**FACULTY OF ENGINEERING AND TECHNOLOGY**

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**PROJECT SYNOPSIS**

On

**“Deep Learning Forensic Tool for Image Authentication using TensorFlow”**

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**1. Introduction, Objective & Scope**

**1.1 Introduction**

In an era marked by the proliferation of digital media, the line between real and manipulated images has become increasingly blurred. With the widespread availability of powerful image editing software and the rise of AI-generated content, it is now more critical than ever to develop innovative tools for image authenticity verification. The primary objective of this project is to create an advanced Convolutional Neural Network (CNN) using TensorFlow, a leading deep learning framework, capable of determining whether a given image is real or computer-generated. This forensic tool aims to address the growing concern of manipulated media by leveraging state-of-the-art deep learning techniques for image authenticity verification.

**1.2 The Significance of Image Authenticity Verification**

Image authenticity verification plays a pivotal role in various domains, including journalism, forensics, and social media. In the age of "deepfakes" and digitally altered content, it has become essential to distinguish between genuine and manipulated images. The consequences of failing to do so can range from misleading news articles and misinformation to more sinister applications like fraud and cyberattacks.

**1.3 The Role of Convolutional Neural Networks**

Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed for image processing tasks. They have demonstrated exceptional performance in various computer vision applications, making them an ideal choice for image authenticity verification. CNNs excel at extracting meaningful features from images and can learn to discern subtle patterns that are often indicative of manipulation.

**1.4 Utilizing TensorFlow for Deep Learning**

TensorFlow, an open-source deep learning framework developed by Google, provides the foundation for our project. Its flexibility, scalability, and extensive ecosystem of tools and libraries make it a preferred choice for developing cutting-edge deep learning models. Leveraging TensorFlow, we can build a robust and efficient CNN architecture to meet the demands of image authenticity verification.

**1.5 State-of-the-Art Techniques for Accuracy**

To ensure the highest accuracy in distinguishing real images from computer-generated ones, this project will incorporate state-of-the-art techniques. This includes utilizing large-scale datasets of real and synthetic images to train the model, implementing data augmentation to improve model generalization. Furthermore, we will explore transfer learning, a technique that leverages pre-trained models to enhance the model's performance.

**1.6 Scope**

The implications of a successful CNN model for image authenticity verification are far-reaching. It can empower journalists, fact-checkers, and content creators to verify the credibility of images, thereby combating the spread of misinformation and ensuring the integrity of media. Additionally, law enforcement agencies and digital forensics experts can utilize this tool to detect tampered evidence and conduct investigations with increased confidence**.**

**2. Review of literature**

**Jordan J. Bird, et al. [1]** proposed this article that presents the CIFAKE dataset, generated with advanced synthetic data methods, for distinguishing real and AI-generated images. The CIFAKE dataset is shared for further research in image authentication.

**LinkedIn Engineering [2]** gave a paper that discusses the results from two embedding-based approaches for distinguishing between synthetic and real profile photos: a learned linear embedding based on a principal components analysis (PCA) and a learned embedding based on an autoencoder (AE).

**Yash Patel [3]** proposed this paper which proposes a method for detecting AI-generated images using perceptual features. The authors use a pre-trained deep neural network to extract features from the images and then train a binary classifier to distinguish between real and AI-generated images. The proposed method is evaluated on several datasets, including CIFAR-10, STL-10, and CelebA, and achieves state-of-the-art performance.

**S. S. Bhatia [4]** proposed this paper which provides a comprehensive survey of deep learning techniques for image and video analysis. It covers various topics such as image classification, object detection, semantic segmentation, and more. The authors also discuss the challenges and future directions of deep learning in image and video analysis.

**Alex Krizhevsky [5]** introduced this paper which presents a deep convolutional neural network (CNN) architecture for image classification. The proposed CNN, called AlexNet, consists of five convolutional layers followed by three fully connected layers. The authors evaluate the performance of AlexNet on the ImageNet dataset and achieve state-of-the-art results.

**Z. Wang, et al. [6]** introduced this paper which investigates the use of different color space channel combinations for identifying AI-generated face images. The authors propose a new method that uses a combination of red, green, and blue channels.

**J. Guan, et al. [7]** introduced this paper which proposes a new method for identifying AI-generated images using a two-stream CNN. The first stream of the CNN extracts features from the global structure of the image, while the second stream extracts feature from the local details of the image. The two streams are then combined to produce a final prediction.

**H. Liu, et al. [8]** introduced this paper which proposes a new method for identifying AI-generated images using texture features. The authors extract a set of texture features from the images using a variety of methods, including Gabor transform, wavelet transform, and local binary patterns (LBP). The features are then classified using a support vector machine (SVM) classifier.

**Y. Qin, et al. [9]** introduced this paper which proposes a new method for identifying AI-generated images using noise features. The authors extract a set of noise features from the images using a variety of methods, including Fourier transform, total variation (TV) denoising, and median filtering. The features are then classified using a SVM classifier.

**W. Sun, et al. [10]** introduced this paper which proposes a new method for identifying AI-generated images using metadata features. The authors extract a set of metadata features from the images, such as file name, file size, and creation time. The features are then classified using a SVM classifier.

**Y. Chen, et al. [11]** introduced this paper that proposes a new method for identifying AI-generated images using GANs. The authors train a GAN to generate fake images, and then use the GAN to extract features from the images. The features are then classified using a SVM classifier.

**J. Yang, et al. [12]** introduced this paper that proposes a new method for identifying AI-generated images using transformer models. The authors train a transformer model to classify images as real or fake. The transformer model is able to learn long-range dependencies in the images, which is helpful for identifying AI-generated images.

**Y. Zhang, et al. [13]** introduced this paper that proposes a new method for identifying AI-generated images using XAI techniques. The authors use a CNN to extract features from the images, and then use a XAI technique called gradient class activation mapping (Grad-CAM) to identify the regions of the image that are most important for classification. The authors found that AI-generated images often have artifacts in the high-frequency regions of the image.

**S. Zhou, et al. [14]** introduced this paper which proposes a new method for identifying AI-generated images using human perception. The authors use a crowdsourcing platform to collect human judgments on whether images are real or fake. The judgments are then used to train a machine learning classifier.

**Z. Wang,** **et al. [15]** introduced this paper which proposes a new method for identifying AI-generated images using adversarial examples. The authors generate adversarial examples for the AI-generated images, and then use a CNN to classify the adversarial examples as real or fake. The proposed method achieves an accuracy of 96.3% on a dataset of AI-generated and real images.

**Y. Liu,** **et al. [16]** introduced this paper which proposes a new method for identifying AI-generated images using physical features. The authors extract a set of physical features from the images, such as noise pattern, color gamut, and compression artifacts. The features are then classified using a SVM classifier. The proposed method achieves an accuracy of 94.7% on a dataset of AI-generated and real images.

**W. Shen, et al. [17]** introduced this paper which proposes a new method for identifying AI-generated images using contextual features. The authors extract a set of contextual features from the images, such as the objectness of the image, the consistency of the scene, and the presence of unrealistic objects. The features are then classified using a SVM classifier.

**Y. Chen, et al. [18]** introduced this paper which proposes a new method for identifying AI-generated images using ensembles of classifiers. The authors train an ensemble of different types of classifiers, such as CNNs, transformer models, and XAI models. The predictions of the individual classifiers are then combined to produce a final prediction. The proposed method achieves an accuracy of 96.7% on a dataset of AI-generated and real images.

**J. Yang, et al. [19]** introduced this paper which proposes a new method for identifying AI-generated images using few-shot learning. The authors train a few-shot learning model to classify images as real or fake using only a small number of training examples. The proposed method achieves an accuracy of 95.3% on a dataset of AI-generated and real images.

**Y. Zhang**, **et al. [20]** introduced this paper which proposes a new method for identifying AI-generated images using continual learning. The authors train a continual learning model to classify images as real or fake in a sequential manner, without forgetting the knowledge learned from previous tasks. The proposed method achieves an accuracy of 95.9% on a dataset of AI-generated and real images.

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