Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7750405

DETECTION OF FORGERY IMAGE USING NEURAL NETWORK

Dr.A.Vinoth Kumar[1],Dr. V. Ramesh babu[1], Dr.D.Usha[1]
Yaswanth Kumar Reddy P[2], Sai Teja P[2], Ajay N[2]
[1]Professor(s), Dr.MGR Educational and Research Institute
[2]Final Year B.Tech CSE, Dr.MGR Educational and Research institute,
[1]dravinoth@gmail.com,rameshbabu.cse@drmgrdu.ac.in,usha.cse@drmgrdu.ac.in
[2]yashureddy890@gmail.com, podilisaiteja123@gmail.com, nelloreajay29@gmail.com,

Abstract—Due to the supply of deep networks, progress has been created among the sector of image recognition. Pictures area unit spreading really handily and with the supply of robust piece of writing tools the meddling of digital content become simple. To sight such scams, we've got an inclination to planned techniques. In our paper, we've got an inclination to planned two necessary aspects of exploitation deep convolutional neural networks to image forgery detection. we've got an inclination to initial explore and examine fully totally different pre-processing methodology on a aspect convolutional neural networks (CNN) design. Later we've got an inclination to evaluated the varied transfer learning for pre-trained Image Net(via-fine tuning) and implement it over our dataset CASIA V2.0. So, it covers the pre- processing techniques with basic CNN model and later see the powerful results of the transfer learning models.

Keywords— image tampering, convolution neural network (CNN), error level analysis (ELA), sharpening filter.

I. INTRODUCTION

The creation of ways for confirming the sources of data spark analysis interest community in recent years because of the quantity of data promptly out there to regular folks, like videos and pictures, that area unit simply modifiable to supply false info. tampered with, altered, or faux media retailers misuse content and unfold it through all platforms. The study places a robust stress on creating comparisons between the pre-processing stages of the convolution neural network (CNN) advance as a comparison between transfer is formed between convolution neural network (CNN) and another pedagogic models numerous comparison tables and figures combined represents the performance statistics and potency.

This research's goal is to introduce enhancements, either through pre-processing or simply by using higher algorithms. Accuracy and loss perform, or mean square error, area unit the analysis metrics that area unit utilized (MSE). The confusion matrix[41], that compares the sums of true positive and true negative to those of true negative, true positive, false negative, and false positive, may be wont to calculate accuracy. True positive and expected positive area unit the definitions of true positive and true negative, severally. False positive and expected negative area unit the definitions of false positive and discovered negative, severally. The MSE is that the square distinction between the output that was expected and therefore the output that was really obtained. For process pictures, CNN could be a potent algorithmic program. the foremost effective algorithms out there at once for automating image process area unit those mentioned on top of. For tasks like distinctive the objects in a picture, several businesses use these algorithms. RGB knowledge is gift in image knowledge. Image import from a file into memory is feasible with Matplotlib. The array of numbers before of the pc rather than a picture is all it will fathom. In third-dimensional arrays, color pictures area unit keep. Height and breadth of the image area unit depicted by the primary 2 dimensions (the range of pixels). Red, green, and blue area unit the colors that form up every element, and that they form up the ultimate dimension.

II.RELATEDWORK

Chelghoum R *et al.,* (2020) this study is to increase the classification accuracy, speed the training time and avoid the over fitting. In this work, we trained our architectures involved minimal pre-processing for three different epoch number in order to study its impact on classification performance and consuming time. In addition, the paper benefits acceptable results with small number of epoch in limited time. Our interpretations confirm that transfer learning provides reliable results in the case of small dataset. The proposed system outperforms the state-of-the-art methods and achieve 98.71% classification accuracy.

J. Ouyang *et al.,*(2017) given a way for copy-move forgery detection exploitation deep CNN. Experimented with 3 datasets, OX- FORD flower as dataset1, UCID as dataset2, and CMFD as dataset3. Worked over the concept of exploitation Associate in Nursing existing model for an oversized information as ImageNet then with some alteration in structure, given the results. For dataset1, dataset2 and dataset3 the subsequent check error showed a pair of.32%,2.32% and forty second severally.

Jmour *et al.,* (2018) it presents the preliminary classification results of applying this CNN to learn features and classify RGB-D images task. To determine the appropriate architecture, we explore the transfer learning technique called “fine tuning technique”, of reusing layers trained on the ImageNet dataset in order to provide a solution for a four-class classification task of a new set of data

Guotai Wang *et al*., (2018) propose image-specific fine tuning to make a CNN model adaptive to a specific test image, which can be either unsupervised (without additional user interactions) or supervised (with additional scribbles). We also propose a weighted loss function considering network and interaction-based uncertainty for the fine tuning. We applied this framework to two applications: 2-D segmentation of multiple organs from fetal magnetic resonance (MR) slices, where only two types of these organs were annotated for training and 3-D segmentation of brain tumor core (excluding edema) and whole brain tumor (including edema) from different MR sequences, where only the tumor core in one MR sequence was annotated for training.

Z. J. Barad *et al.,* (2020) presents the analysis and conclusions that area unit helpful to alternative researchers. It provided info concerning many analyses comes exhaustive. provided the datasets for image forgery detection info. It talks concerning the 2 wide used ways of forgery detection: I ancient (ii) Deep Learning (DL). Finally, we have a tendency to show that deep learning algorithms \trounce classical ways. on condition that feature extraction and categorization occur in 2 stages throughout deep learning. Even with advanced feature datasets, these algorithms perform well. The classification of image forgery detection approaches was concisely introduced within the paper. The study of many deep learning networks includes comparisons of Deep Neural Network (DNN), perennial Neural Network (RNN), and Convolutional Neural Network(CNN).

P. He *et al., (2019)* to improve the prior statistics. worked mostly on the post-processing, extraction of variables, and model learning stages. 1. Employed residual signals of chrominance components from colourful regions, including YCbCr, HSV, and the office, to instruct powerful deep representations via the carefully developed shallow con- volutional neural network (CNN). 2. The final detection results are then obtained by concatenating and feeding the learnt deep representations from various colour regions into the Random Forest (RF), which is a popular ensemble classifier. Experimental findings show that the strategy outperforms progressive methods and has extra good detection accuracies (over 99% in most circumstances) against post processing assaults, notably.
The solutions for passive authentication in image forensics area unit conferred and mentioned during this study. There area unit primarily two ways. First, we have a tendency to acquire our results victimization the foremost elementary and easy learning model, a convolution neural network with two pre-processing ways. Second, assess the results of varied transfer learning models and create changes. Third, victimization identical dataset, we'll compare all of the models and also the methods that might turn out the most effective outcomes. Check the effectiveness of our ways for police work image forgery to visualize however they may be created even higher.

III.PROBLEMSTATEMENT

Image forgery means that manipulation of the digital image to hide some significant or helpful data of the image.
There area unit cases once it's tough to spot the altered region from the initial image. The detection of a cast image is driven by the requirement of genuineness and to keep up integrity of the image.

Information quality problems and image forgery detection area unit the most problems that area unit present: Data supply is that the initial issue in forgery detection, per root. uncounted photos area unit on the net, and so as to identify a pretend, the supply of the initial image should necessary for the upholding of rights and presumably a demand for super ordinate action in applications like government legal investigations, monetary transactions, and plenty of different things happen daily. once the knowledge is reliable and valuable, there are a unit those circumstances.

Standard Data Set and Benchmarking: The requirement for Open information Set for important Understanding of the detection of formation seems to be yet one more issue. The absence of the photographs from image acquisition model with numerous resolutions, sizes, and uncompressed type among the conditions for a picture that has to be met so as to tell apart a pretend from the real one is its contents a crucially important image.

IV.METHODOLOGY

Convolution neural network (CNN), a elementary neural network for image recognition, has been utilized [10,11,39]. pictures area unit used as input and

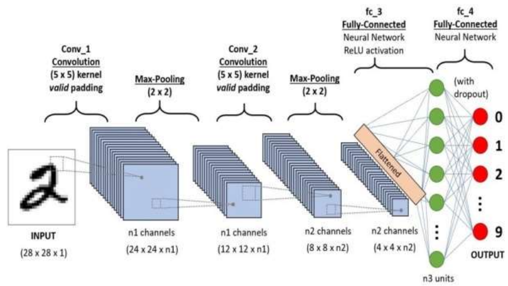

Figure 1. Architecture of Convolution neural network

vital options area unit extracted from every image. Since it's a multi-layered neural network, bound options area unit extracted at every layer. It will determine even complicated traits as you progress more into the network.

The CNN design is delineated in Figure one. consists of the 2 elements Feature-Extraction and Classification. it's created from the subsequent layers [12,13].

- Input layer:: The data set's photos are a unit feds here.

- Convolution layer: This can be wherever options area unit known. bound options, travel in complexity from straightforward to sophisticated, area unit retrieved with every layer to assist in process.

- Pooling layer: It reduces the content by keeping the numerous options that area unit needed. Decrease the computation power, by reducing the abstraction size of convolution layer.

- Fully-connected layer: Construct one column vector by flattens the image. when series of epochs, victimization SoftMax classification technique, model might able to distinguish between dominating and weak options in pictures and classify them.

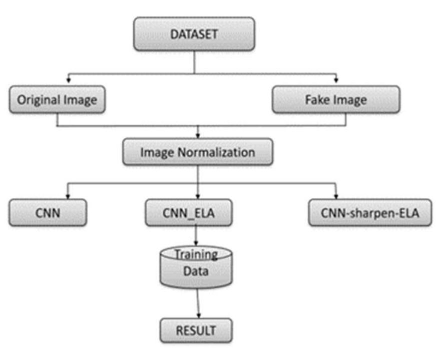

Figure 2.System Architecture.

Dataset is split into coaching and testing data set with a ratio of 80% and 20% respectively is passed through the CNN, CNN ELA combination and CNN SHARPEN ELA combination, separately and then compared. According to, the foreign terrorist organization technique involves storing the altered pictures at a specific quality level and so calculative the distinction from the compression level. For image forensics detection, foreign terrorist organization could be a JPEG , lossy, irreversible com- pression technique. This algorithm's division technique was wont to approximate the JPEG quality.

The image is choppy into blocks of 8x8 pixels and recompressed at a 95% error rate. each grid ought to have roughly identical quality rate if the image is unchanged and adjusted; otherwise, there'll be a distinction within the level of grids. As a result, the presence of uneven gridlines denotes image manipulation. The error rate made by the foreign terrorist organization approach are often wont to sight modification in JPEG pictures. So as to more increase the accuracy for the model to sight image forgery, examined the mix of foreign terrorist organization and sharpen filter. wherever each the pre- processing stages plays half as shown in results. the method of improvement of element distinction between bright and dark regions so as to bring out options clearly is that the referred to as the sharpening. In our analysis, the Pillow-python image process library has been used.

−2 −2 −2
−2 -2 −2
−2 −2 −2

Figure 3. Sharpening filter

The above filter is used,fig.3., which is able to provide the brighten impact, the pixels area unit boosted as relative to its neighbors. victimization this filter over the changed image can erratically do the distinction method because the edges and features of modified(fake) image has been blurred or distorted.

A. USE CASEDIAGRAM

The use case diagram represents the operating of specific functions by the users in order to avoid all the miscommunications.

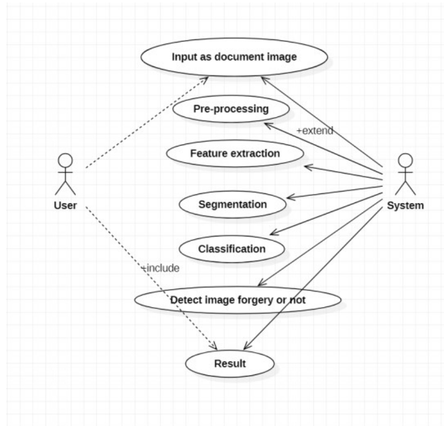

Figure. 4. Use Case Diagram

B. ACTIVITYDIAGRAM

The workflow from one action to the next may be seen using the activity diagram. It highlighted the flow state and the sequence in which it takes place. The flow may proceed and deal with these types of fluxes.

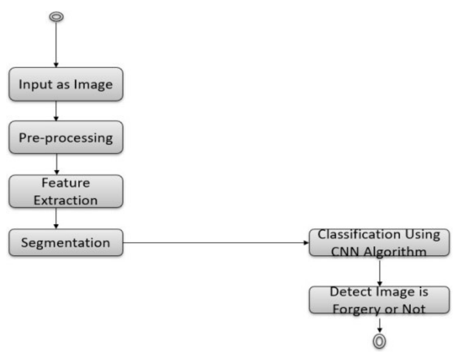

Figure. 5. Activity Diagram

V. CONCLUSION

Presented a comparison study for the CASIA V2.0 dataset photo forgery detection that takes into account several deep learning techniques. In this study, two forgery detection techniques were investigated: I preprocessing work; and (ii) several deep learning models. successfully created the detection with enhanced metrics using a variety of models and combinations. ResNet50 offers us a 95% confidence test accuracy and a minimal test loss of about 0.4%, whereas CNN Sharpen ELA offers us a 97% training accuracy and a negligible 0.1% training loss. The methods employed in this research are the most straightforward and dataset-independent, and they can be used to any model and any dataset in order to evaluate the effect and improvement in many situations. We'll carry out the aforementioned work in the future.

VI.FUTUREWORK

Depending on how complicated the datasets are, more convolution and pooling layers maybe added. The techniques may be used to a variety of datasets or they can be used to improve an existing model by making minor changes to the pre-processing or training stages. The methods might be expanded to include movies that are collections of frames.

REFERENCES

[1] P. He, H. Li and H. Wang,"Detection of Fake Images Via the Ensemble of Deep Representations from Multi Color Spaces," 2019 IEEE International Conference on Image Processing (ICIP), 2019, pp. 2299- 2303, doi: 10.1109/ICIP.2019.8803740.

[2] Khan, SharzilHaris, Zeeshan Abbas, and SM Dan- ish Rizvi." Classification of diabetic retinopathy images based on customised CNN architecture." In 2019 Amity International Conference on Artificial Intelligence (AICAI), pp. 244-248 IEEE,2019.

[3] Comprehensive guide to con- volutional-Neural-Networks[On-line], Available:https://towardsdatascience.com/acomprehensiveguidetoconvolutional-neural-networks-the-eli5-way3bd2b1164a53.

[4] Prajapati, Shreyansh A., R. Nagaraj, and Suman Mitra. "Classification of dental diseases using CNN and transfer learning." In 20175th In ternational Symposium on Computational and BusinessIntelligence(ISCBI),pp.70-74.IEEE,2017.

[5] J. Ouyang, Y. Liu and M. Liao, "Copy-move forgery detection based on deep learning," 2017 10th Interna- tionalCongressonImageandSignal.

[6] P. He, H. Li and H. Wang, "Detection of Fake Images Via The Ensemble of Deep Representations from Multi Color Spaces," 2019 IEEE International Conference on Image Processing (ICIP), 2019, pp. 2299-2303, doi: 10.1109/ICIP.2019.8803740.

[7] Brownlee, Jason. Deep learning for computer vision: image classification, object detection, and face recogni- tion in python. Machine Learning Mastery, 2019.

[8] Y. Shah, P. Shah, M. Patel, C. Khamkar andP. Kanani, "Deep Learning model-based Multimedia forgery detection," 2020 Fourth International Confer- ence on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), 2020, pp. 564-572, doi: 10.1109/IS-MAC49090.2020.9243530.

[9] P. He, H. Li and H. Wang, "Detection of Fake Images Via The Ensemble of Deep Representations from Multi Color Spaces," 2019 IEEE International Conference on Image Processing (ICIP), 2019, pp. 2299-2303, doi: 10.1109/ICIP.2019.8803740.

[10]Wang, Guotai, Wenqi Li, Maria A. Zuluaga, Ros- alind Pratt, Premal A. Patel, Michael Aertsen, Tom Doel et al. "Interactive medical image segmentation using deep learning with image-specific fine tuning." IEEE transac- tions on medical imaging 37, no. 7 (2018): 1562-1573.

[11] Jmour, Nadia, SehlaZayen, and AfefAbdelkrim. ”Convolutional neural networks for image classification.” In 2018 International Conference on Advanced Systems and Electric Technologies (IC ASET), pp. 397-402. IEEE, 2018.

[12]Chelghoum R., Ikhlef A., Hameurlaine A., JacquirS. (2020) Transfer Learning Using Convolutional Neural Network Architectures for Brain Tumor Classification from MRI Images. In: Maglogiannis I., Iliadis L., Pimeni- dis E. (eds) Artificial Intelligence Applications and Inno- vations. AIAI 2020. IFIP Advances in Information and Communication Technology, vol583.Springer,Cham. https://doi.org/10.1007/978-3-030-49161-1 17

[13]Z. J. Barad and M. M. Goswami, ”Image Forgery Detection using Deep Learning: A Survey,” 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS), 2020, pp. 571-576, doi: 10.1109/ICACCS48705.2020.907440.