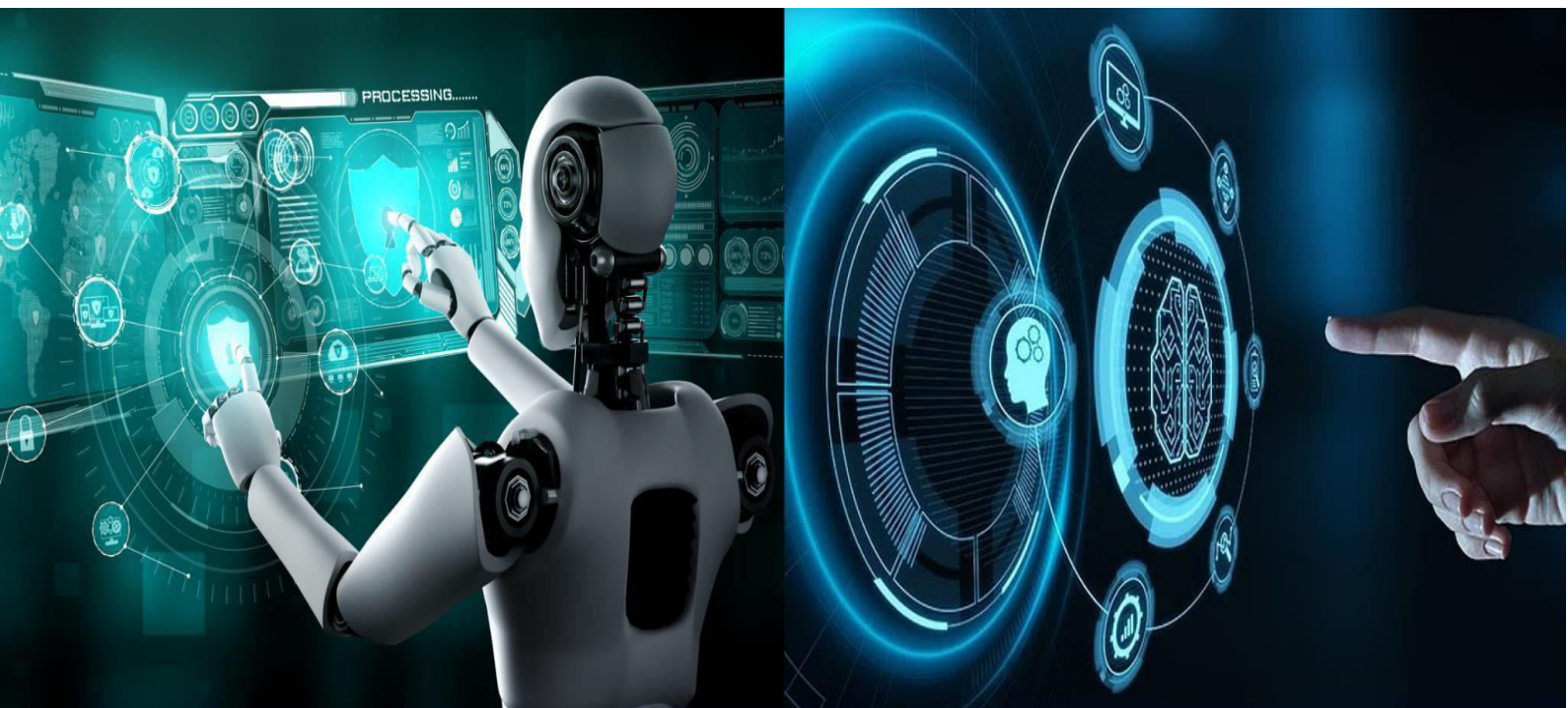




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Intelligent System for Digital Image Forgery Detection using ML and AI

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ABSTRACT: This project focuses on the development of a robust image forgery detection system utilizing Convolutional Neural Network (CNN) classification techniques. Image forgery, including techniques like copy-move, splicing, and retouching, has become increasingly prevalent in the era of digital manipulation. The proposed CNN-based approach leverages deep learning to automatically learn distinctive features and patterns associated with manipulated regions, enabling accurate and efficient forgery detection. Through extensive experimentation and evaluation on diverse datasets, the system demonstrates superior performance in identifying forged regions within images, providing a valuable tool for digital forensics and ensuring the integrity of visual content.

KEYWORDS: Image forgery detection, Convolutional Neural Network, CNN, Classification technique, Digital forensics, Copy-move, Splicing, Retouching, Deep learning, Forgery detection, Visual content integrity.

I. INTRODUCTION

In an era characterized by the widespread availability of powerful image editing tools and the ease of disseminating visual content through various digital platforms, the issue of image forgery has become a critical concern. Image forgery encompasses a range of deceptive techniques, including copy-move, splicing, and retouching, designed to manipulate the integrity and authenticity of visual content. Detecting such manipulations is paramount for ensuring trustworthiness in domains like journalism, digital forensics, and legal proceedings. This project endeavors to address this challenge through the implementation of a sophisticated image forgery detection system, employing cutting-edge Convolutional Neural Network (CNN) classification techniques.

The choice of Convolutional Neural Networks arises from their unparalleled capability to automatically learn hierarchical features from images. These deep learning architectures have demonstrated remarkable success in various computer vision tasks, including object recognition, scene understanding, and image segmentation. By training a CNN model on a diverse dataset comprising both authentic and manipulated images, the system can discern subtle patterns and inconsistencies indicative of forgery. This approach promises to provide a powerful tool for forensic analysts and investigators seeking to identify manipulated regions within images, thereby upholding the veracity of visual content in an increasingly digitized world.

Furthermore, the significance of this project extends beyond the realm of digital forensics. The proliferation of manipulated images has far-reaching implications for society, encompassing misinformation, deception, and erosion of trust in visual media. Therefore, a robust and efficient image forgery detection system not only serves as a crucial resource for experts in the field, but also contributes to the broader goal of preserving the integrity and credibility of visual content across various domains and industries.

II. METHODOLOGY

1. Data collection and preprocessing:

- Gather Diverse Dataset: Accumulate a diverse dataset of images comprising both authentic and manipulated samples, covering various forgery techniques like copy-move, splicing, and retouching.
- Dataset Annotation: Manually annotate the dataset to provide ground truth labels indicating the location and type of forgery in each image.
- Data Preprocessing: Normalize pixel values to a standardized range, apply data augmentation techniques (e.g.,



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rotation, flipping) to increase dataset variability, and resize images to a uniform dimension suitable for input to the CNN model.

2. CNN Architecture Design:

- Define Sequential Model: Implement a Convolutional Neural Network (CNN) using a sequential model architecture. Configure layers including convolutional layers, max-pooling layers, and dense layers to facilitate feature extraction and classification

3. Model Training:

- Initialize Weights: Initialize the CNN model's weights using a suitable initialization method (e.g., Xavier or He initialization) to ensure effective learning during training.
- Define Loss Function: Select an appropriate loss function (e.g., binary cross-entropy) to quantify the discrepancy between predicted and ground truth labels.
- Choose Optimization Algorithm: Utilize an optimization algorithm (e.g., Adam optimizer) to adjust model weights during training, aiming to minimize the defined loss function.
- Train the Model: Feed the preprocessed dataset through the CNN model in batches, iteratively adjusting weights through forward and backward propagation. Monitor training progress and adjust hyperparameters (e.g., learning rate) as necessary.

4. Model Evaluation:

- Validation Split: Split the dataset into training and validation sets to assess model performance during training and prevent overfitting.
- Metrics Selection: Utilize appropriate evaluation metrics (e.g., accuracy, precision, recall, F1-score) to quantify the model's ability to detect various types of forgeries.
- Fine-tuning: If necessary, fine-tune the model architecture or hyperparameters based on validation set performance.

5. Testing and Validation :

- Separate Test Set: Hold out a portion of the dataset for final testing to evaluate the model's generalization to unseen data.
- Evaluate Performance: Assess the model's performance on the test set using chosen evaluation metrics, ensuring it maintains accuracy and reliability in real-world scenarios.

6. Result Analysis and Interpretation:

- Analyse False Positives/Negatives: Examine misclassifications to identify patterns or specific forgery scenarios where the model may be less accurate.
- Visualize Activations: Visualize activations in different layers of the CNN to gain insights into the features the model has learned.

Software requirement specification:

1. Python (version 3.6 or higher): Python is the primary programming language used for developing and running the CNN-based image forgery detection system.
2. TensorFlow or Py Torch: Install a deep learning framework such as TensorFlow or Py Torch to implement and train the Convolutional Neural Network (CNN) model.
3. NumPy: NumPy is a fundamental library for numerical computations in Python and is used extensively for array manipulation and mathematical operations.
4. OpenCV: OpenCV provides a wide range of tools for image processing and manipulation, which are crucial for preprocessing input images.
5. Matplotlib: This library is useful for generating visualizations and plots to analyse model performance and results.
6. Jupyter Notebook or IDE of choice: Use a Jupyter Notebook or a preferred integrated development environment (IDE) for coding, experimentation, and result visualization.

Hardware requirement specification:

1. CPU: A multi-core processor with a clock speed of at least 2.5 GHz is recommended for efficient model training and evaluation.
2. RAM: A minimum of 16 GB RAM is advisable for handling large datasets and running resource-intensive computations during model training.
3. GPU (Optional but highly recommended): If available, a dedicated Graphics Processing Unit (GPU) with CUDA support significantly accelerates deep learning computations, reducing training times.
4. Storage: Sufficient disk space (at least 100 GB) for storing datasets, model checkpoints, and experiment results.

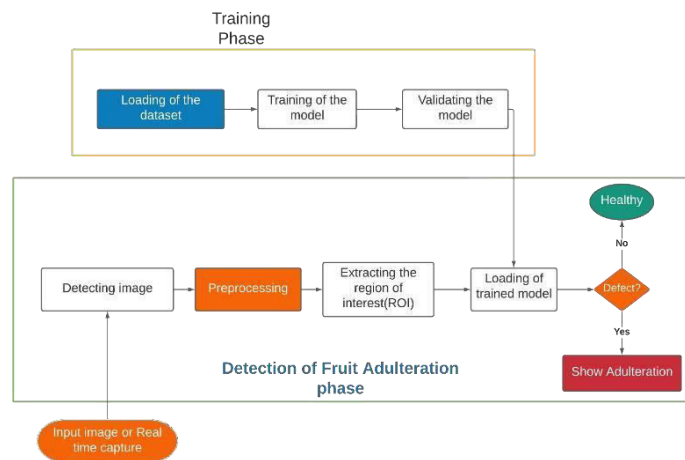


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5. Display: A monitor with a resolution of 1920x1080 pixels or higher is recommended for visualizing results and code execution.

III. SYSTEM ARCHITECTURE



The system architecture consists of two phases the training phase and the detection of image forgery phase. In the training phase first we load the data set of CMS which contains naturally added image pixel pattern as well as the artificial added image pixel pattern in it. Once the data set is loaded then we will train the model and validate the model for the training dataset for better accuracy.

Once the model is trained, we will test the trained model for the various images of oranges and apples. In the image forgery detection phase, first we are going to take the input image or real time capture image from the user and then the system is going to detect the image for the required resolution. After detecting the image, the system pre-processes the image and extract the region of interest. The trained model is loaded and the preprocessed image is given to the model to check whether the image is healthy or not. If the image is healthy then the system will display the image is healthy if not then the system will show it is unhealthy and displays the concentration of formal in it.

The proposed system consist of the following components.

- Dataset Collection:** The dataset is collected from CFS and manually from google images. The Datasets contains fresh as well as artificially added image pixel pattern images in it. Images of apple and orange are collected and used for training.
- Data Preprocessing:** In this module first the image is resized and then it is converted from RGB to gray scale using ski-image method. Ski-image, is an open source Python package designed for image preprocessing.
- Feature Extraction:** In this module the features of image like texture and shape is used to identify the image. Once the image is identified, then the infected area of image is extracted using contour area method. The primary function here is to identify and outline the target object that is the apple or orange image for segmentation. It requires some prior knowledge of the target object's shape, especially for complicated things. After identifying the shape of the image then the counter is used to segment one portion of an image that has unique characteristics when compared to other regions of the image.
- Building and training CNN Model:** CNN model is built using the layers provided in the keras library. The CNN have a large number of hyper-parameter, they focus on having convolution layers of 3x3 filter with a stride 1 and always use same padding and maxpool layer of 2x2 filter of stride 2 and follows this arrangement of convolution and max pool layers consistently throughout the whole architecture.

IV. FUTURE SCOPE

- Multi-Modal Fusion:** Incorporate additional modalities, such as metadata, text, or audio, to create a multi-modal forgery detection system. This would enhance the system's capability to detect sophisticated forgeries that may involve multiple types of manipulation.



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2. **Adversarial Robustness:** Implement techniques to enhance the system's resilience against adversarial attacks. This could involve adversarial training, input perturbation, or incorporating techniques from adversarial machine learning to make the model more robust.
3. **Real-time Processing Optimization:** Further optimize the system for real-time forgery detection by exploring hardware acceleration options like deploying on specialized processing units or leveraging edge computing capabilities.
4. **Fine-grained Forgery Localization:** Develop techniques to provide more detailed information about the detected forgeries, such as segmenting manipulated regions into finer subregions, allowing for precise localization of alterations.
5. **Continual Learning and Transfer Learning:** Implement strategies for continual learning and transfer learning to adapt the model to evolving forgery techniques and new types of manipulations without the need for retraining from scratch.
6. **Forensic Analysis Tools Integration:** Integrate the forgery detection system with existing forensic analysis tools and workflows, allowing for seamless incorporation into established digital forensics pipelines.
7. **User Interface and Accessibility:** Enhance the user interface to provide more intuitive interaction, allowing users to easily upload images for forgery detection and interpret results. Consider accessibility features for users with diverse needs.
8. **Feedback Mechanism:** Implement a feedback loop where users can provide input on the detected forgeries. This could be used to improve the system's performance and adapt to specific use cases or evolving forgery patterns.
9. **Cloud-based Deployment:** Develop a cloud-based version of the forgery detection system to enable easy scalability and accessibility, especially for organizations with large-scale forgery detection needs.

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