

CHAPTER 7

RESULTS AND DISCUSSIONS

The results of the experiments conducted on the THUFV and the SDUMLA-HMT datasets are analyzed. The performance metrics accuracy, precision, recall, and F1-score are examined to analyze how well the models perform under various conditions. The training time is also analysed as it determines the practicality for real-world applications, particularly in resource-constrained environments.

The different FVR models applied to the SDUMLA and THUFV datasets are compared in Table 7.1.

Table 7.1 Comparison of Results of THUFV and SDUMLA Dataset

Dataset	Comparison Factor	Original	Labelled (Without Augmentation)	Labelled and Augmented images	Labelled and Augmented images
		VGG16			Motion Tolerant Model
SDUMLA	Number of images	3816	3816	114480	114480
	Training Time (in minutes)	64	46	210	172
	Accuracy (%)	94.31	95.45	97.10	99.76
THUFV	Number of images	220	220	7700	7700
	Training Time (in minutes)	18	13	48	32
	Accuracy (%)	92.50	96.34	98.60	99.89

The impact of labelling, dataset augmentation, and the application of a motion-tolerant model can be analyzed from the Table 7.1. The original set of images is expanded through labelling and augmentation. The number of images is thus increased from 3,816 to 114,480 for SDUMLA and from 220 to 7,700 for the THUFV dataset. This augmentation process led to a substantial improvement in model accuracy. The accuracy of various configurations for the dataset is plotted in Figure 7.1.

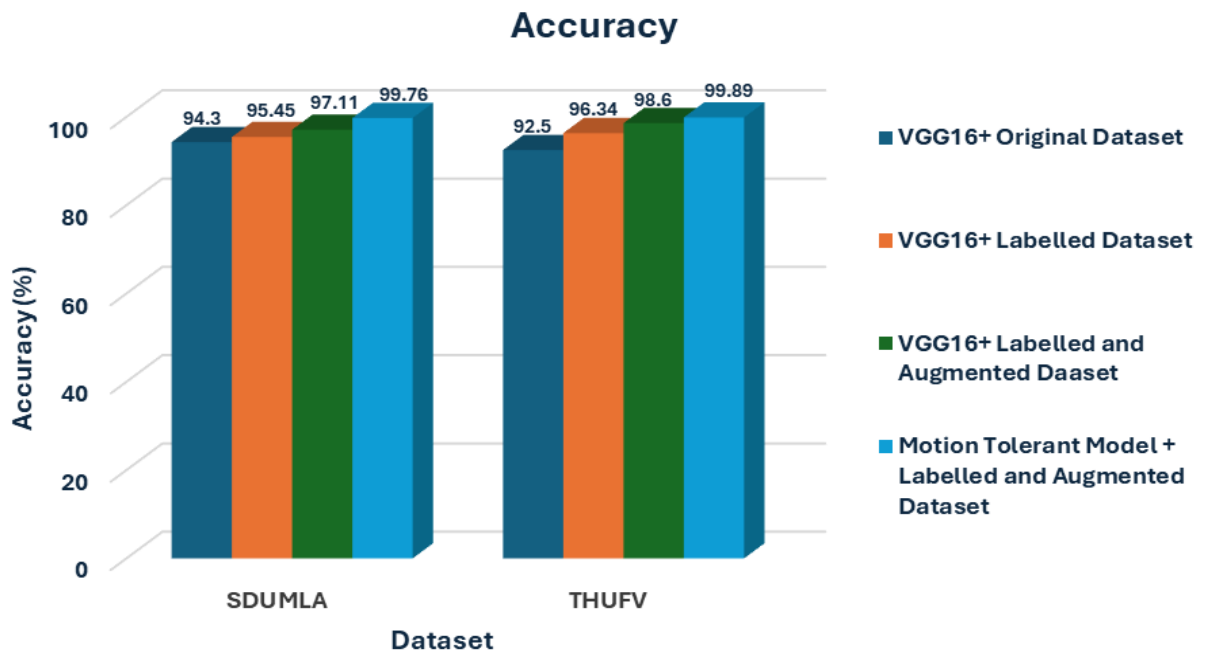


Figure 7.1 Accuracy of Different Configurations for SDUMLA and THUFV Datasets

The overall accuracy of the VGG16 model on the SDUMLA dataset has been improved by 2.81% after applying labelling and augmentation techniques. The motion-tolerant model further increased the accuracy to 99.76% with a total increase of 5.46%. Similarly, for the THUFV dataset also the accuracy increased by 6.1% with labelling and augmentation. The accuracy of the Motion-Tolerant model has further increased to 99.89%, with a total increase of 7.39%. The precision obtained for different configurations on both datasets is plotted in Figure 7.2.

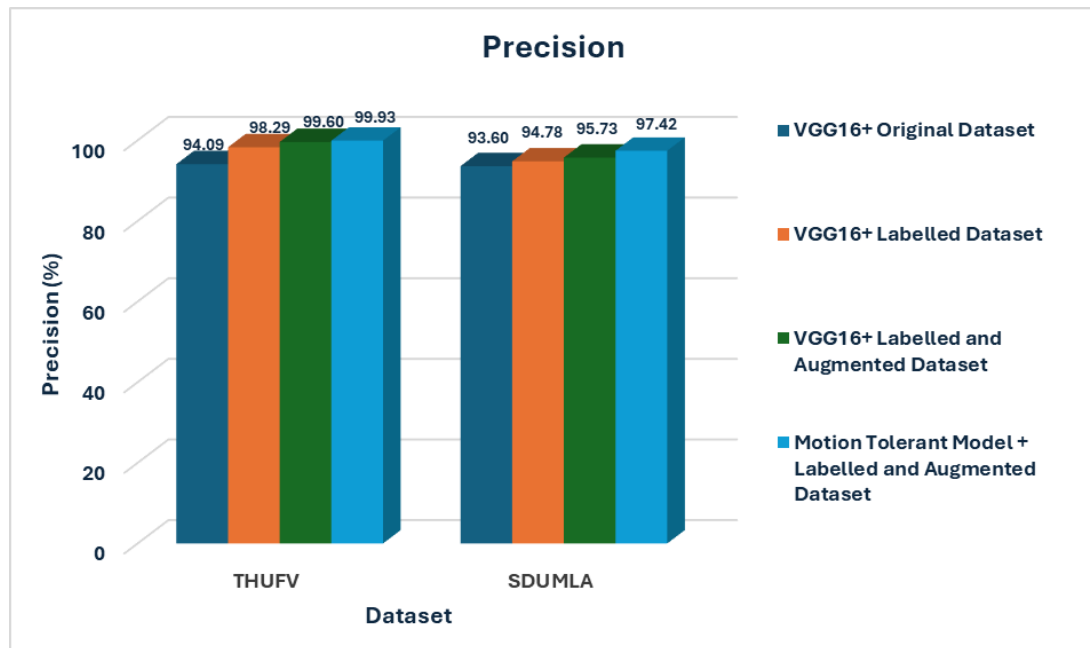


Figure 7.2 Precision of Different Configurations for SDUMLA and THUFV Datasets

High precision in each dataset indicates that the model's positive predictions are correct, implying that the number of false positives is low. A minimal false-positive rate is crucial for maintaining security and ensuring that only authorized users gain access.

Figure 7.3 shows the improvement in recall for different model configurations for the THUFV and SDUMLA datasets.

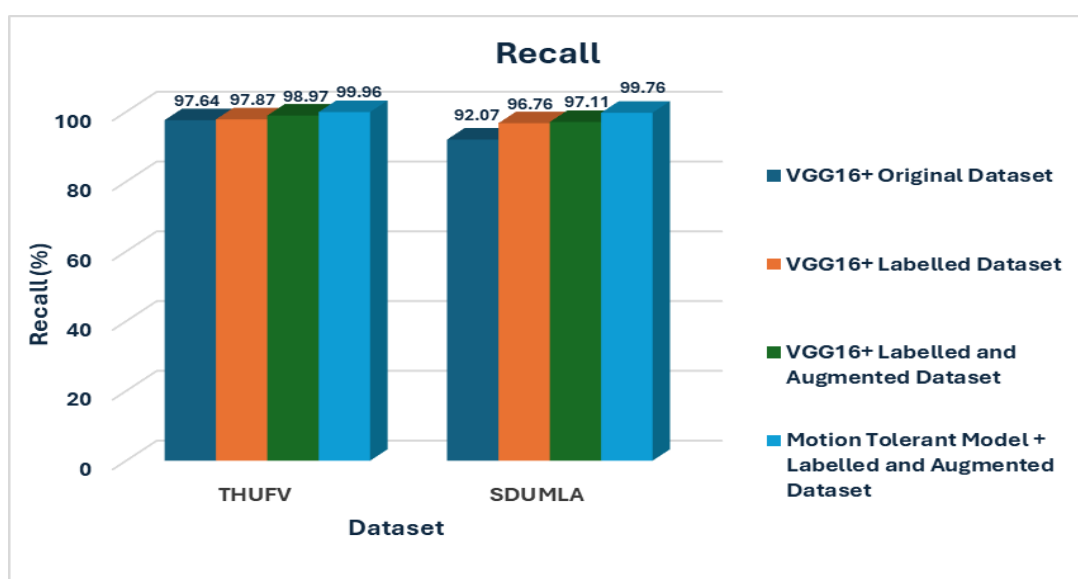


Figure 7.3 Recall of Different Configurations for SDUMLA and THUFV Datasets

A high recall of 99.96% for the THUFV dataset and 99.76% for the SDUMLA dataset has been achieved for the Motion Tolerant model. This indicates the ability of the model to identify true positives, which is important for the FVR system to accurately identify all authorized users.

F1-Score is highly relevant for FVR because the system must accurately identify legitimate users (true positives) while rejecting unauthorized access attempts (true negatives). Figure 7.4 illustrates the F1 score of various models applied to the two datasets, THUFV and SDUMLA.

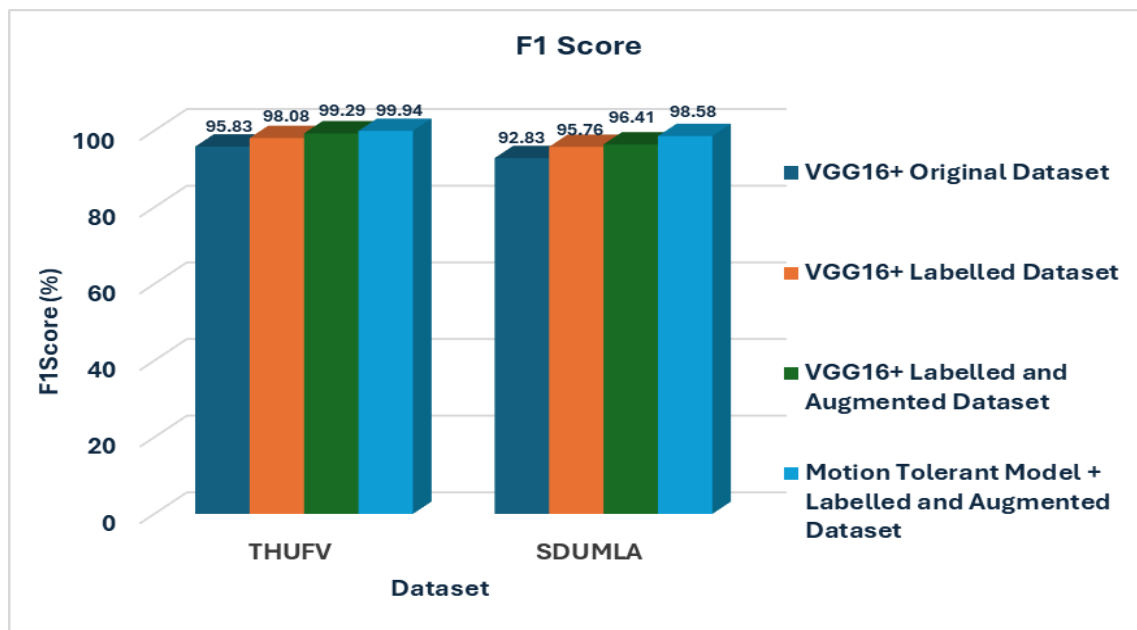


Figure 7.4 F1-Score of Different Configurations for SDUMLA and THUFV Datasets

A good F1-score has been achieved for both datasets, with 99.94% for the THUFV dataset and 98.58% for the SDUMLA dataset for the Motion Tolerant model. This high F1-score suggests that the system effectively balances security and accessibility.

In DL, the training time of models is an important factor, particularly when dealing with large datasets and complex architectures. As training time affects the efficiency of model development, reducing training time without compromising accuracy and performance is a key goal in optimizing DL models. In this work, different strategies, such as dataset labelling, augmentation, and the use of specialized architecture, significantly impacted the training duration. The experiments were carried out in Python on a PC with an i7-12650H CPU, GeForce RTX 2050 GPU, and 16GB of RAM.

Figure 7.5 provides a comparison of training times of different configurations for both datasets.

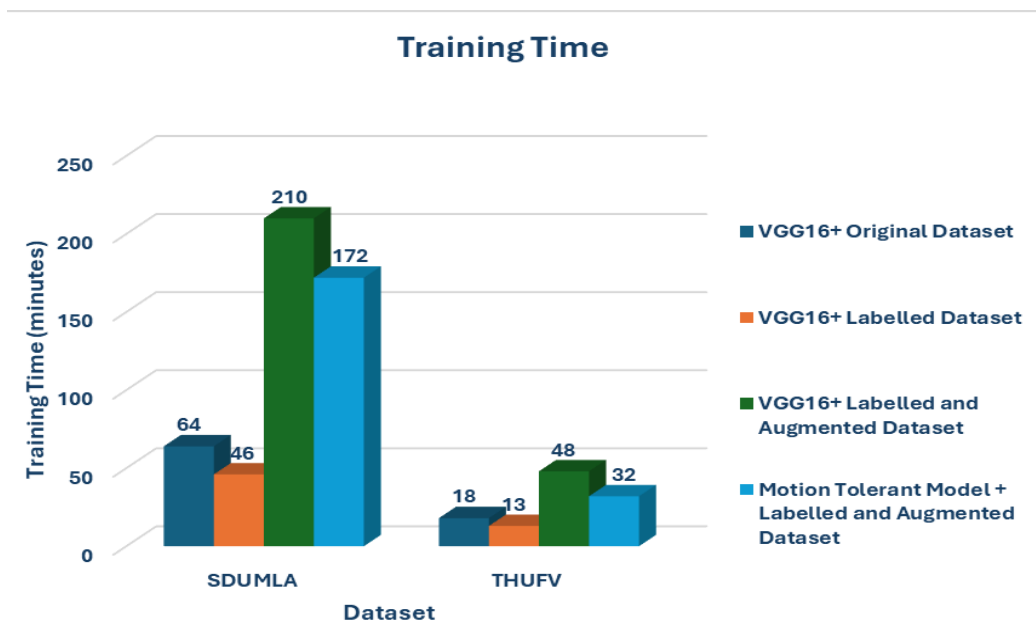


Figure 7.5 Comparison of Training Time for Different Configurations on SDUMLA and THUFV Datasets

Using a labelled dataset reduces the training time of VGG16 for the SDUMLA dataset from 64 minutes to 46 minutes. But the training time rises to 210 minutes when augmentation is applied to the dataset, indicating the complexity brought by the increased dataset size. However, the use of the Motion-Tolerant model reduced the training time to 172 minutes with a notable decrease of 38 minutes. The THUFV dataset requires a shorter training time across different configurations, due to the smaller size and complexity of the dataset compared to SDUMLA. The original VGG16 model takes 18 minutes to train, which is reduced to 13 minutes with the labelled dataset. Even though augmentation increased the training time to 48 minutes, the motion-tolerant model reduced it to 32 minutes.

The comparison of accuracy demonstrated the models' ability to learn and generalize from the datasets, while the precision, F1-score, and recall analysis provided in-depth information about how well the models identified true positives and reduced false positives and negatives. The analyzes of training time highlights that the DL models are influenced by the type of dataset, labelling, augmentation, and the model architecture.