Multimodal biometrics of fingerprint and signature recognition using multi-level feature fusion and deep learning techniques

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ABSTRACT

Providing security in biometrics is the major challenging task in the current situation. A lot of research work is going on in this area. Security can be more tightened by using complex security systems, like by using more than one biometric trait for recognition. In this paper multimodal biometric models are developed to improve the recognition rate of a person. The combination of physiological and behavioral biometrics characteristics is used in this work. Fingerprint and Signature biometrics characteristics are used to develop a multimodal recognition system. Histograms of oriented gradients (HOG) features are extracted from biometric traits and for these feature fusions are applied at two levels. Features of Fingerprint and Signatures are fused using concatenation, sum, max, min, and product rule at multilevel stages, these features are used to train deep learning neural network model. In the proposed work, Multi-level feature fusion for multimodal biometrics with a deep learning classifier is used and results are analyzed by a varying number of hidden neurons and hidden layers. Experiments are carried out on SDUMLA-HMT, machine learning and data mining lab, Shandong University fingerprint datasets, and MCYT signature biometric recognition group datasets, and encouraging results were obtained.

Keywords:
Deep Neural Network
Feature Fusion
Fingerprint
Multimodal Biometrics
Signature

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1. INTRODUCTION

In today’s world, almost all security systems are using biometric recognition techniques. Biometric recognition has become the day-to-day activity for a bigger population. Daily usage like a mobile phone to bank locker all the systems are integrated with biometric security. In the coming days, these biometric recognition systems will be in almost all the areas of our day-to-day activity. By increasing usage of such a system with an increase in population, recognition will become more complex day by day. A lot of research is going on multimodal biometric recognition. Since by using multimodal biometric traits more secured system can be developed over a unimodal biometric system [1]. When it comes to biometric traits two factors are considered, one is an extrinsic feature and another one intrinsic feature. The Extrinsic features can be visible from the outside and these features can be harmed by external factors [2]. Example fingerprint, face, etc. can be harmed in the accident. The Intrinsic features cannot be visible from the outside and these features cannot be harmed by external factors. Example finger vein, palm vein, etc. And biometric traits are broadly

Journal homepage: http://ijeecs.iaescore.com
classified as physiological and behavioral biometrics characteristics, where the face, fingerprint, iris, etc. fall under physiological characteristics and signature, voice and gait. fall under behavioral biometrics characteristics. The Biometric recognition system is designed using four components they are, sensor module, feature extraction module, matching module, and decision-making module. Biometric recognition systems are categorized into two systems one is unimodal and another is a multimodal biometric recognition system. Unimodal uses single biometric traits where multimodal uses more than one biometric trait. Some of the unimodal biometric systems are explored in previous work on face and signatures biometric traits [3, 4]. In a multimodal system, a fusion of more than one biometric trait could be explored. Fusion could be explored at different levels. Fusion fall under four different levels they are sensor, feature, score, and decision. Recent research is more attractive towards the use of the deep learning method since it can handle limitations that are facing by machine learning techniques [5-7]. In the proposed work, a new multimodal biometric recognition modal is explored, which uses multi-level HOG feature fusion of signature and fingerprint with deep learning algorithm for recognition. Convolution neural networks (CNNs) [8] are designed and a softmax classifier is used for image classification. Adam optimization and categorical cross-entropy were used as optimizer and loss function respectively.

2. LITERATURE SURVEY

A Lot of research is going on for decades on unimodal and multimodal biometrics recognition. In the past few years due to the advancement of technology in computer hardware, deep learning concepts are gaining more interest in research. Using the deep learning technique biometric recognition and verification showed better results [9] shown in Table 1. In this paper fingerprint and signature, biometric traits are considered, so previous works on fingerprint and signature biometric recognition and verification are compared in both unimodal and multimodal systems.

| Title                                                                 | Deep Learning Architecture          | Dataset                  | Results                  |
|-----------------------------------------------------------------------|-------------------------------------|--------------------------|--------------------------|
| Multimodal Face Biometrics by Using Convolutional Neural Networks [10]| Self-designed CNN                  | Multi-PIE                | 98.35% accuracy          |
| Audio-VisualSpeaker Recognition via Multimodal Correlated Neural Networks [11] | Self-designed CNN                  | Videos from TV series naming | 97.85% accuracy          |
| A Novel Multi-Model Biometric Fusion Approach Using Palm-Print & Face Biometric [12] | NN and SVM                         | Sample Images            | Cumulative match score good results. |
| Multimodal Biometric Authentication Using Back Propagation Artificial Neural Network [13] | ANN classification                  | Sample Images            | 98.44% accuracy          |
| Multimodal Feature Level Fusion based on Particle Swarm Optimization with Deep Transfer Learning [14] | Modified VGG                       | NICE II database Competition | 5.55% EER                |
| FKP and Iris Based Multimodal Biometric System Using PCA with NFNN [15] | Neuro-Fuzzy Neural Networks (NFNN) | PolyU FKP and CASIA Iris database VERA Fingervein, Color Feren and AR face database | EER of 0.23%            |
| Score fusion off finger vein and face for human recognition based on convolutional neural network model [16] | Traditional CNN feature extraction | Cumulative match score good results. | 99.89% accuracy          |
| Periocular biometrics for non-ideal images: with off-the-shelf Deep CNN & Transfer Learning approach [17] | Pre-trained Alex net, Googlenet, Resnet 18, Resnet 50, Resnet 101, VGG 16 and VGG 19 | UBIPr database | Max. testing accuracy of 96% with VGG 19 |

From the above literature survey, it has been observed that deep learning techniques will improve multimodal biometric recognition. And not more work is done on fingerprint and signature biometric combinations for larger data sets. In this paper new modals is proposed where Multi-level feature fusion is done on multimodal biometrics [18] of fingerprint and signature traits using deep learning architecture.

3. DATABASE USED FOR EXPERIMENTATION

3.1. Fingerprint database

SDUMLA-HMT fingerprint database from the machine learning and data mining lab, Shandong University (SDUMLA) [19] is used for experimentation. 40 users with 6 fingerprint samples of the left thumb of each person are considered for experimentation. Fingerprint samples are shown in Figure 1. 

Indonesian J Elec Eng & Comp Sci, Vol. 22, No. 1, April 2021 : 187 - 195
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Level 1 fusion is carried out with SUM, MAX, MIN, PRODUCT and concatenation method and in level 2 concatenation method is applied.

- **SUM operation**: \( C_{ij} = A_{ij} + B_{ij} \)
- **MAX operation**: \( C_{ij} = \max(A_{ij}, B_{ij}) \)
- **MIN operation**: \( C_{ij} = \min(A_{ij}, B_{ij}) \)
- **Product operation**: \( C_{ij} = A_{ij} \cdot B_{ij} \)
- **Concatenation**: \( C_{ij} = [A_{ij} \ B_{ij}] \)

Where \( A_{ij} \) is HOG feature vector of standard signature and \( B_{ij} \) is HOG feature vector of upsampled signature. Similar steps carried out for fingerprint data sets.

5. THE NEURAL NETWORK MODEL

In this paper using Python with Keras Library Deep learning neural networks are created by following the model life-cycle steps deep learning neural networks are created [24]. Steps as follows define network, compile network, Fit network, evaluate network and make predictions.

Networks are defined in sequence order

```python
model = Sequential()
model.add(Dense(5, input_dim=2))
model.add(Dense(1))
```

Consider the example Input dim are several input neurons, value 5 is a number of hidden neurons, and an output neuron is 1. In this paper more than 100 input neurons, more than 500 hidden neurons, and 40 neurons as output neurons, since 40 different multiclass classifications are expected as output.

```python
model = Sequential()
model.add(Dense(8, input_dim=4, activation='relu'))
model.add(Dense(3, activation='softmax'))
```

Since the proposed work is explored on multiclass classification softmax activation function is used at the output layer. Complex deep learning models are also defined and explored in this work using more than one hidden layer.

```python
# create model
model = Sequential()
model.add(Dense(756, input_dim=252, activation='relu'))
model.add(Dense(252, activation='relu'))
model.add(Dense(40, activation='softmax'))
```

In this paper, 252 input neurons with 756 hidden neurons in the first hidden layer and 252 hidden neurons in the second hidden layer, and an output layer with 40 neurons are used in one of the case studies. Compile network: Multiclass logarithmic loss or categorical cross-entropy is used with the ‘adam’ optimization algorithm. Fit network: Model batch size and epochs are assigned to fit the model in this step. After this step evaluation of the model is done by checking classification accuracy and finally, predictions for new data sets are executed.
6. EXPERIMENTS

In this paper, the main aim is to improve the recognition rate of fingerprint and signature biometric traits for larger data sets. SDUMLA-HMT fingerprint database and MCYT biometric recognition group signature database are used for experimentation. Fused features are used to train and test the deep learning neural network. An example of the fused feature [25, 26] using concatenation technique is:

\textbf{Features fusion:} Consider a example of fused feature, \( X_1 \) is a HOG feature of fingerprint and \( Y_1 \) is a HOG feature of signature, after concatenation output is \( Z \), therefore, first three samples of each person give \( Z_1 \) to \( Z_{40} \), forty rows with column (number of columns depends on fusion technique used) and last column with the class label name data matrix are created, this data matrix is used to train the deep learning neural network. Similarly, for the testing phase, the same procedure for the remaining three data samples without a class label column is used for experimentation.

\[
\text{Concatenation Technique-} X_1 = [X_1, X_2, \ldots X_{36}] \quad Y_1 = [Y_1, Y_2, \ldots Y_{36}] \\
Z = [X_1, X_2, \ldots X_{36}, Y_1, Y_2, \ldots Y_{36}] \\
Z_1 = [X_1, X_2, \ldots X_{36}, Y_{37}, Y_{38}, \ldots Y_{7241}]
\]

a. Unimodal biometrics: Initial experiments were explored on unimodal systems, where HOG features are extracted from the standard database and upsampled database of fingerprint and signature separately. Unimodal HOG features [27] are fused using SUM, MAX, MIN, PRODUCT, and concatenation method, and fused feature vector from (1) (2) of each method is set as input to the neural network.

b. Multimodal biometrics: Experiments are carried out on multimodal biometric recognition where features fused while executing unimodal experiments are considered from fingerprint and signature biometrics, these features are fused once again using the concatenation method, and results are plotted. These multilevel Fingerprint and Signatures are fused using concatenation, sum, max, min, and product rule at multilevel stages as shown in Figure 4, these features are used to train deep learning neural network model. Example, After fusion from (1) (2) of HOG fingerprint features of 3 training samples and HOG signature features of 3 training samples, data with class label name in the last column is used to train deep learning neural network, remaining 3 samples of fingerprint and signatures are fused and data without label name is used for testing the deep learning network gives the output class name and classification accuracy is analyzed.

c. Deep learning model: In the proposed work, by varying input neurons, hidden neurons, and hidden layers different deep learning models are designed and explored. Deep learning models were designed using Keras libraries using python.

d. Experiments of unimodal system: The MCYT signature data sets consist of 75 users with 15 genuine and 15 forgery signatures. For this experiment, 40 people with 6 data samples of each person are used. HOG features of the first 3 samples of each person’s Standard signature data sets and 1:2 ratio upsampled signature data sets are fused using SUM, MAX, MIN, PRODUCT, and concatenation techniques. The neural network model is designed for the required input. The remaining 3 samples of each person are used for testing. The same procedure is executed for the fingerprint database, here 40 user’s left thumb 6 data samples of each user are considered.

e. Experiments of multimodal system: The feature vector obtained in level 1 after SUM, MAX, MIN, PRODUCT, and concatenation technique of Unimodal system is used for the second level of fusion. Feature vector obtained from each technique in level 1 of both signature HOG features and Fingerprint HOG features are fused using Concatenation method in level 2 and these multi-level fused vector data is set as an input for neural network and results are plotted. Neural network model concerning input neuron 1:2, 1:3, and 1:4 ratio hidden neurons models are implemented. Extending the experimentation neural network model with multiple hidden layers of 756 hidden neurons in the first layer and 256 hidden neurons in the second layer is implemented and results are plotted.

7. RESULTS

The results are based on Level 1 feature fusion: The experiment is conducted on unimodal biometrics. Original database and upsampled database are fused using the concatenation technique, and the concatenated feature vector is set as an input for the neural network. The classification accuracy is given in Table 2. The results are based on level 2 feature fusion: signature and fingerprint feature vector obtained from level 1 SUM, MAX, MIN, PRODUCT, and concatenation technique fusion is fused in level 2 using concatenation technique. Feature vector obtained after both level 1 and level 2 fusions is set as an input for neural network and results are plotted. The classification accuracy of the neural network model is given in Table 3.

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Table 2. Unimodal system: single level feature fusion

| Biometric traits                                      | Fusion technique | Neural Network Model Classification accuracy |
|-------------------------------------------------------|------------------|--------------------------------------------|
| MCYT Standard Signature data sample and 1:2 ratio up sampled data | Concatenation    | 85%                                        |
| SDUMLA Standard fingerprint data sample and 1:2 ratio up sampled data | Concatenation    | 60%                                        |

Table 3. Multimodal System: multi-level feature fusion

| Biometric traits                                      | Multi-Level Fusion technique | Neural Network Model Classification accuracy |
|-------------------------------------------------------|------------------------------|--------------------------------------------|
| MCYT Standard Signature data sample and 1:2 ratio up sampled data | Level 1: Concatenation    | 91.66%                                    |
| SDUMLA Standard fingerprint data sample and 1:2 ratio up sampled data | Level 2: Concatenation    | 92.5%                                    |
| Level1: Unimodal biometrics                           | Level 1: SUM                | 91.66%                                    |
| Level2: Multimodal Biometrics                         | Level 2: Concatenation      | 92.0%                                    |
|                                                     | Level 1: MIN                |                                            |
|                                                     | Level 2: Concatenation      |                                            |
|                                                     | Level 1: Product             |                                            |
|                                                     | Level 2: Concatenation      |                                            |

Figure 5 shows the classification accuracy of each network model with different fusion techniques used in both level 1 and level 2 fusions. Figure 5 shows the plot for data available in Table 3, the x-axis shows fusion techniques at both level 1 and level 2 respectively and, the y-axis shows classification accuracy. Results based on varying hidden neurons: From Table 3 it has been observed that the level 1 product method and level 2 concatenation methods showed good results, that results are obtained by developing four neural network models by varying hidden neurons. The results of all four models are given in Table 4.

Figure 6 shows the classification accuracy of the network model by varying hidden neurons used in the hidden layer’s x-axis shows various neurons used in the hidden layers, the y-axis shows classification accuracy.
accuracy. Results based on varying hidden layers: From Table 4 it has been observed 756 hidden neurons showed good results, the same neural network model is extended by adding multiple hidden layers. The results of the single hidden layer with 756 hidden neurons and multiple hidden layers with 756 hidden neurons are given in Table 5. In the literature survey many works show more than 95% classification accuracy, but for very limited data sets. In the proposed work 93.33% accuracy was achieved for larger data sets. From the literature it has been observed that, no other work is proposed with the fusion of fingerprint and signature biometric traits at multi-level with deep learning model for classification. When compared with unimodal fingerprint, in proposed model recognition rate is increased by 8.33% and for signature samples proposed model recognition rate is increased by 33.33%.

![Figure 6. Hidden neurons vs neural network model classification accuracy](image)

### Table 5. Multimodal System: Multi-level feature fusion for different hidden layers

| Biometric traits                                         | Hidden Layer                  | Neural Network Model Classification accuracy |
|----------------------------------------------------------|-------------------------------|---------------------------------------------|
| MCYT Standard Signature data sample and 1:2 ratio up sampled data | 756 Neurons (single layer)    | 93.33%                                      |
| SDUMLA Standard fingerprint data sample and 1:2 ratio up sampled data | 756 Neurons (first layer)     | 85.50%                                      |
| Level1: Unimodal biometrics (concatenation)               | 252 Neurons (second layer)    |                                             |
| Level2: Multimodal Biometrics (Product)                   |                               |                                             |

8. CONCLUSION

In this paper, several experiments are carried out by varying hidden neurons and hidden layers of the neural network model. By examining the entire neural network model best models are selected and results are explored. In the proposed method multilevel feature fusion for an upsampled database is implemented by using a deep neural network model. The main idea of this work is to obtain better classification accuracy in multimodal signature and fingerprint biometric. However, there will be no fixed method to design deep learning networks like how to choose hidden neurons, hidden layers, activation function, etc. From the experiment, it has been observed that the proposed model increases the classification accuracy of multimodal biometrics over unimodal biometrics recognition for larger data sets. In Multilevel feature fusion combination of concatenation and product operations showed a better result of 93.33% of classification accuracy when experimented on a single layer with 756 hidden neurons.

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