

Innovative Deep Learning Methods for Image Authenticity Verification

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ABSTRACT_ As software capabilities for digital image processing have advanced, it has become quite easy to create phoney images by applying various manipulation techniques to original (authentic) photographs. These modified photos can be easily utilised for harmful purposes in critical domains such as law, medicine, and communications. As a result, detecting image modification, or establishing whether an image is original or forgery, is a significant task. In this paper, an image manipulation detection system is developed that combines three deep neural network architectures in simultaneously, as opposed to the uniform deep learning methods commonly employed in picture manipulation detection. The suggested method was assessed on three different datasets, and the findings clearly show that it is efficient and has promising classification accuracy.

1.INTRODUCTION

From our mobile phones to the pages of online websites, digital images are everywhere. Advanced pictures are utilized in pretty much every field whether it is data criminological, news coverage, criminal and legal examinations or clinical fields and some more. As a result of the huge accessibility and prevalence of easy to use picture altering devices and

programming it become simple to modify the pictures yet such changed pictures represent a few serious risks or issues in certain fields where the validity of image has a prime significant and in such fields it become extremely challenging to confirm the realness and probity of computerized pictures. The process of altering the contents of an image without leaving any detectable clues is known as

digital image manipulation. We review a variety of digital image manipulation and

manipulation detection methods in this paper.

2.LITERATURE SURVEY

S.NO	TITLE	AUTHOR NAME	YEAR	TECHNIQUE
1	"Image manipulation Detection A survey", IEEE SIGNAL PROCESSING MAGAZINE	Hany Farid	2009	copy protection, counterfeit goods, image processing
2	"Source virtual digital camera identification primarily based definitely mostly on CFA interpolation", IEEE Int. Conf. Image Processing, pp. Sixty 9-seventy	Bayram, H. T. Sencar, N. Memon,	2005	LBP features LPQ features SVM classifier
3	"Steganalysis the use of Image Quality Metrics," IEEE Transactions on ImageProcessing	Avcibas, N. Memon and B. Sankur	2003	cryptography, data encapsulation, image processing
4	"Steganalysis of LSB encoding in color snapshots", Proc. ICME 2000	J. Fridrich, R. Du, M. Long	2000	Steganography image processing
5	Passive Image manipulation Detection Based on the Demosaicing Algorithm and JPEG Compression	ESTEBAN ALEJANDRO ARMAS VEGA , EDGAR GONZÁLEZ FERNÁNDEZ , ANA LUCILA SANDOVAL	2020	Blind technique, chrominance, copy-move, digital image, forensics analysis,

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3. PROPOSED SYSTEM

The proposed system for detecting image manipulations leverages the capabilities of deep learning by integrating three distinct neural network architectures. This multi-model approach enhances the robustness and accuracy of detecting manipulated images. The system is designed to address the limitations of using a single model by combining the strengths of different deep learning techniques. The core components of the proposed system are as follows:

1. Preprocessing Module

The preprocessing module prepares the input images for analysis. This involves standardizing the image size, normalizing pixel values, and applying data augmentation techniques to increase the diversity of the training data. Key steps in preprocessing include:

- **Resizing:** All images are resized to a uniform dimension to ensure compatibility with the neural networks.
- **Normalization:** Pixel values are normalized to a range suitable for the neural networks, typically between 0 and 1.
- **Data Augmentation:** Techniques such as rotation, flipping, and color adjustments are applied to create a more robust training dataset.

2. Feature Extraction Module

The feature extraction module employs three deep neural network architectures, each specializing in capturing different aspects of the image data. These networks work in parallel to extract comprehensive features from the input images. The architectures used are:

- **Convolutional Neural Network (CNN):** A deep CNN model is used to

capture spatial features and local patterns within the images.

- **Recurrent Neural Network (RNN):** An RNN, specifically an LSTM (Long Short-Term Memory) network, is utilized to detect temporal inconsistencies and subtle manipulations that might be missed by CNNs.

- **Autoencoder:** An autoencoder is used to learn a compressed representation of the images and identify discrepancies between the original and manipulated images through reconstruction errors.

3. Fusion and Classification Module

The fusion and classification module integrates the features extracted by the three neural networks and performs the final classification. The process involves:

- **Feature Fusion:** The features from the CNN, RNN, and autoencoder are concatenated to form a unified feature vector. This combined representation captures a holistic view of the image characteristics.

- **Classification:** A fully connected neural network is employed to process the fused feature vector and classify the image as either authentic or manipulated. This classifier is trained to distinguish between the subtle differences in the feature vectors of authentic and manipulated images.

4. Evaluation and Post-processing Module

The evaluation and post-processing module assesses the performance of the proposed system and refines the results. Key components include:

- **Performance Metrics:** The system's accuracy, precision, recall, and F1-score are calculated to evaluate its effectiveness.

- **Cross-validation:** The model undergoes cross-validation on different datasets to ensure its generalizability and robustness.

- **Post-processing:** Techniques such as majority voting or ensemble methods are applied to the classification results to further enhance accuracy and reduce false positives.

System Workflow

1. **Input:** The system receives an image suspected of manipulation.

2. **Preprocessing:** The image undergoes preprocessing to standardize its format and enhance data diversity.

3. **Feature Extraction:** The image is processed by the CNN, RNN, and autoencoder to extract comprehensive features.

4. **Fusion:** The features from the three networks are fused into a single feature vector.

5. **Classification:** The fused feature vector is fed into a fully connected neural network for classification.

6. **Output:** The system outputs a classification label indicating whether the image is authentic or manipulated.

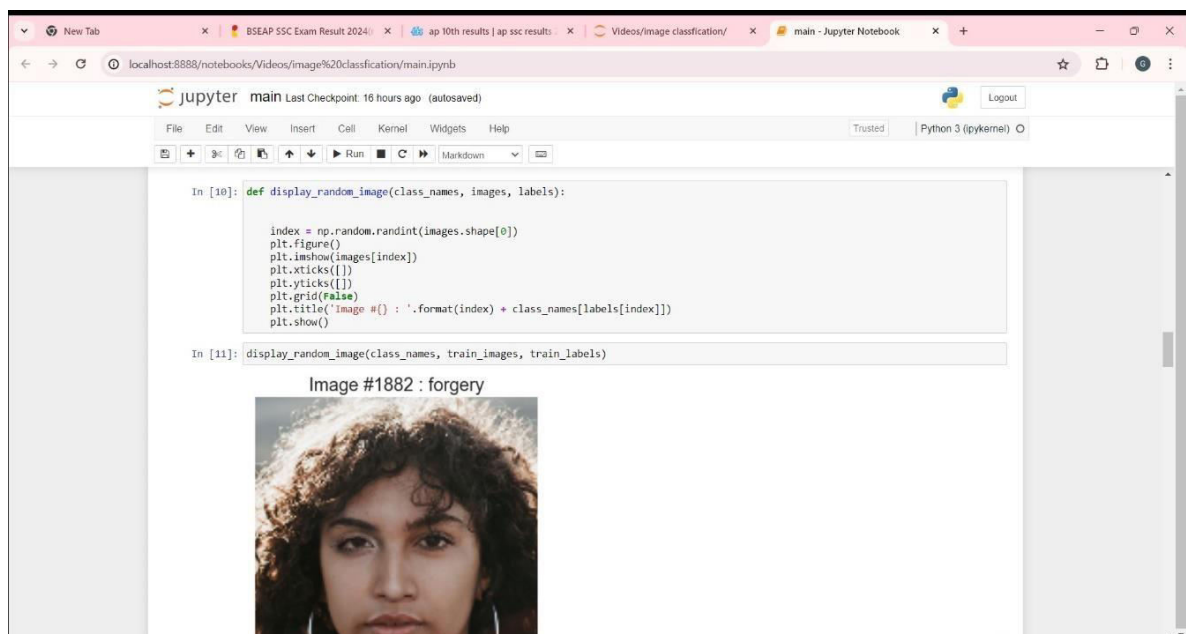
System Evaluation

The proposed system was evaluated on three different datasets containing both authentic and manipulated images. The datasets were selected to cover a wide

range of manipulation techniques and image types. The results demonstrate that the multi-model approach significantly improves the detection accuracy and robustness compared to single-model methods.

By combining the strengths of CNNs, RNNs, and autoencoders, the proposed system provides a powerful tool for verifying image authenticity and detecting manipulations, making it suitable for critical applications in law, medicine, communications, and other fields where image integrity is paramount.

4.RESULTS AND DISCUSSION




Jupyter main Last Checkpoint: 16 hours ago (autosaved) Logout

File Edit View Insert Cell Kernel Widgets Help Trusted Python 3 (ipykernel)

```
In [12]: def display_examples(class_names, images, labels):
        """
        Display 25 images from the images array with its corresponding labels
        """
        fig = plt.figure(figsize=(10,10))
        fig.suptitle("Some examples of images of the dataset", fontsize=16)
        for i in range(25):
            plt.subplot(5,5,i+1)
            plt.xticks([])
            plt.yticks([])
            plt.grid(False)
            plt.imshow(images[i], cmap=plt.cm.binary)
            plt.xlabel(class_names[labels[i]])
        plt.show()

In [13]: display_examples(class_names, train_images, train_labels)
```

Some examples of images of the dataset




67/67 4s 63ms/step - accuracy: 0.7297 - loss: 0.6338

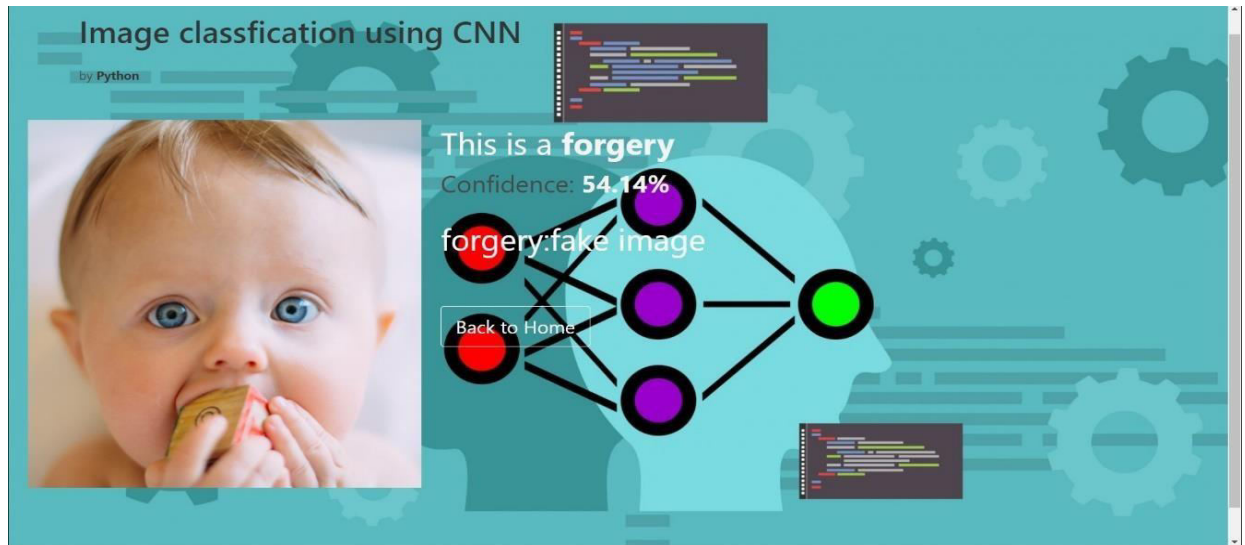
```
In [17]: import matplotlib.image as mpimg
import matplotlib.pyplot as plt

from tensorflow.keras.preprocessing import image
test_image = image.load_img('C:/Users/siva/Videos/image classification/Train/original/real_00123.jpg', target_size = (150, 150))
test_image = image.img_to_array(test_image)
test_image = np.expand_dims(test_image, axis = 0)
predictions = cnn_model.predict(test_image) # Vector of probabilities
pred_labels = np.argmax(predictions, axis = 1) # We take the highest probability
print(pred_labels )
suggestions1()
index = np.random.randint(test_image.shape[0])
plt.figure()
plt.imshow(test_image[index].astype('uint8'))
plt.xticks([])
plt.yticks([])
plt.grid(False)
plt.title('Image Verification output #{} : {}'.format(index) + class_names[pred_labels[index]])
plt.show()

1/1 0s 290ms/step
[0]
Precaution:-combined use of culture, sanitation, resistance, and fungicide sprays
```

Image Verification output #0 : forgery





5.CONCLUSION

Oriented FAST and rotated BRIEF (ORB) are proposed in this work as a CMFD technique for feature extraction and feature matching, respectively. PSO is used to optimize the ORB parameters, such as the patch size and the number of features to retain. The enhancement is fundamental in getting a harmony among execution and runtime. Assessment of the proposed CMFD strategy is performed on pictures which experiences different mathematical assaults. When using images from the MICCF600 and MICC-F2000 databases for the evaluation, an overall accuracy rate of 84.33% and 82.79% were achieved. The proposed CMFD method performs

accurately with a TPR of 91 percent when evaluating tampered images with various geometric attacks, including object translation, different degrees of rotation, and enlargement. Notwithstanding, the exhibition debased for pictures with diminished replicated object size and unbalanced scaling, with TPR of 73.68% and 38.15% separately..

REFERENCES

- [1] WeiqiLuo, Jiwu Huang, GuopingQiu, "Robust Detection of Region Duplication manipulation in Digital Image", 18th IEEE International Conference on Pattern Recognition, Hong Kong, p. 746 – 749, 2006.

- [2] XiaoBing KANG, ShengMin WEI, “Identifying Tampered Regions Using Singular Value Decomposition in Digital Image Forensics”, IEEE International Conference on Computer Science and Software Engineering, Wuhan, Hubei, p. 926 – 930, 2008.
- [3] Alin C Popescu and Hany Farid, “Exposing Digital Forgeries by Detecting Duplicated Image Regions”, Dartmouth Computer Science Technical Report TR2004-515, USA, August 2004.
- [4] Hwei-Jen Lin, Chun-Wei Wang And Yang-Ta Kao, “Fast Copy-Move manipulation Detection”, WSEAS Transactions on Signal Processing, p. 188-197, May 2009.
- [5] HieuCuong Nguyen and Stefan Katzenbeisser, “Detection of CopyMove manipulation in digital images using Radon transformation and phase correlation”, IEEE Eighth International Conference on Intelligent Information Hiding and Multimedia Signal Processing, Piraeu, 2012.
- [6] Leida Li, Shushang Li, Hancheng Zhu, “An efficient scheme for detecting Copy- Move forged images by local binary patterns”, Journal of Information Hiding and Multimedia Signal Processing, Vol. 4, No. 1, pp. 46-56, January 2013.
- [7] Hailing Huang, Weiqiang Guo, Yu Zhang, “Detection of Copy-Move manipulation in Digital Images Using SIFT Algorithm”, IEEE Pacific-Asia Workshop on Computational Intelligence and Industrial Application, Wuhan, China, 2008. Seung-Jin Ryu, Min-Jeong Lee, and Heung-Kyu Lee, “Detection of Copy-Rotate-Move manipulation Using Zernike Moments”, Information Hiding Lecture Notes in Computer Science Volume 6387, pp 51-65, 2010.
- [8] Jessica Fridrich, David Soukal, and Jan Lukáš, “Detection of CopyMove manipulation in Digital Images”, Digital Forensic Research Workshop, Cleveland, Ohio, USA, 2003.
- [9] YanjunCao ,Tiegang Gao , Li Fan , Qunting Yang, “A robust detection algorithm for Copy-Move manipulation in digital images”, Journal of Forensic Science International, p. 33—43, 2012.