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# Comparative Study of Deep Learning-based Finger Vein Biometric Authentication System

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# Introduction

- ➢ Finger vein biometric system is a promising biometric system that uses pattern recognition techniques based on images of human finger vein patterns.
- ➢ Takes only about 0.8 seconds to verify one input finger vein sample.
- ➢ Near Infrared light is used in image capturing devices for this system.

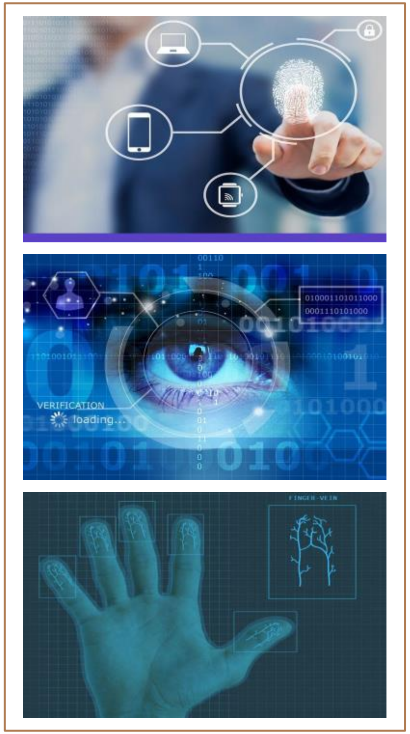


**Fig. 1: Biometric Authentication**

# Steps of Finger Vein Biometric System

- Finger Vein Recognition
  - Image Acquisition
  - Pre-Processing
    - Image Assessment
    - ROI (Region Of Interest) Selection
    - Image Enhancement & Normalization
  - Feature Extraction
    - Vein Based Method
    - Local Binary Based Method
    - Dimensionality Reduction Based Method
    - Minutiae Based Method
  - Matching
    - Distance Based Method
    - Classifier Based Method

# Steps of Finger Vein Biometric System (Cont.)

- Image Acquisition
- Pre-Processing
- Feature Extraction
- Classification

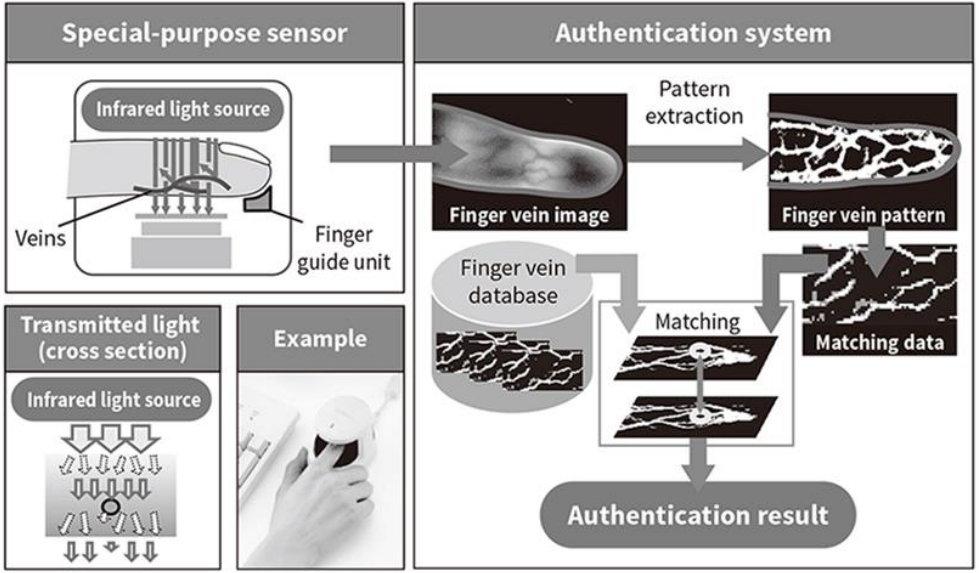


Fig. 2: Finger Vein Authentication

# Motivation

- ❑ Finger vein biometric system
  - ➢ Very low risk of forgery or theft.
  - ➢ Non-invasive, contactless imaging.

- ❑ Deep Learning
  - ➢ Deep learning is popular for its stability and accuracy in performance.
  - ➢ Can deal greatly with the different image qualities.
  - ➢ Gives comparatively more approvable results than other methods.

# Objective

- ➢ To study the existing finger vein recognition systems.
- ➢ To observe the difference among multiple proposed systems and to find out the best method for recognition system.
- ➢ Propose a new method using deep learning.

# What is Deep Learning?

- ➢ A part of machine Learning family.
- ➢ An AI function that mimics the workings of the human brain in processing data for use in detecting objects, recognizing speech, translating languages and making decisions.
- ➢ The learning can be supervised or unsupervised.
- ➢ Used for both feature extraction and classification.

# Deep Learning Architectures

- ➢ Convolutional Neural Network (CNN)
  - ❑ AlexNET
  - ❑ LeNet-5
  - ❑ DenseNet
  - ❑ VGG-Net-16
  - ❑ ResNet
- ➢ Deep Neural Network (DNN)

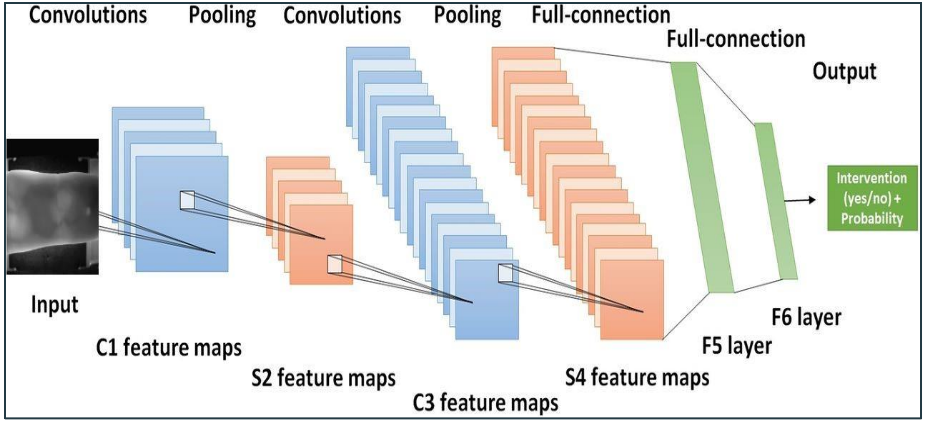


Fig. 3: **Deep Learning Architecture**

# Deep Learning Architectures (Cont.)

- LeNet-5
  - Seven layers and it contains some features including convolution layers, subsampling layers, and two or three fully connected layers.
  - Sufficiently good for image classification.
  - Lacks in complex classification problems with large datasets.

# Deep Learning Architectures (Cont.)

- AlexNet
  - five convolution layers and two fully-connected layers.
  - Reduces the complications of image processing.
  - The fully connected layers are  computationally expensive.

# Deep Learning Architectures (Cont.)

- **VGG-Net-16 :**
  - **13 convolutional layers, 5 pooling layers, and 3 FCLs.**
  - **Higher performance in feature extraction.**
  - **Slow to train.**

# Deep Learning Architectures (Cont.)

- **ResNet: Are implemented with double or triple layer that contains non linearities (ReLU) and batch normalization in between.**

# Deep Learning Architectures (Cont.)

- ❑ **DenseNet:**
  - ➢ **Uses skip connectivity which improves the skip connection structure of ResNet.**
  - ➢ **Decreases the networks' computation-efficiency**

# Deep Learning Architectures (Cont.)

- **Deep Neural Network (DNN):**
  - **A part of the Artificial Neural Network where there are multiple layers between input and output layers**
  - **Is able to learn features that optimally represent the given training data.**

# Datasets

- ➢ **SDUMLA-HMT**
- ➢ **FV-USM**
- ➢ **HKPU**
- ➢ **UTFV**

**Fig:4 - (a) FV-USM**

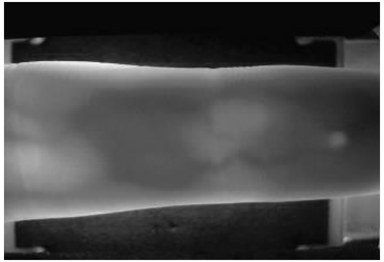

**Fig:4 - (b) SDUMLA-HMT**

# Evaluation Matrices

- **False Acceptance Rate(FAR): FAR is an error that occurs when the un-enrolled finger vein image is accepted as an enrolled finger vein image.**

  *FAR=False Positive/(False Positive+True Negative)*

- **False Rejection Rate(FRR): FRR  is an error that indicates that the enrolled finger vein image is rejected as an un-enrolled finger vein image.**

  *FRR=False Negative/(False Negative+True Positive)*

# Evaluation Matrices (Cont.)

- **Equal Error Rate(EER): When the proportion of false acceptance rate(FAR) and the proportion of false rejection rate(FRR) are equal , then the common value is the EER.**

- **Accuracy: Accuracy is actually the ratio of the correct classified data and all classified data.**
  *Accuracy = (True Positive+True Negative)/(True Positive+True Negative+False Positive+False Negative)*

# Performance Analysis of Different Architectures

# Table: 1

| Method | Paper | Year | Dataset | Performance (%) |
| --- | --- | --- | --- | --- |
| DNN | Qin et al[7] | 2015 | FV-USM[1], HKPU[2] | EER = 0.70 and 1.50 |
| LeNet-5 | Itqan et al[4] | 2016 | Personal dataset | Average accuracy = 96 |
| Reduced-complexity four-layer CNN | Radzi et al[6] | 2016 | Personal dataset | RR = 100.00 and 99.38 |
| VGG-Net-16 | Hong et al[8] | 2017 | personal dataset, personal dataset SDUMLA-HMT | EER = 0.396, 1.275 and 3.906 |
| AlexNet | Liu et al[5] | 2017 | SDUMLA-FV | RR = 99.53<br>EER = 0.80 |

# Performance Analysis of Different Architectures
# Table: 1 (Cont.)

| Method | Paper | Year | Dataset | Performance (%) |
|---|---|---|---|---|
| CNN | Meng et al[9] | 2017 | DataTang | Accuracy = 99.4<br>ERR = 0.21 |
| ResNet | Kim et al[12] | 2018 | SDUMLA-HMT, HKPU | EER = 3.0653 and 0.8888 |
| DRFRDL | Rakkimuthu et al[13] | 2019 | SDUMLA-HMT | Accuracy = 95 |
| DenseNet | Song et al [17] | 2019 | SDUMLA-HMT, HKPU-FV(version-1) | EER = 2.35 and 0.33 |

# Performance Analysis of Different Architectures Table: 1 (Cont.)

| Method | Paper | Year | Dataset | Performance (%) |
|---|---|---|---|---|
| Unet, RefineNet, SegNet | Jalilian et al[14] | 2019 | UTFVP[3] | EER = 0.64, 1.76 and 2.21 |
| CNN with depthwise separable convolution | Kang et al[18] | 2019 | Personal Dataset | EER = 2.13 |
| CNN-LSTM | Kuzu et al[19] | 2020 | Personal dataset | Accuracy = 99.13% |

# Discussion

- AlexNet shows the highest accuracy and lower EER on SDUMLA dataset.
- DenseNet also gives lower EER on same dataset.
- The most important thing is, these architectures are used or proposed in recent years by the researchers.

# Contribution of this Paper

- ➢ Recent and noteworthy deep learning models have been assembled.
- ➢ Multiple datasets and evaluation metrics that are generally used to evaluate performance have been discussed in this paper.
- ➢ Provides a single platform where researchers would get all deep learning based finger vein authentication architectures for their purposes.

# CONCLUSION

- Most of the CNN architectures are computationally slow when it comes to large datasets, but shows higher performance in feature extraction.
- DNN is able to learn the features from training data, still sometimes it fails to extract discriminative features.

# Future Plan

- ➢ Introducing a new method by combining the traditional feature extraction method and deep learning based classifier.
- ➢ Improving recognition accuracy and robustness by solving alignment and image quality issues.
- ➢ Making the system capable of performing on several large datasets for performance evaluation.

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# Thank You