CHAPTER 8

CONCLUSION AND FUTURE WORK

8.1 CONCLUSION

The increased need for a secure and reliable biometric solution in applications such as access control, financial transactions, identity verification, etc, highlights the importance of a more secure authentication system. The uniqueness of the vein patterns lying beneath the skin is difficult to alter, making it more secure compared to many other biometrics. Advanced techniques enable the DL model to learn intricate features from large datasets, leading to improved accuracy and robustness.

The first work compares the performance of a modified UNET with the VGG16 model for the FVR task. VGG16 acquired better accuracy than UNET by 3.33% and 2.95% for THUFV and SDUMLA-HMT datasets, respectively. The accuracy obtained for VGG16 for THUFV and SDUMLA-HMT datasets is 92.5% and 94.31%, respectively.

For a biometric authentication system, the accuracy is a big concern, and hence, the VGG16 model needs further improvement. So, the second work focused on labelling the dataset for training the VGG16 model. The hybrid algorithm that labels the vein patterns guides the model during the learning process. This leads to an improvement in accuracy by 3.84% on THUFV and 1.14% on SDUMLA datasets. Labelling also helped to reduce training time. The training time decreased by 5 minutes on the THUFV dataset and by 18 minutes on the SDUMLA dataset. After labelling, the accuracy obtained for the THUFV dataset is 96.34% and for the SDUMLA dataset is 95.45%. The overfitting of the model needs to be reduced, and performance still needs to be increased for accurate authentication.

The third work focuses on improving the training dataset through advanced data augmentation strategies. The transformation methods and GAN-based techniques are used to increase variability in the input data. This increased the accuracy by 6.1% on the THUFV dataset and 2.79% on SDUMLA. This approach also helped the model to reduce overfitting as the model is trained with a wider range of variations in images. However, the increased number of images resulted in an increased training time of 35 minutes for THUFV and 164 minutes for the SDUMLA dataset. The accuracy obtained for the

THUFV dataset is 98.6%, and the SDUMLA dataset is 97.10% need further improvement, as accuracy close to 100% is expected for an authentication system.

In the fourth work, a Motion-Tolerant DL architecture was developed that incorporates the advantages of the first three works. The motion-tolerant model can handle variations in the movement or positioning of the user's finger during the scanning process. This architecture effectively mitigates overfitting with a comparatively high accuracy of 99.89% for the THUFV dataset and 99.76% for the SDUMLA dataset. The accuracy has been improved by 7.39% for the THUFV dataset and 5.45% for the SDUMLA dataset when compared to VGG16. The model is validated using the Receiver Operating Characteristic (ROC) curve and Equal Error Rate (EER). A stable ROC curve across different thresholds indicates robustness to varying conditions. The low EER of 1.73% for the SDUMLA dataset and 1.42% for the THUFV dataset, along with AUC values very near to 1 (0.993 for SDUMLA and 0.991 for THUFV), confirm the model's ability to balance sensitivity and specificity. This signifies its high reliability in practical applications.

The integration of hybrid labelling algorithms, advanced augmentation techniques, and the motion-tolerant architecture significantly improves the performance of the model in FVR tasks. These approaches not only reduce overfitting but also outperform traditional models, particularly for FV images acquired through contactless scanners. The combined results of these studies represent a significant advancement in the creation of more reliable and accurate biometric systems.

8.2 LIMITATIONS OF THE WORK

The limitations of the work are:

1. The unavailability of real-time FV images due to the lack of access to FV scanners in India restricts the ability to validate the model on live data and assess its performance in practical, real-world scenarios.

2. The variation in vein patterns before the age of 20 and after the age of 50 needs age-specific model training, collecting data over time from individuals. The feature extraction process should be enhanced to specifically capture more stable and

distinctive aspects of vein patterns that remain consistent even with age-related changes.

3. Recognition may be less accurate for individuals with conditions such as anaemia, circulatory disorders, diabetes, or obesity, as these can affect blood flow, vein visibility, and the distinctness of vein patterns.
4. The model is limited in handling rapid finger movements, such as scanning while walking, as these can introduce significant motion blur and misalignment, resulting in capturing low-quality images.
5. Finger vein recognition systems may exhibit reduced performance under extreme temperature conditions, as variations in blood viscosity and vessel contraction or dilation can affect vein visibility and image quality.

8.3 FUTURE WORK

Light-weight models for real-time processing can be explored in the future. This allows FVR systems to operate in situations with limited resources, such as embedded systems or mobile devices. Another important area is to develop methods to identify vein patterns from visible light images. This facilitates a more flexible authentication for web-based applications using the existing camera in tablets, smartphones, and webcams. A more accurate model can be developed by combining the information from near infrared and visible light images, which helps the system to utilize the advantages of both, thereby improving the performance. The security of the entire authentication system can be further improved by ensuring secure storage of tamper-proof records, and automated verification by smart contracts using blockchain technology.