the object, which invoke the trained model
3. As the trained model is invoked, it explicitly triggers the backend container, which has the necessary model functions and input parsing libraries.
4. The input image is parsed to ELA format and returned back to the trained CNN object.
5. The object classifies whether the image is tampereded with or not, and returns the result to the end-user.

4.3 Sequence Diagram

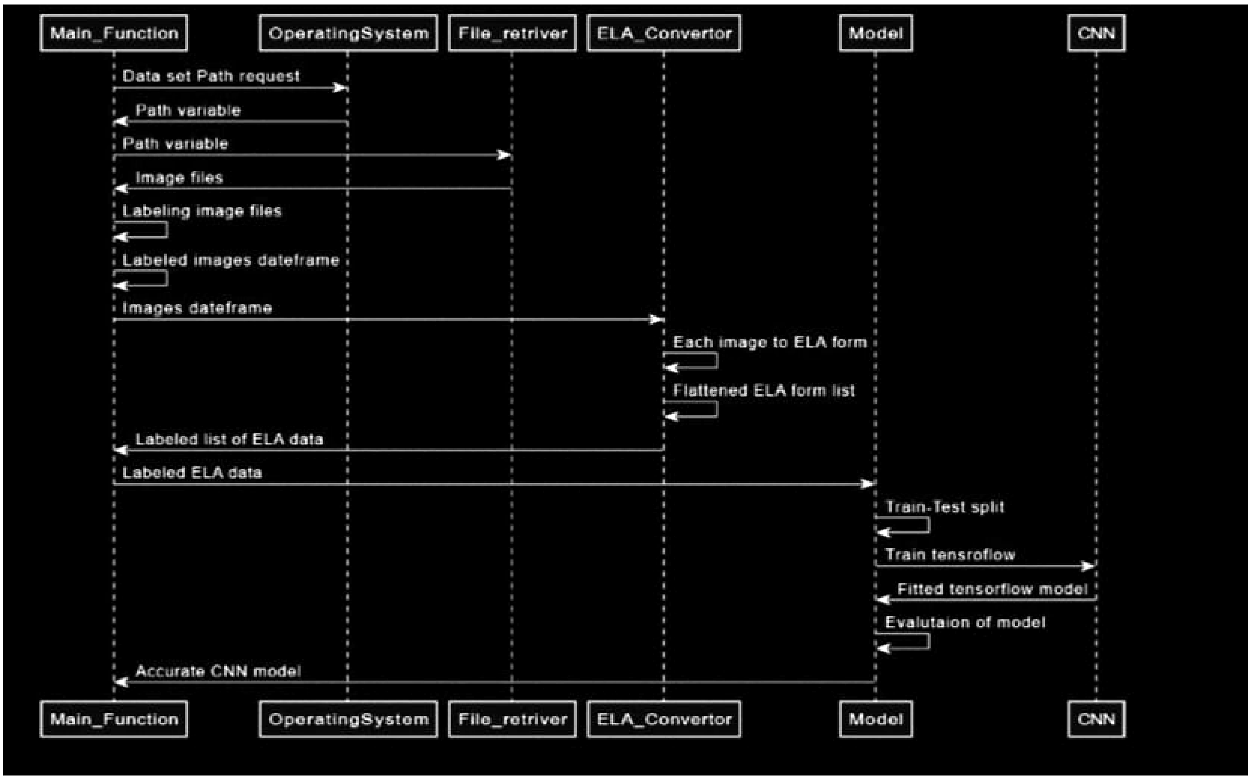


Fig.3 Sequence Diagram

The above sequence diagram shows the execution steps of the CNN for the Back-end. Note that here there is no Active state (bar line), as there is no application for transaction usage, in turn, all the state is considered active (dotted line).

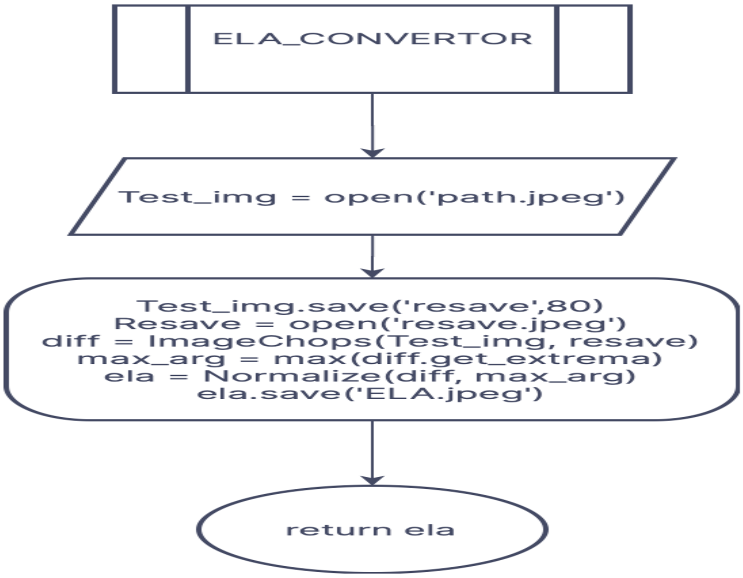
1. The Main function stands for the initial execution program which is triggered by the user.
2. File retriever is used to access the path after checking the metadata of the file.
3. ELA_converter converts image to Error Level Analysis format.
4. Model class is a core Machine learning handling class, which takes care of training and evaluation of the model.
5. CNN, for keras, to have sequential layering in deep learning models.

Chapter 5: Implementation and Results

5.1 Data Preprocessing

The whole idea for JPEG image tamper detection rests on the Error level obtained from double compression of the same image. The image is compressed to 80% of its original value. As JPEG is a lossy compression, recompression of the image will degrade the intensity of the RGB grid(pixel) value. Using this, the original image pixel values are subtracted, then converted back to an image of the difference in the value, this resultant image is referred to as an Error level image. See. Figures 1 & 2, for working.

```
function ELA_Image(Image):
        image = open(Image).convert('RGB')
        image.save('resave_path.JPEG', quality=80)
        resaved = open('resave_path.JPEG')
        diff=Numpy.array(image) - Numpy.array(resaved)
        diff.save('ELA.JPEG')
```



```
Test_img = open('path.jpeg')
```

```
Test_img.save('resave',80)
Resave = open('resave.jpeg')
diff = ImageChops(Test_img, resave)
max_arg = max(diff.get_extrema)
ela = Normalize(diff, max_arg)
ela.save('ELA.jpeg')
```

Fig 4. Flowchart of Error level analysis

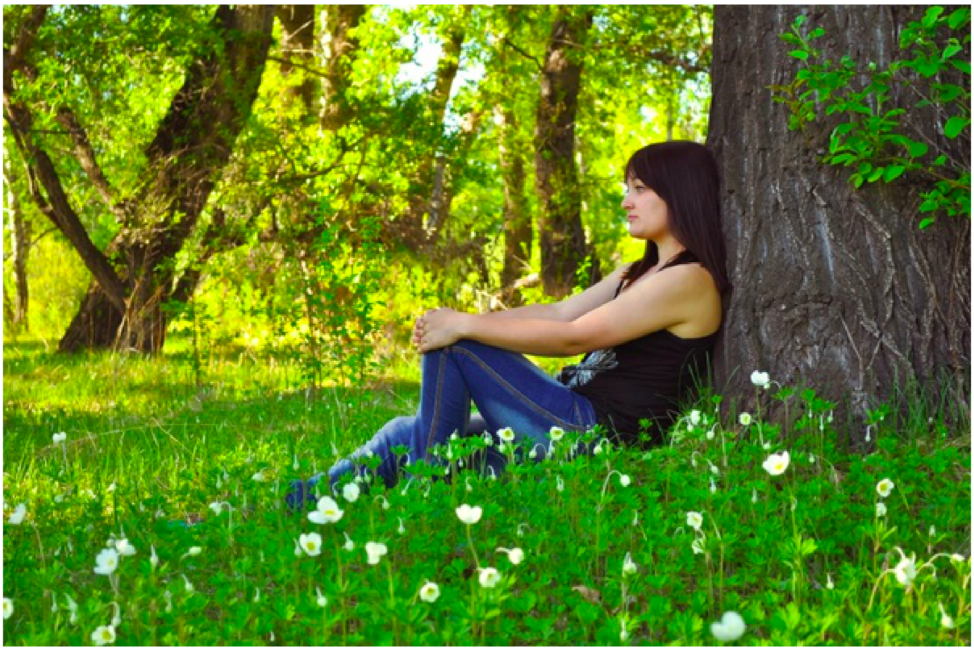


Fig.5 ELA Test Image

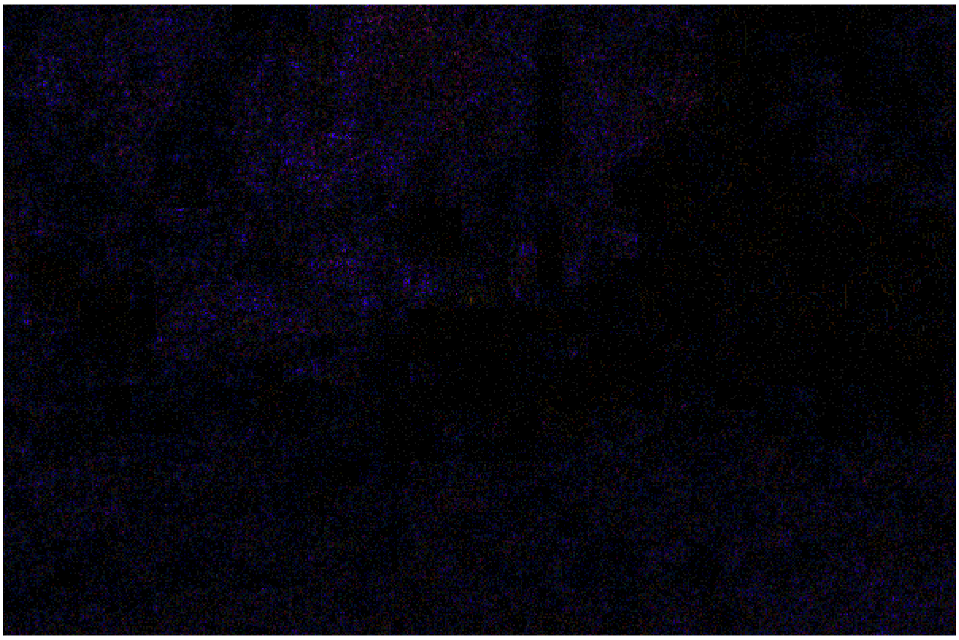


Fig.6 ELA output

5.2 Methodology for classification

The image file is converted into ELA format binary with Quality of 90 over 100 while enhancing the RGB values brightness. This is again converted back to a list of RGB value formats ranging from 0 to 255, with consideration as 256 values per pixel. This list in splitted to training and testing sets for CNN model. The CNN model is sequential connected with 2 Max Pooling layers between Dense layers. The CNN is also enriched with ADAM optimizer for the optimization of weight and loss function for every training input.

5.3 Implemented Models

SL. NO.	Models	Tuning	Test Results
1	LeNet-5	Parameters - 650978 Layers - 5 Convolutions - 3	Accuracy: 0.8096 Recall: 0.8068 Precision: 0.8127 F1 score: 0.808
2	AlexNet	Parameters - 1349754 Layers - 8 Convolutions - 5	Accuracy: 0.8049 Recall: 0.8108 Precision: 0.8108 F1 score: 0.8108
3	VGG-16	Parameters - 395870 Layers - 16 Convolutions - 13	Accuracy: 0.8116 Recall: 0.8080 Precision: 0.8138 F1 score: 0.8093
4	Inception Block	Parameters - 295162 Layers - 27 Convolutions - 22	Accuracy: 0.8424 Recall: 0.8408 Precision: 0.8480 F1 score: 0.8421

Hybrid architecture similar to Inception block and AlexNet was developed to improve the results. See Figure 3 for the architecture overview. The major change apart from hyper-parameter tuning is seen in the use of ‘Leaky_relu’ as the activation function in initial layers. The advantage of using this is to avoid dead neurons. By convection, the final layer activation function is still ‘Softmax’.

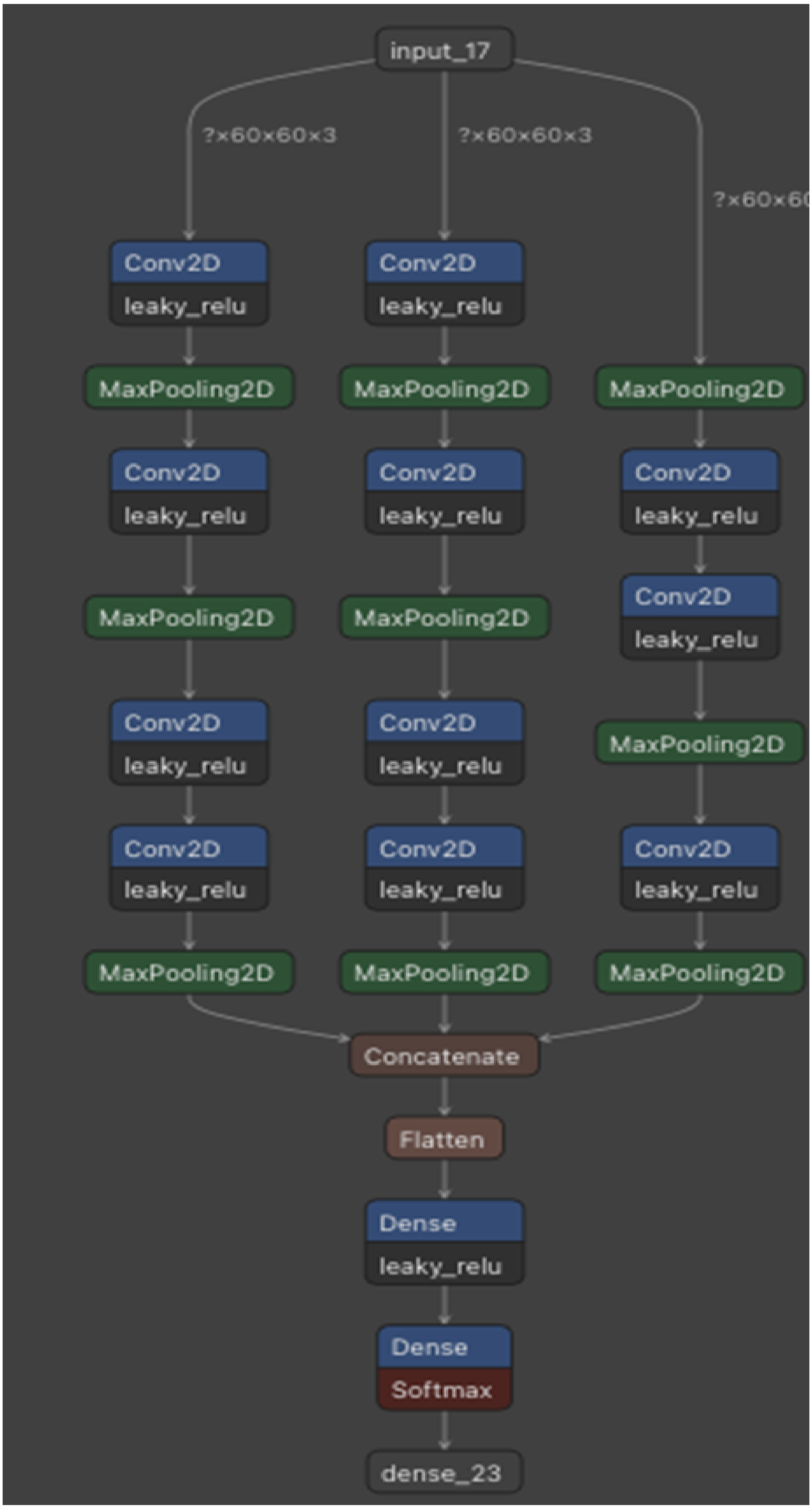


Fig 7. Experimental Model

Performance Evaluation: There are a few estimations used to assess the presentation. The absolute most significant estimations utilized are referenced underneath. Coming up next is significant wording, which is important to grasp the presentation estimations:

True Positive (TP): quantity of altered pictures, which are named altered.

False Negative (FN): quantity of altered pictures, which are delegated true..

True Negative (TN): quantity of credible pictures, which are ordered as authentic.

False Positive(FP): quantity of valid pictures, which are named tampered ones.

Accuracy - Accuracy estimates the level of the pictures that are accurately ordered by the classifier. It is registered as

Accuracy = (TP + TN)/(TP + TN+FN + FP)

True Positive Rate (TPR) - True Positive Rate (TPR), otherwise called Awareness or Review, gauges the level of real altered pictures (up-sides) that are accurately named such. It is determined as

True positive rate = TP/(TP + FN)

True Negative Rate (TNR) - True Negative Rate (TNR), otherwise called Particularity, gauges the level of real true pictures (negatives) that are accurately named such. It is processed utilizing the accompanying recipe

True negative rate = TN/(TN+FP)

False Positive Rate (FPR) measures the level of genuine valid pictures (negatives) that circular segment misclassified as altered. It is equivalent to 1 short TNR and processed as: False positive rate = FP/(FP+ TN) = 1-TNR

Error rate - It estimates the level of the pictures that are not accurately grouped. It is determined as

Error rate (FN+FP)/(TP + TN+FN + FP)

Precision: It is all the points that are declared to be positive but what percentage of them are truly positive.

Precision = True Positive/Predicted Positive

Recall: It is all the points that are truly positive but what percentage is declared positive.

Recall = True Positive/Actual Positive

F1-Score: It is a weighted average of precision and recall, which is used to measure test accuracy. When the F1 score is '1' it is the best and on '0' it is the worst.

F1 = 2 * (precision * recall) / (precision + recall)

Note:- Precision and Recall needs to be high for effective calculation for F1-score.

The model result is as follows:

Accuracy - 0.8570
Precision - 0.8609
Recall - 0.8545
F1 score - 0.8556

The result shown above is the accuracy of classification on validation set and not just only on the training and test set. To prevent the model from overfitting we have used some regularization approaches as well as implemented manual stopping criteria such as early stop, i.e. to stop training if there is no significant improvement in the validation loss (val_loss) when compared to increase in training accuracy.

5.3 Result

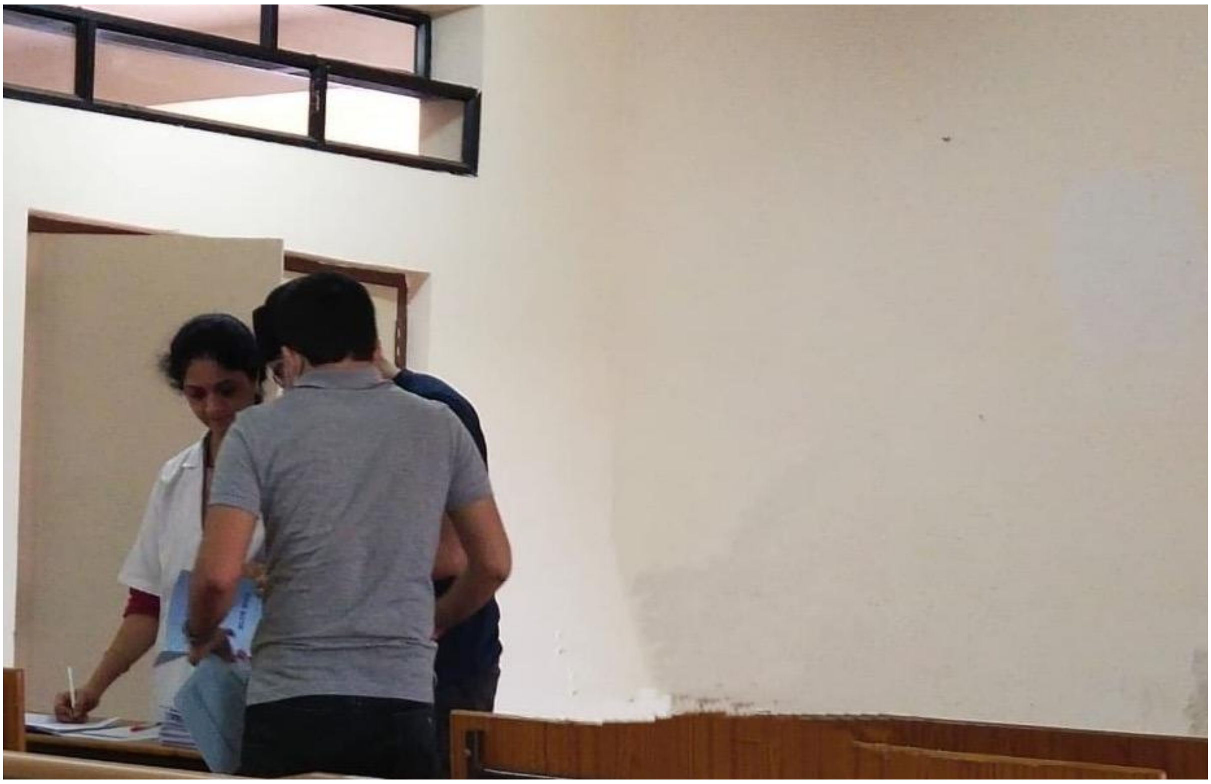


Fig.8 Original Image

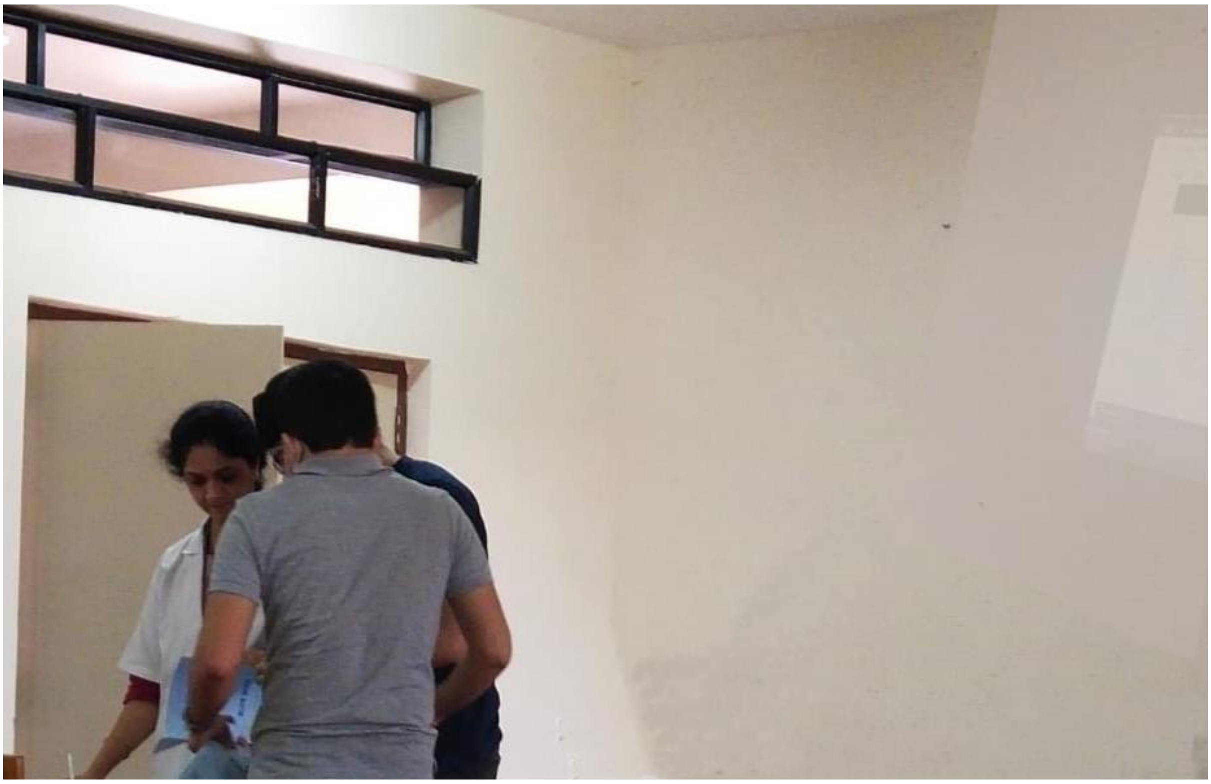


Fig.9 Tampered Image

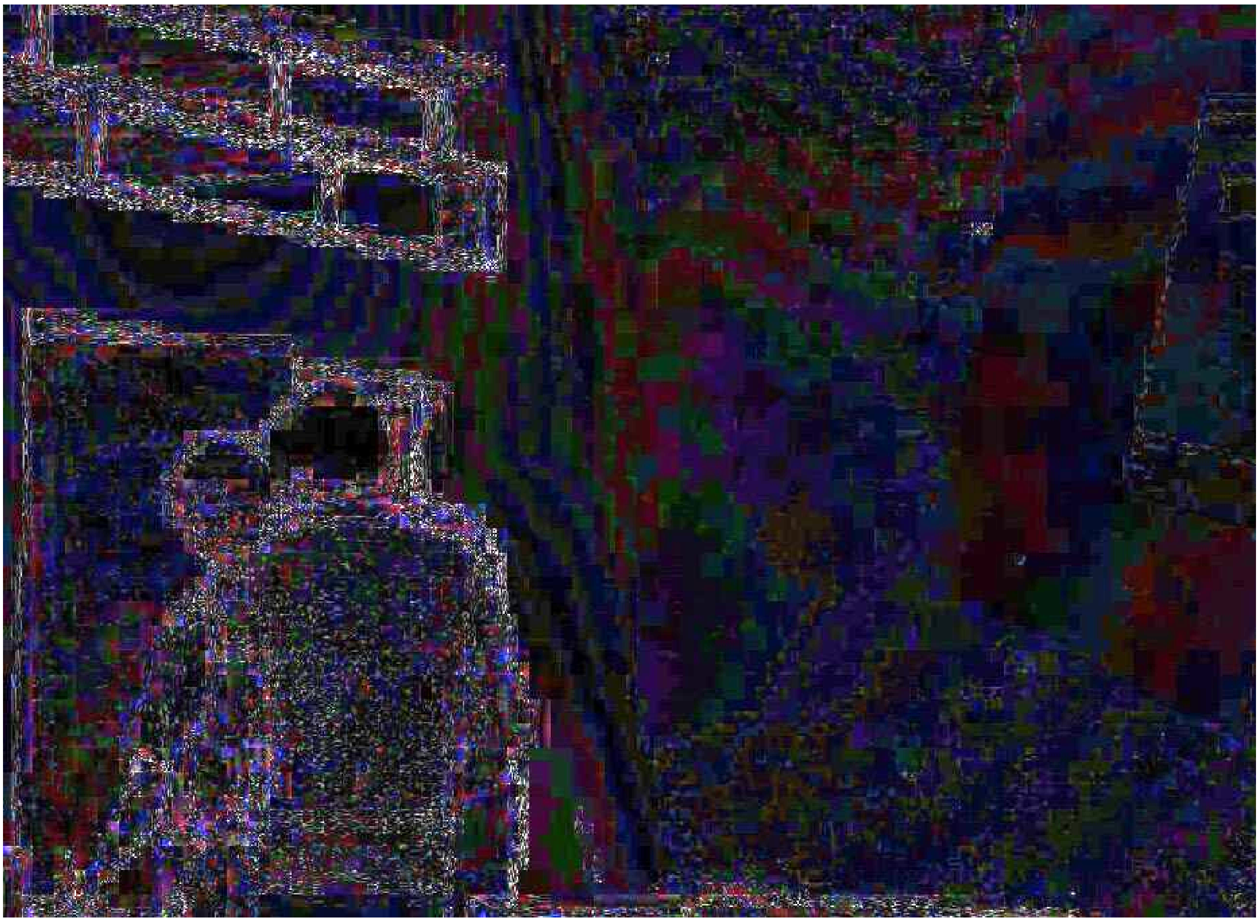
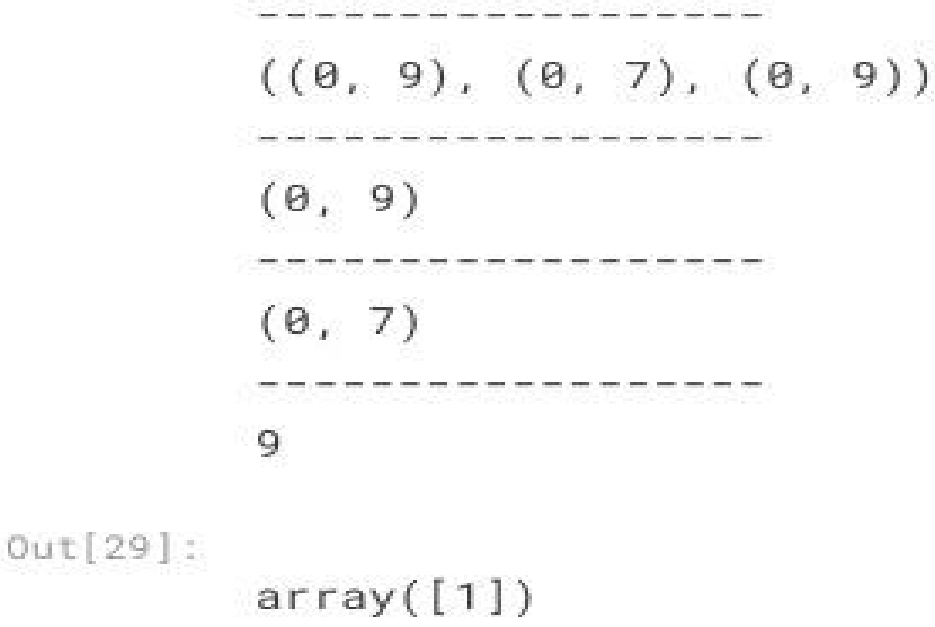


Fig.10 ELA Of Tampered Image



```
--------------------
((0, 9), (0, 7), (0, 9))
--------------------
(0, 9)
--------------------
(0, 7)
--------------------
9

Out[29]:
         array([1])
```

Fig.11 Model output

Chapter 6: Conclusion And Future Scope

6.1 Conclusion

As everyday new image editing products and applications have become easier and simpler to use, the negative effect of manipulating images for personal and financial gain have been increasing. This is a critical issue in the field of crime investigation as well as internet pornography. But, it is noticeable that most of these image manipulation is done on mobile devices upon JPEG images.

To address this problem and to authenticate images in criminal justice. We have developed a new Deep learning architecture to classify between tampered and non-tampered images. The results of this model were better than the transfer learning model as shown in the comparative study.

Finally, we like to conclude by saying that it was in our best interest to try and help all the concerned people in the field of image forensics.

6.2 Future Scope

The present working of the model was built and tested upon passive image tampering, like copy-move-paste using the CASIA V2 dataset. Limiting the converted image to a size of 60x60. It can be further improved on different scale size images ranging from 120x120 to 1080x720. Also, on the note for detecting active image manipulation such as gaussian blur, etc.

Apart from increasing the classification boundary, we could also try and compare other advanced transfer learning architectures like Xception, Noisy-Student, etc. As well as to use the latest state of art image classifier Coca model, and try to combine that with Faster RCNN and other RPN-based networks.

REFERENCES

[1] SeungJu Cha , UiJung Kang ,EunJung Choi, "The Image Forensics Analysis of Jpeg Image Manipulation”, International Conference on Software Security and Assurance (ICSSA), IEEE 2018.

[2] Nor Bakiah Abd Warif, Mohd. Yamani Idna Idris , Ainuddin Wahid Abdul Wahab, Rosli Salleh, "An Evaluation of Error Level Analysis in Image Forensics”, 5th International Conference on System Engineering and Technology, IEEE 2015.

[3] Monagi H. Alkinani, "Effects of Lossy Image Compression on Medical Image Registration Accuracy”, International Conference on Consumer Electronics (ICCE), IEEE 2021

[4] Shuai Tan, Zhi Tan, " Improved LeNet-5 Model Based On Handwritten Numeral Recognition”, 2019 Chinese Control And Decision Conference (CCDC), IEEE 2019.

[5] Aiquan Yuan, Gang Bai, Lijing Jiao, Yajie Liu, "Offline Handwritten English Character Recognition based on Convolutional Neural Network”, 10th IAPR International Workshop on Document Analysis Systems, IEEE 2012.

[6] Yung Lu, “Image Classification Algorithm Based on Improved AlexNet in Cloud Computing Environment”, International Conference on Industrial Application of Artificial Intelligence (IAAI), IEEE 2020.

[7] Ali Abd Almisreb, Nursuriati Jamil, N. Md Din, "Utilizing AlexNet Deep Transfer Learning for Ear Recognition”, Fourth International Conference on Information Retrieval and Knowledge Management, IEEE 2018

[8] Ningbiao Tang, Keqiang Yue, Xueying Yue, Hao Liu, Wenjun Li, "Automatic classification for corneal ulcer using a modified VGG network”, international Conference on Artificial Intelligence and Computer Engineering (ICAICE) , IEEE 2019.

[9] Abitya Bagaskara, Muhammad Suryanegara, "Evaluation of VGG-16 and VGG-19 Deep Learning Architecture for Classifying Dementia People”, 4th International Conference of Computer and Informatics Engineering (IC2IE), IEEE 2021.

[10] S. Kavitha, B. Dhanapriya, G. Naveen Vignesh, K.R.Baskaran, "Neural Style Transfer Using VGG19 and Alexnet”, international Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA), IEEE 2021.

[11] Jun-Liu Zhong and Chi-Man Pun, "An End-to-End Dense-InceptionNet for Image Copy-Move Forgery Detection”, TRANSACTIONS ON INFORMATION FORENSICS AND SECURITY, IEEE 2020.

[12] Jinming Zhang, Zuren Feng, "Inception DenseNet With Hybrid Activations For Image Classification”, 6th International Conference on Systems and Informatics (ICSAI 2019), IEEE 2019.

[13] Kunihiko Taya, Nobutaka Kuroki, Nobutaka Kuroki, Nobutaka Kuroki, Masahiro Numa, "Detecting tampered regions in JPEG images via CNN”, 18th International New Circuits and Systems Conference (NEWCAS), IEEE 2020.

[14] S Manjunatha,Malini M Patil "Deep learning-based Technique for Image Tamper Detection”, Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), IEEE 2021.

[15] Mamoru Nakahara, Nariaki Imamura, Shota Furukawa, "Tampered Regions Detection for JPEG Images by Using DCT Coefficients of Re-Saved Image”, 20th International Symposium on Communications and Information Technologies (ISCIT), IEEE 2021.

[16] Vinod Mall, Anil K. Roy, Suman K. Mitra, "Digital Image Tampering Detection and Localization Using Singular Value Decomposition Technique”, Fourth National Conference on Computer Vision, Pattern Recognition, Image Processing and Graphics (NCVPRIPG), IEEE 2013.

[17] Rayan Sulaiman Khalaf, Asaf Varol, "Digital Forensics: Focusing on Image Forensics”, 7th International Symposium on Digital Forensics and Security (ISDFS), IEEE 2019.

[18] Tiziano Bianchi, Alessandro Piva, "Detection of Nonaligned Double JPEG Compression Based on Integer Periodicity Maps”, IEEE Transactions on Information Forensics and Security, IEEE 2012.

[19] - Wang Junwen, Liu Guangjie;Dai Yuewe, Wang Zhiquan, "Detecting JPEG image forgery based on double compression”, Journal of Systems Engineering and Electronics, IEEE 2009.

Copy of Final_report_Image_tamper_detection.docx.pdf

ORIGINALITY REPORT

14%	6%	12%	%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	S Manjunatha., Malini M Patil. "Deep learning-based Technique for Image Tamper Detection", 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), 2021 Publication	2%
2	medium.datadriveninvestor.com Internet Source	2%
3	SeungJu Cha, Uijeong Kang, EunJung Choi. "The Image Forensics Analysis of JPEG Image Manipulation (Lightning Talk)", 2018 International Conference on Software Security and Assurance (ICSSA), 2018 Publication	1%
4	Abitya Bagaskara, Muhammad Suryanegara. "Evaluation of VGG-16 and VGG-19 Deep Learning Architecture for Classifying Dementia People", 2021 4th International Conference of Computer and Informatics Engineering (IC2IE), 2021 Publication	1%

5	Mamoru Nakahara, Nariaki Imamura, Shota Furukawa. "Tampered Regions Detection for JPEG Images by Using DCT Coefficients of Re-Saved Image", 2021 20th International Symposium on Communications and Information Technologies (ISCIT), 2021 Publication	1 %
6	Jinming Zhang, Zuren Feng. "Inception DenseNet With Hybrid Activations For Image Classification", 2019 6th International Conference on Systems and Informatics (ICSAI), 2019 Publication	1 %
7	dokumen.pub Internet Source	1 %
8	S. Kavitha, B. Dhanapriya, G. Naveen Vignesh, K.R. Baskaran. "Neural Style Transfer Using VGG19 and Alexnet", 2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA), 2021 Publication	1 %
9	ijarcsms.com Internet Source	1 %
10	ijream.org Internet Source	1 %

11	Monagi H. Alkinani. "Effects of Lossy Image Compression on Medical Image Registration Accuracy", 2021 IEEE International Conference on Consumer Electronics (ICCE), 2021 Publication	1 %
12	Nor Bakiah Abd Warif, Mohd. Yamani Idna Idris, Ainuddin Wahid Abdul Wahab, Rosli Salleh. "An evaluation of Error Level Analysis in image forensics", 2015 5th IEEE International Conference on System Engineering and Technology (ICSET), 2015 Publication	<1 %
13	Vinod Mall, Anil K. Roy, Suman K. Mitra. "Digital image tampering detection and localization using singular value decomposition technique", 2013 Fourth National Conference on Computer Vision, Pattern Recognition, Image Processing and Graphics (NCVPRIPG), 2013 Publication	<1 %
14	Aiquan Yuan, Gang Bai, Lijing Jiao, Yajie Liu. "Offline handwritten English character recognition based on convolutional neural network", 2012 10th IAPR International Workshop on Document Analysis Systems, 2012 Publication	<1 %
	www.semanticscholar.org	