CHAPTER-6

Conclusions and Scope of Future Work

In the digital age, facial retouching detection is a crucial component of image forensics. As the popularity of image editing tools and social media platforms continues to surge, the potential for manipulated and deceptive visual content also increases. Our study has brought attention to the critical need for precise and reliable techniques for identifying facial retouching, since it is essential for maintaining the integrity of photos used in a variety of settings, such as internet communication, law enforcement, and journalism.

6.1 Conclusions

This comprehensive study has explored various facets of transfer learning in the context of two distinct datasets that vary in terms of editing tools employed, size, and data distribution. Our research has demonstrated the flexibility and adaptability of these retouching classification by utilising two different transfer learning models i.e. ResNet50 and VGG16 and two different fine-tuning optimizers like Adam and RMSprop. Furthermore, four different train-test split ratios were investigated, which shed light on how well the model performed with different data distributions. This research has introduced a Transfer Learning (TL) model, ResNet50, as a robust solution for facial retouching detection, showcasing its superiority over VGG16. Below is a brief presentation of the review of the outcomes of these different approaches.

- Transfer learning(TL) method significantly reduces the computational resources required for model training, making it a more efficient and cost-effective choice. Furthermore, it necessitates less labelled data for training, ultimately resulting in a reduction in computation time, thereby accelerating the model development process.

- In the case of VGG16, we observed that it exhibits superior performance when the Adam optimizer is applied during the fine-tuning phase, as opposed to RMSprop. Notably, for Dataset 1, the model's efficacy remains consistent, delivering maximum 98.08% of classification accuracy for data partitioning at 50%-50% compared to other remaining split ratios. On the other hand, for Dataset 2, our findings indicate a remarkable accuracy of 97.19% in terms of macro average for retouching classification, even though the split ratio for this dataset stands at 60%-40%. These insights provide valuable guidance for model selection and parameter optimization in specific scenarios, demonstrating the adaptability of VGG16 across different dataset characteristics and split ratios.
- In case of ResNet50 model, for Dataset 1, the model gives validation accuracy ~98% for both the optimizers, Adam and RMSprop and for all data partitioning. In terms of the performance parameters, ResNet50 give nearly equal accuracy of ~98% for 50%-50% and 80%-20% train test splits. Moreover, the model gives better performance when RMSprop optimizer is used during fine-tuning over Adam for all data partitioning. With reference to dataset 2, this pre-trained model gives highest classification accuracy for 80%-20% data partitioning with RMSprop optimizer used during fine-tuning. Hence, the ResNet50 model can give trustworthy classification results for 80%-20% train test split ratio than the others. moreover, the performance robustness is increasing with RMSprop used during fine-tuning.
- Compared to the training accuracy, incremental validation accuracy over epochs, and decremented rate of cross entropy during training and evaluation, ResNEt50 architecture gives best performance in terms of learning the features. Consequently, the ResNet50 compared to VGG16 gives better classification accuracy.

The findings reveal that utilizing RMSprop as the optimizer significantly enhances classification efficiency. Notably, ResNet50 demonstrates exceptional generalization capabilities, consistently achieving top accuracy on both Dataset 1 and Dataset 2 which are having diverse and contrasting data characteristics with an 80%-20% train-test split ratio. These results underscore the potential of ResNet50 in real-world applications, confirming its value in the field of image forensics and retouching detection. This research not only contributes to the advancement of image analysis techniques but also opens new avenues for improved authenticity verification in multimedia content. The

6.2 **Scope of Future Work**

The scope of this research is both extensive and dynamic, encompassing a range of critical dimensions in the field of facial retouching detection. This research aims to broaden its reach by incorporating diverse datasets, thereby assessing model generalization across a wider spectrum of retouching characteristics. Furthermore, this research seeks to adapt its findings to real-time applications, making strides in the development of retouching detection for multimedia platforms. As the field of transfer learning evolves, an array of architectures will be considered for study, each tailored to specific retouching detection tasks. Ethical and legal considerations will be examined to address the implications of retouched images in various domains. Additionally, user-friendly interfaces will be developed for practical implementation. Moreover, the generalizability of the developed models across different domains, such as image forensics and content verification, will be explored. Collaborations with experts from various disciplines will provide insights into the societal and psychological implications of retouched imagery. The multidimensional scope of this research underscores its relevance and potential to impact a wide range of fields, from technology to ethics and societal well-being.