Executive Summary

Digital photos are the most often used media for visual data transport in the modern era of digitalization. Digital images are now being used in previously unimaginable ways in a variety of industries, including criminal investigation, medical science, journalism, sports, and image forensics, all of which require image authenticity. Images can be altered using a range of tools that are either free or available for a low cost. Certain techniques can distort images to such an extent that the human visual system has difficulty distinguishing between tampered and real images. As a result, detecting image counterfeiting is a difficult task. Over the previous decade, tremendous progress has been made in the field of image forgery detection. However, as image manipulation technologies get more sophisticated, there is still a need for thorough scrutiny in this area.

The purpose of this research is to develop a novel model based on deep learning using error level analysis detection features that are related to entropy and information theory, normalized mutual information in image pre-processing, including a binary cross-entropy loss function in the very last softmax activation layer, and various applications of a label encoder.

Using error level analysis, we can discover image data compression ratios and afterward apply these images to a convolutional neural network to assess whether the image is forged. Experiments demonstrate that by implementing the ELA technique, the CNN model's training efficiency may be significantly increased, and the overall accuracy can surpass 96 percent. In comparison to existing models, the proposed model offers various advantages, including reduced layer count, a shorter training period, and increased efficiency.

Additionally, we covered two key aspects of image forgery detection when utilizing deep convolutional neural networks. We begin by evaluating and comparing a variety of pre-processing techniques, including normalization, error level analysis, and label encoding, which is then fed to convolutional neural network (CNN) architectures. Later, we examined various transfer learning techniques for pre-trained ImageNets (through fine-tuning) and applied them to our CASIA V2.0 dataset. Thus, it discusses pre-processing strategies using a basic CNN model and then examines the transformative effect of transfer learning models. The dissertation also contains proposals for further development of this topic.