

# MSDSM Final Year Project Presentation

Presentation Attack Detection in Biometric  
Security Using Deep Learning Techniques - A  
Comparative Analysis

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# Agenda

- A quick overview of the problem
- Previous works on the problem
- Current work by presenter
- Observations and conclusion

# What is FRS?

- Fingerprint Recognition System [3]

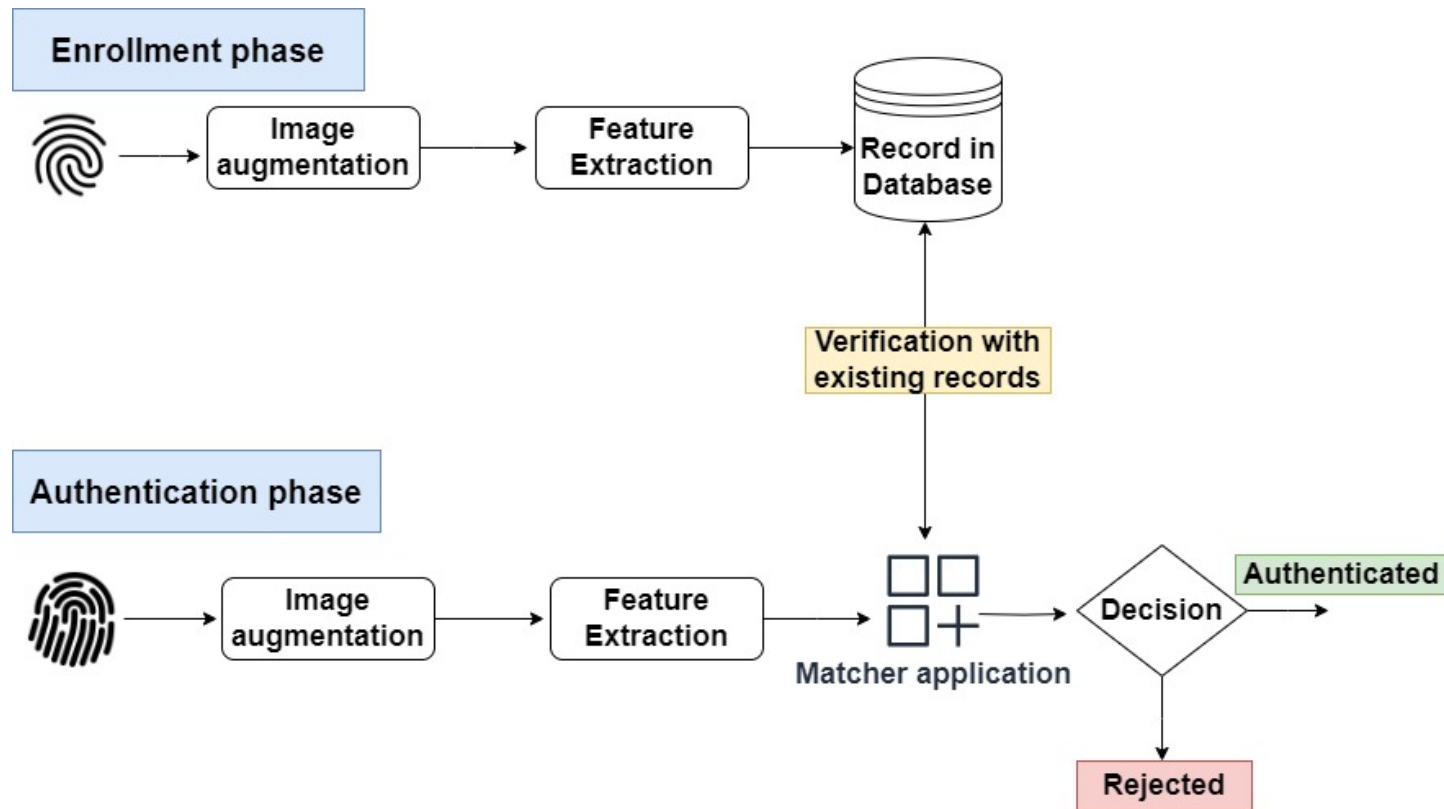


Figure 1

# What are PA and FPAD?

- Presentation Attack (PA) – methods to deceive the FRS
- Fingerprint Presentation Attack Detection (FPAD) – methods to detect the deception

# What are fake fingerprints?

- Fake finger prints can be made from various materials like Ecoflex, Wood Glue, Play-doh, Gelatin etc using direct or latent fingerprint impressions of subjects.



Real



Ecoflex  
X



Gelatin



Latex



Wood  
glue

Figure 2 : Real and fake fingerprint samples

# Related Works

- Adversarial Representation Learning Coupled with Style Transfer for Cross-Sensor Generalization [4]

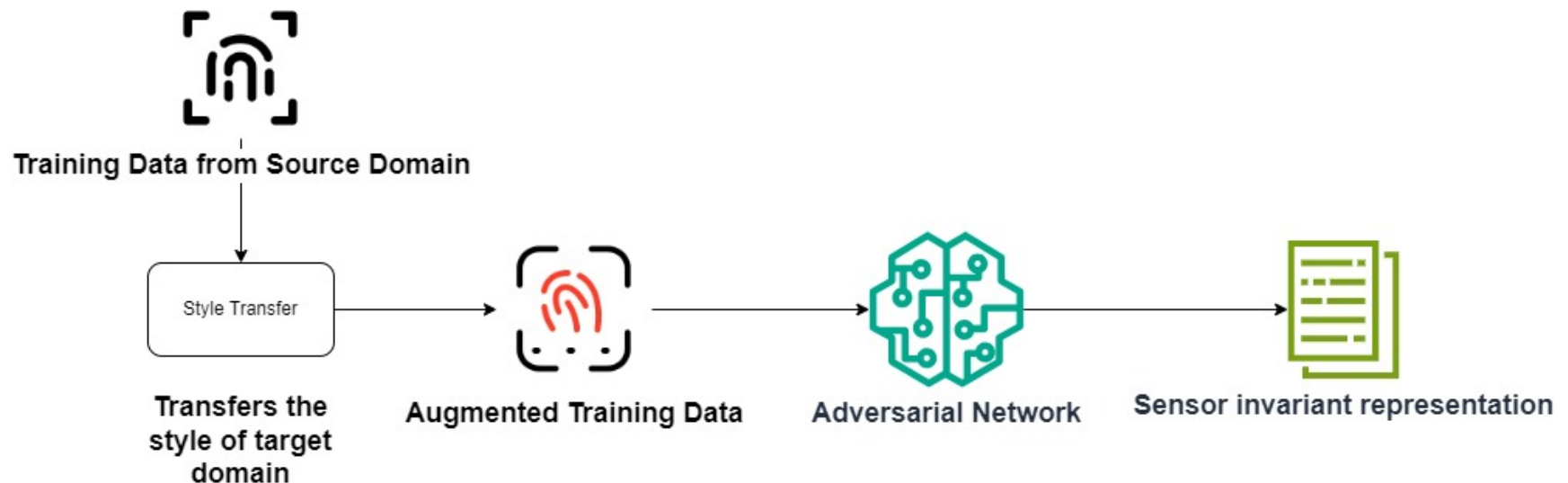


Figure 3 : Flow diagram for this approach

# Related Works

- Convolution Auto-encoders on Short Wave Infrared (SWIR) Images of Fingerprints [5]

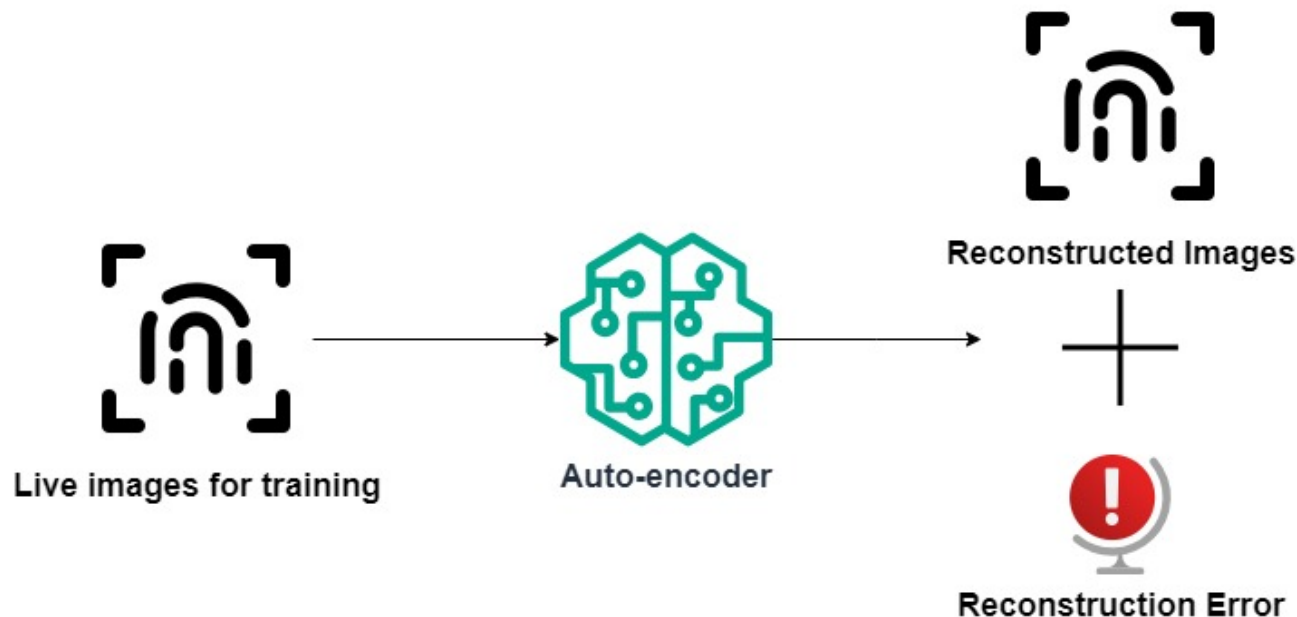


Figure 4 : Flow diagram for this approach

# Related Works

- Feature Denoising through Suppression of Noise Channels [6]

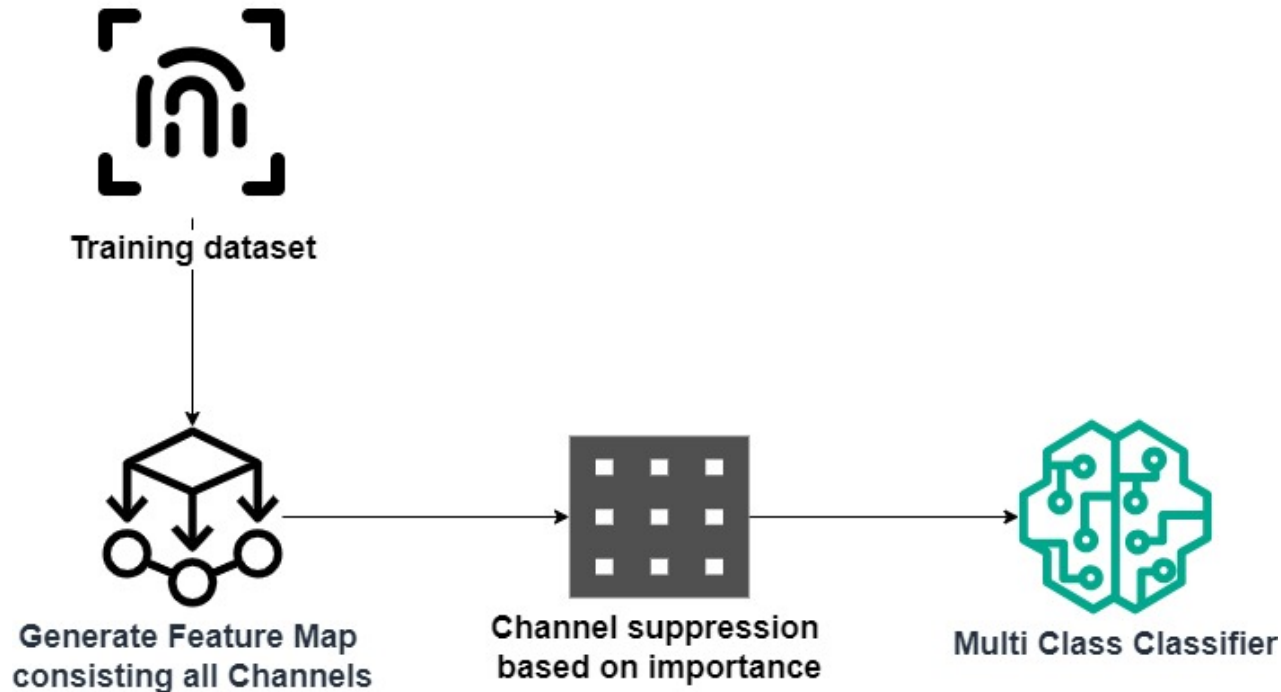


Figure 5 : Flow diagram for this approach



# Objectives

- Study the performance a state-of-the-art CNN model, namely VGG16 [2], on LivDet-2011 [1] dataset
- Compare the performance of 2 shallow CNN models with that of the VGG16 [2] model on the same dataset

# Dataset used

- LivDet-2011 Dataset [1] has been used to train the models
- Contains roughly 16000 fingerprint images from 4 sensors – Biometrika, Italdata, Digper and Sagem
- 4000 from each sensor, equally divided into training and testing

# Exploring VGG16 Model

- Training a pre-trained VGG16 [2] model on LivDet 2011 (Sagem sensor) dataset [1]
- Model accuracy peaks at around 50 epochs of training

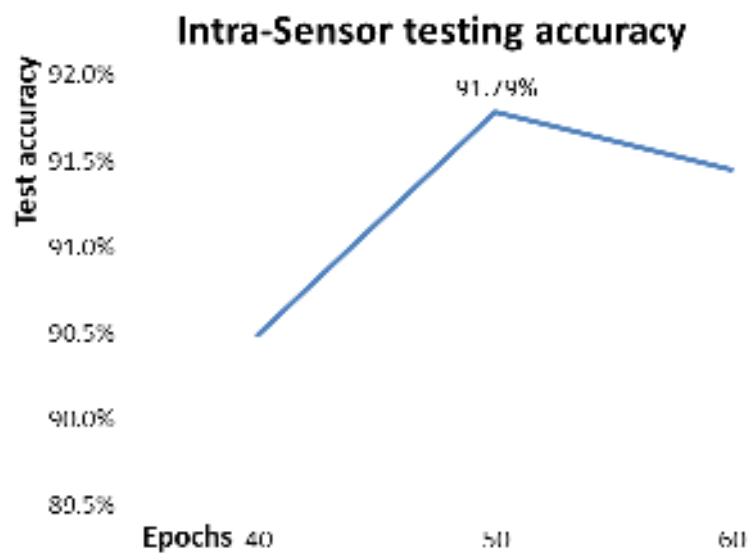


Figure 6

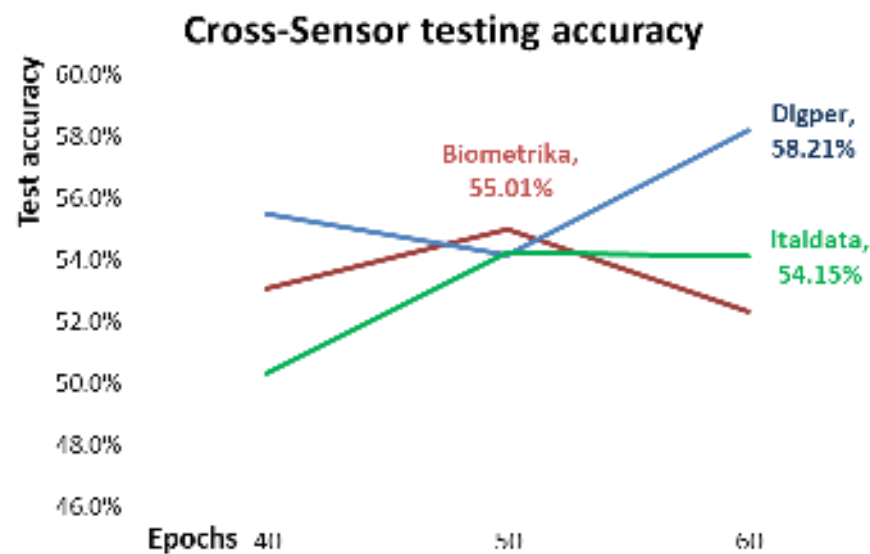


Figure 7

# Exploring shallow CNN architectures

## Shallow CNN on LivDet-2011 Dataset (Sagem Sensor) [1]

- 8 layers
- 2 convolution layers, 2 max-pooling layers, 2 dense layers, 1 flatten layer and a final Softmax layer

## Shallow CNN on LivDet-2011 Dataset (Digper Sensor) [1]

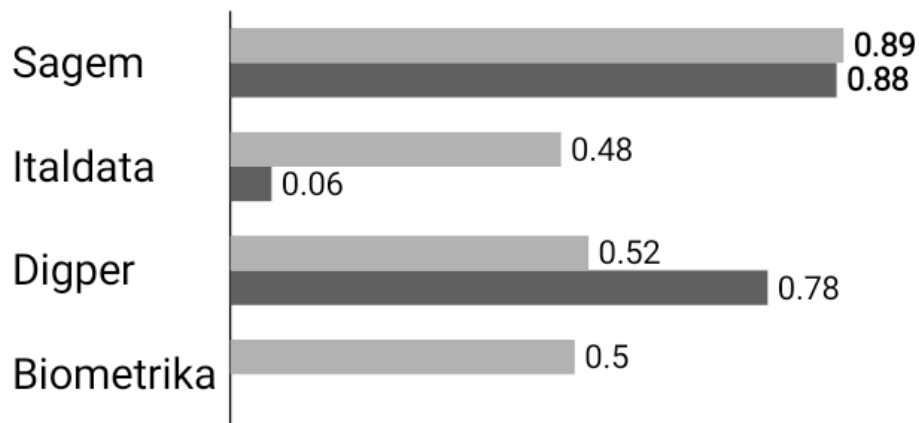
- 9 layers
- 2 convolution layers, 2 max-pooling layers, 3 dense layers, 1 flatten layer and a last Softmax layer

# Shallow CNN (Sagem Sensor)

Table 1: Testing accuracy of this model

Sensor	Testing Accuracy
Sagem	88.95%
Digper	55.29%
Biometrika	50.05%
Italdata	46.42%

Precision  
■ fake ■ live



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Figure 8

IIT Indore

Recall  
■ fake ■ live

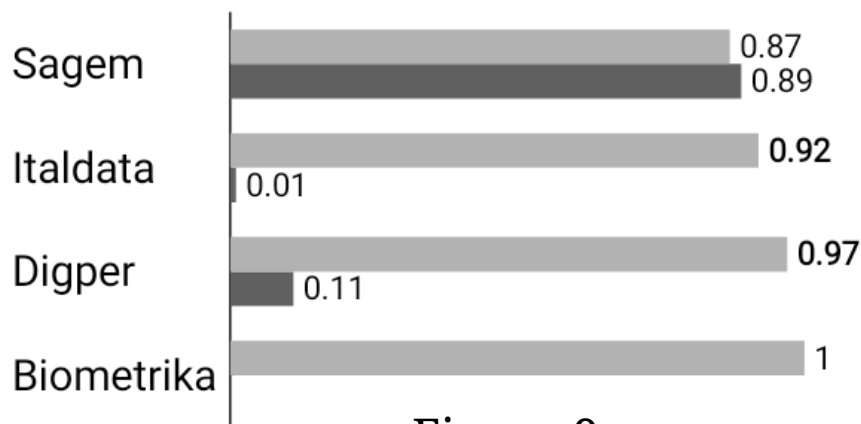


Figure 9

13

# Shallow CNN on LivDet-2011 Dataset (Sagem Sensor) using Adam optimizer

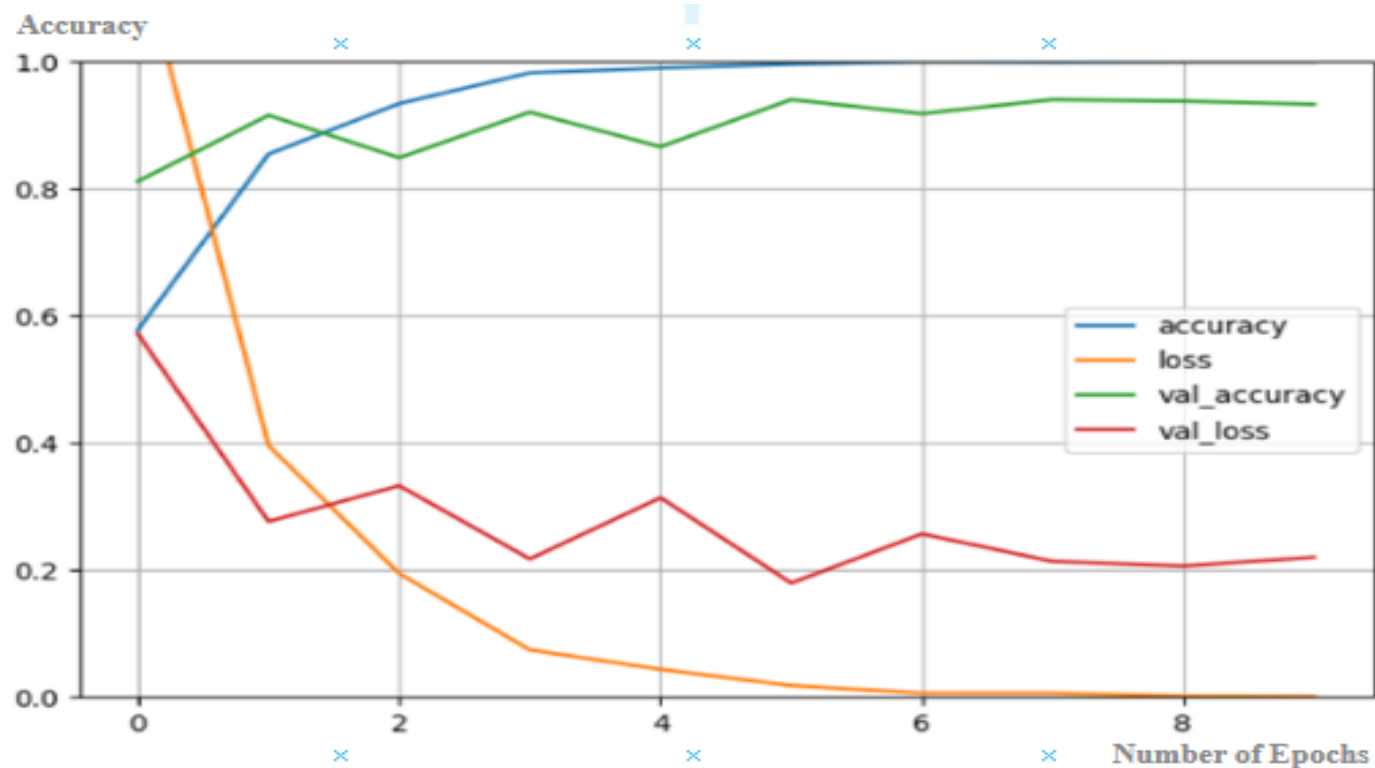


Figure 10 : Accuracy and loss curve using Adam optimizer

# Shallow CNN on LivDet-2011 Dataset (Sagem Sensor) using SGD optimizer

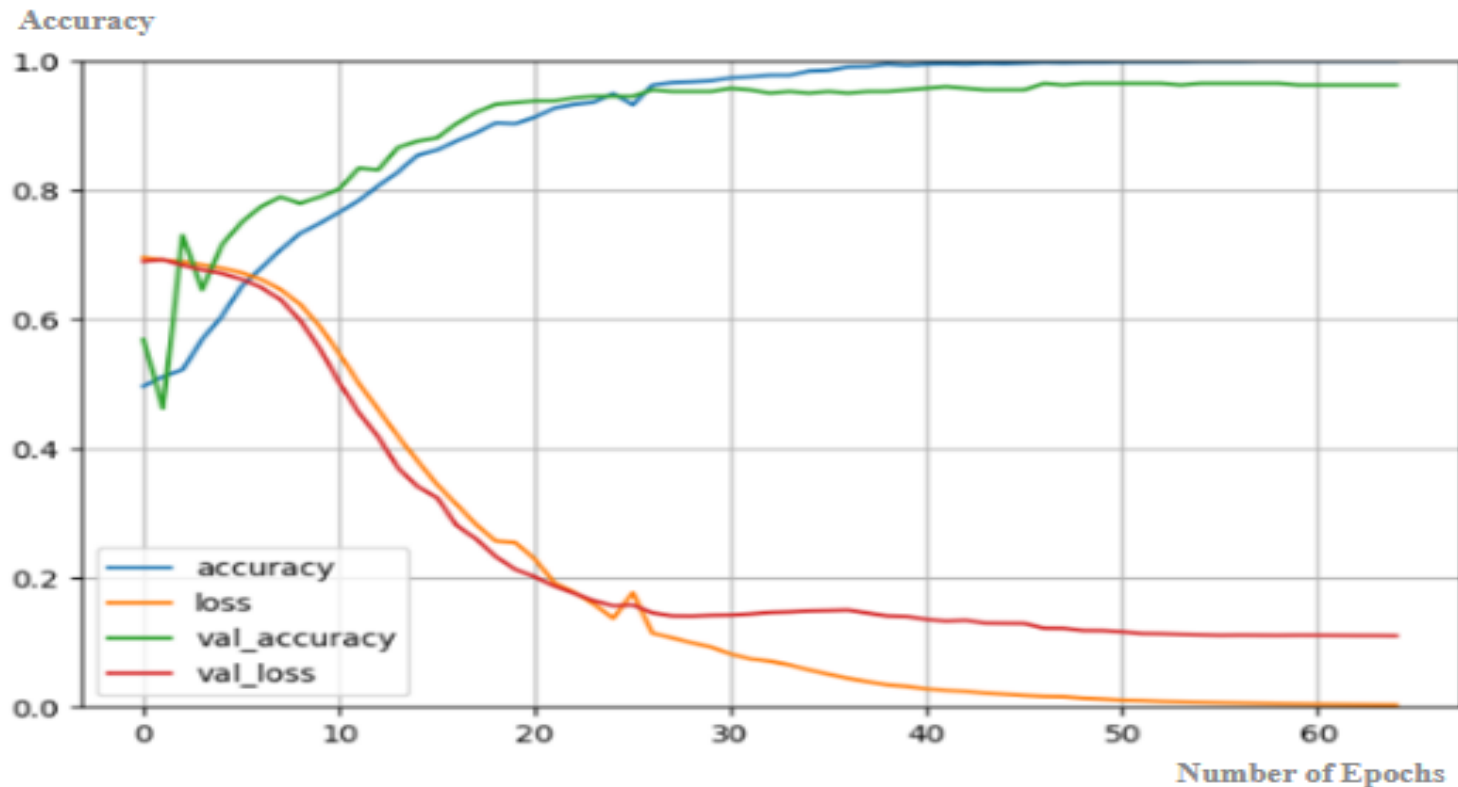


Figure 11 : Accuracy and loss curve using SGD optimizer

# Shallow CNN (Digper Sensor)

Table 2: Testing accuracy of this model

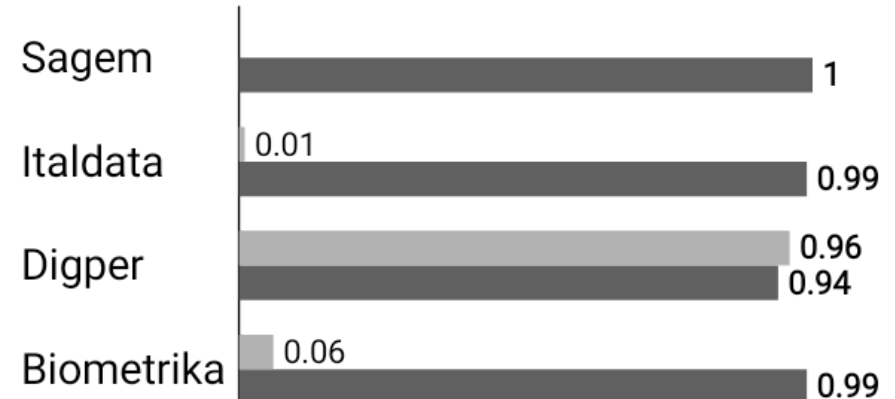
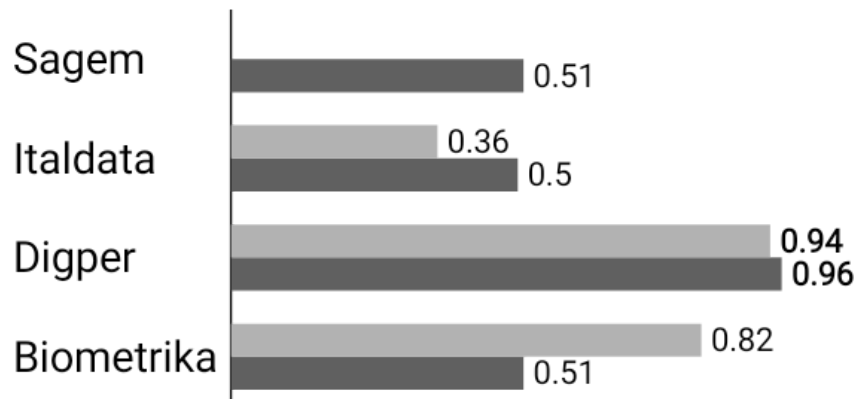
Sensor	Testing Accuracy
Sagem	94.72%
Digper	54.01%
Biometrika	51.50%
Italdata	51.90%

Precision

■ fake ■ live

Recall

■ fake ■ live





# Shallow CNN on LivDet-2011 Dataset (Digper Sensor) using Adam optimizer

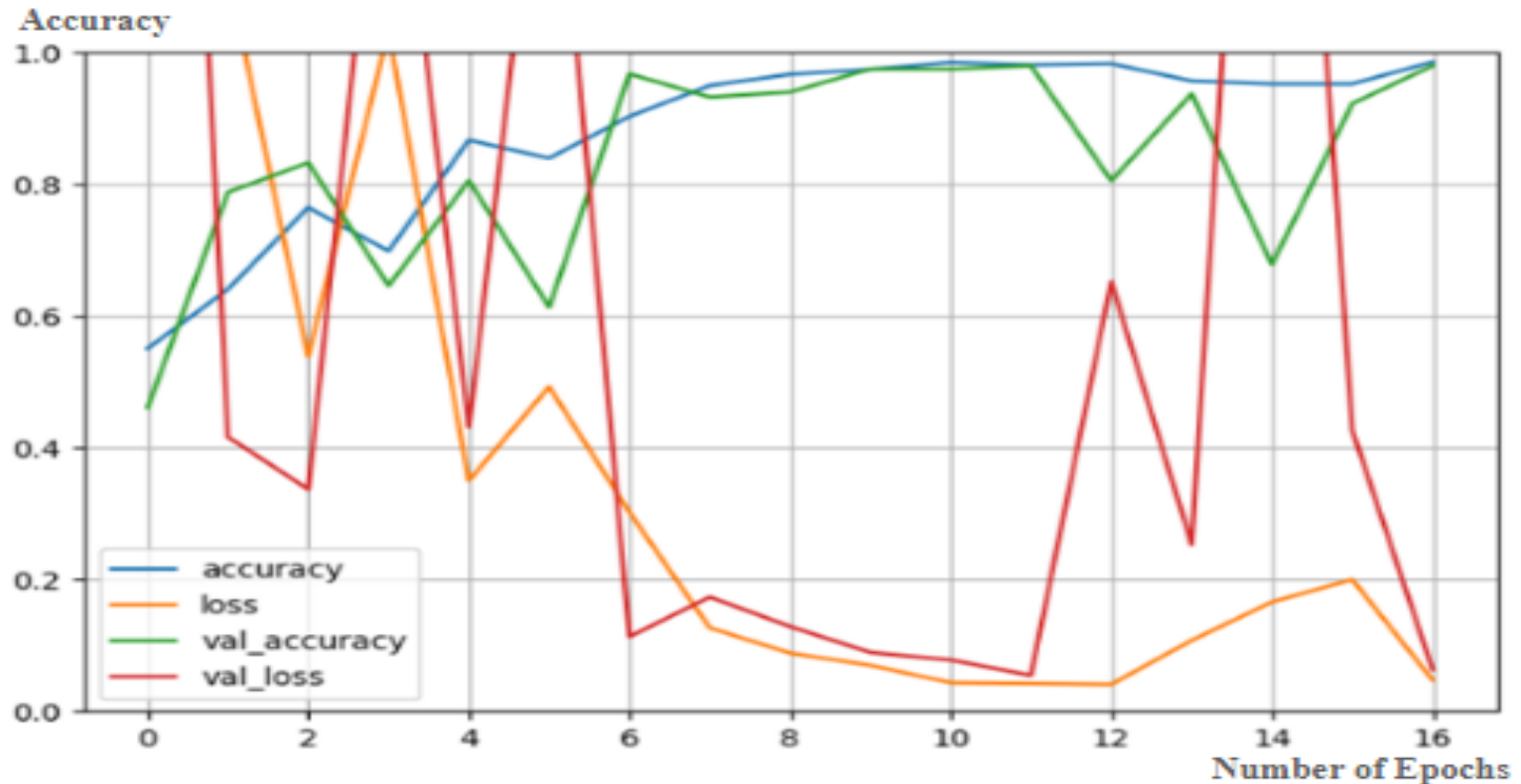


Figure 14 : Accuracy and loss curve using Adam optimizer

# Observations

- VGG16 model (Sagem sensor) shows intra-sensor testing accuracy of 91.79% , cross sensor testing accuracy of 58%.
- Shallow CNN network (Digper sensor) exceeds this intra-sensor testing accuracy, attaining 94.72%
- Shallow CNN network (Sagem sensor) attains a comparable cross-sensor accuracy 55.29%
- Both shallow networks exhibit high recall values, specially the one trained on Digper sensor data.
- Both shallow networks took up to 70% less time to train

# Conclusion

- The observations suggest potential effectiveness of shallow CNN models over deep architecture models
- If used collectively in form of **Ensemble Classifiers** they might prove to be more efficient as well as more practical

# Acknowledgements

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# Thank You

# References

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# Appendix



Plagiarism report