



## A New Facial Image Deviation Estimation and Image Selection Algorithm (Fide-Isa) for Facial Image Recognition Systems: The Mathematical Models

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### ABSTRACT

Deep learning models have been successful and shown to perform better in terms of accuracy and efficiency for facial recognition applications. However, they require a huge amount of data samples that were well annotated to be successful. Their data requirements have led to some complications which include increased processing demands of the systems where such systems were to be deployed. Reducing the training sample sizes of deep learning models is still an open problem. This paper proposes the reduction of the number of samples required by the convolutional neural network used in training a facial recognition system using a new Facial Image Deviation Estimation and Image Selection Algorithm (FIDE-ISA). The algorithm was used to select appropriate facial image training samples incrementally based on their facial deviation. This will reduce the need for a huge dataset in training deep learning models. The experiment was implemented using MATLAB R2020a in a system with a 2.6 GHz processing speed. Preliminary results indicated a 100% accuracy for models trained with 54 images (at least 3 images per individual) and above.

### INTRODUCTION

Face recognition is a biometric method used in recognizing an element using facial features. It is characterized by high accuracy of a physiological approach without being intrusive (Ogbuju et al., 2020). Face recognition as a biometric method has brought the attention of many researchers in different fields ranging from computer vision, psychology, business, security and image processing (Alqadi et al., 2020; Coskun et al., 2017). Despite their importance, some factors affect the performance of face recognition systems. This includes changes in postures, scene illumination, orientation, field of view and database sizes (Ogbuju et al., 2020; Almabdy & Elrefaei, 2019; Arafah et al., 2020; Coskun et al., 2017).

Several techniques have been proposed for face recognition applications, this includes deep learning which has shown better performance than other models in terms of accuracy and processing (Coskun et al., 2017;

### ARTICLE INFO

#### Article History

Received: October, 2021

Received in revised form: November, 2021

Accepted: January, 2022

Published online: February, 2022

### KEYWORDS

Facial Recognition, Convolutional Neural Network, Deep Learning, Facial Image Deviation Estimation

Filippidou & Papakostas, 2020; Ling et al., 2020; Marsot et al., 2020; Swapna et al., 2020; Tao et al., 2019). CNNs had been applied successfully to solve several computer vision problems with great success attributed to using large-scale data samples (Pei et al., 2019). However, due to difficulties in sample collection and requirement for training with large-sample data, deploying CNNs for daily attendance management still remains a challenge (Pei et al., 2019; Parkhi et al., 2015). Training a deep learning model with huge amount of data allows the model to learn from different variations that exists in the images and that may be required for recognition (Peng et al., 2016).

To address the sample requirement issues of CNN face recognition, Pei et al., (2019) proposes the application of data augmentation to enlarge the datasets by deploying several geometric transformation, filters and enhancement mechanisms. The result indicated an improvement in the accuracy of the system,

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however, the complexities of the system also increased. Reducing the computational complexities of deep learning networks, and their dependence on large accurately annotated databases for training deep learning models is still an open research area that requires urgent attention (Nagpal et al., 2019). Peng et al., (2016) applied modelling methods to reduce the need for huge datasets. This was achieved in three phases; application of spatial transformation learning for aligning faces spontaneously and design of robust face recognition system. This paper proposes the reduction of the number of training samples a CNNs will require for training and still obtain a state of the art performance. A Facial Image Deviation Estimation and Image Selection Algorithm (FIDE-ISA) was developed to select appropriate training samples based on their deviation in an incremental manner. The method adopted in this paper will ensure that images with closely related features, that is, minimum deviation are avoided while those with wider

deviations are selected to capture the diversity of the samples. The remaining part of the paper is organized as: methods and materials used were described, and lastly the performance metrics were presented.

## MATERIALS AND METHODS

### *Facial Image Deviation Estimation and Image Selection Algorithm (FIDE-ISA)*

FIDE-ISA is an algorithm that was designed to estimate the deviations within facial images of an individual and selects the best images for training a deep learning facial recognition model. To achieve this successfully, five facial landmarks were detected which are:

- i. Left eye
- ii. Right eye
- iii. Nose
- iv. Left side of the mouth
- v. Right side of the mouth

Figure 1 shows a facial image with the facial landmarks of interest.

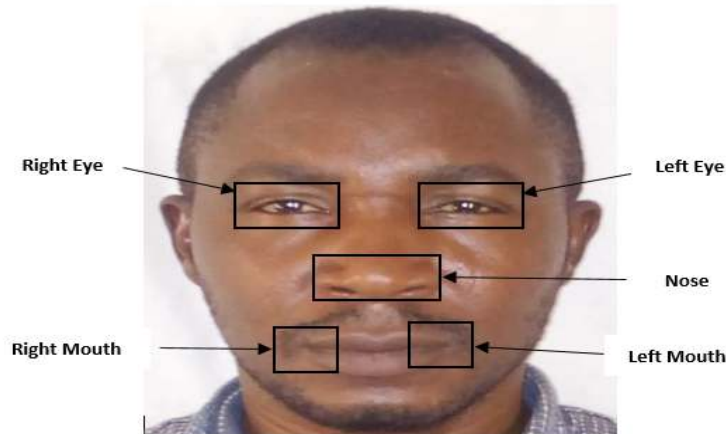


Figure 1: Facial landmarks (Siyaka et al., 2021)

The facial landmarks used in Figure 1 were detected using MTCNN model which stands for (Multi-task Cascaded Convolutional Neural Network) used in face detection. MTCNN was adopted for both facial landmark detection and face detection because of it produces better

results than any face detection model. After detecting the facial landmarks, the Euclidean distances between the coordinates of the base image and the deviated image is calculated as illustrated in Figure 2.

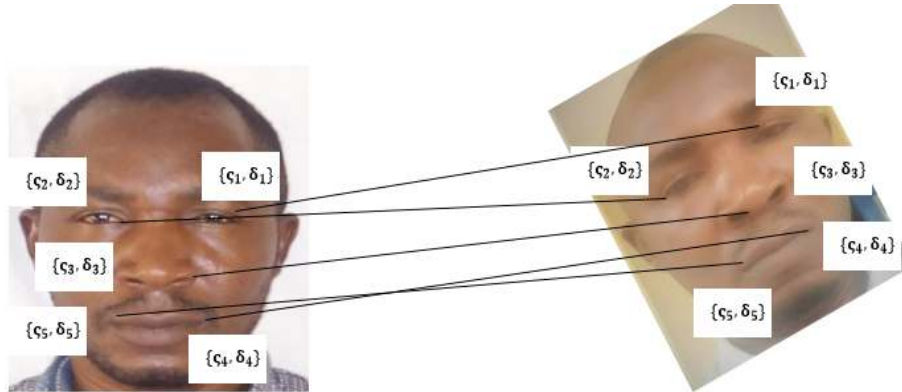


Figure 2: Coordinates of Facial Landmarks for Base Image and Deviated Image (Siyaka *et al.*, 2021)

Given a facial image "I" with five facial landmarks, the landmarks can be represented as:

$$L = (\{c_1, d_1\}, \{c_2, d_2\}, \{c_3, d_3\}, \{c_4, d_4\}, \{c_5, d_5\}) \quad (1)$$

Where  $c_1 : c_5$  are the x-coordinate of left eye, right eye, nose, left mouth and right mouth respectively. Similarly,  $d_1 : d_5$  are the y-coordinates of left eye, right eye, nose, left mouth and right mouth respectively. The landmarks of the given image were combined to form a vector and represented as:

$$V = [c_1, d_1, c_2, d_2, c_3, d_3, c_4, d_4, c_5, d_5] \quad (2)$$

For M number of images, the image landmarks can therefore be represented as:

$$V = [V1, V2, V3, \dots, VM] \quad (3)$$

The distance ( $D_{i,j}$ ) between the base image (image 1) and the deviated image (image 2) can be calculated using the vectors of landmarks V and is given as:

$$D_{i,j} = \sqrt{\sum (V1_{i,j} - V2_{i,j})^2} \quad (4)$$

Where,  $i$  is the index of the landmark:  $i = 1: 10$ , and  $j$  is the image index:  $j=1: M$ . For M number of images and 10 facial landmarks, a distance matrix is formed with dimension M-by-10 as follows;

$$D_{i,j} = \begin{bmatrix} D_{1,1} & D_{1,2} & D_{1,3} & \dots & D_{1,10} \\ D_{2,1} & D_{2,2} & D_{2,3} & \dots & D_{2,10} \\ D_{3,1} & D_{3,2} & D_{3,3} & \dots & D_{3,10} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ D_{M,1} & D_{M,2} & D_{M,3} & \dots & D_{M,10} \end{bmatrix} \quad (5)$$

The deviation of the deviated image (Image j) was calculated by obtaining the square root of the mean of  $D_j$  as shown in Equation (3.6).

$$\phi_j = \sqrt{\frac{1}{10} \left( \sum_{i=1}^{10} D_{i,j} \right)} \quad (6)$$

The final result is an array of  $\phi_j$  for all :  $j=1: M$ , from which the images were sorted in order of maximum deviation from the base image after which a number of the most deviated images greater than one were selected for training. The FIDE-ISA algorithm is shown in Figure 3

**Algorithm 1: FIDE-ISA**

**Input:** Images

**Output:** Sorted/Selected Images

```
i. Start
ii. Acquire Images
iii. Preprocess the images
iv. Select base image and deviated images
v. For j=1:M
    a. For i=1:N
        i. Detect facial landmarks ( $L_i$ ) coordinates using the MTCNN deep learning model of all images
        ii. Crop Faces using Bounding Box
        iii. Calculate the Euclidean distance between the base image and deviated images
    b. End for
vi. End for
vii. For j=1:M-1
    a. Estimate the deviation between the base image coordinates and the deviated images
viii. End for
ix. Sort images in order of decreasing deviation
x. Select top P number of images for training
xi. If accuracy < 100%
    a. P=P+1
    b. Go to step x
xii. Else
xiii. Return selected images
xiv. Stop
```

Figure 3: FIDE-ISA Algorithm

### Experimentation and Results

In order to evaluate the effectiveness of the proposed FIDE-ISA, a pre-trained deep learning face recognition model (AlexNet) was trained using an online face dataset (faces94). The images were collected and divided into training images comprising of 18 individuals. For each individual, a maximum of 13 images was chosen for training while two images for each

individual was set aside for testing. The images were pre-processed and the appropriate images for training the face recognition model were selected using FIDE-ISA. Relevant features were extracted using AlexNet while classification was done using Softmax transfer learning. The steps followed achieving this is shown in the flowchart in Figure 4.

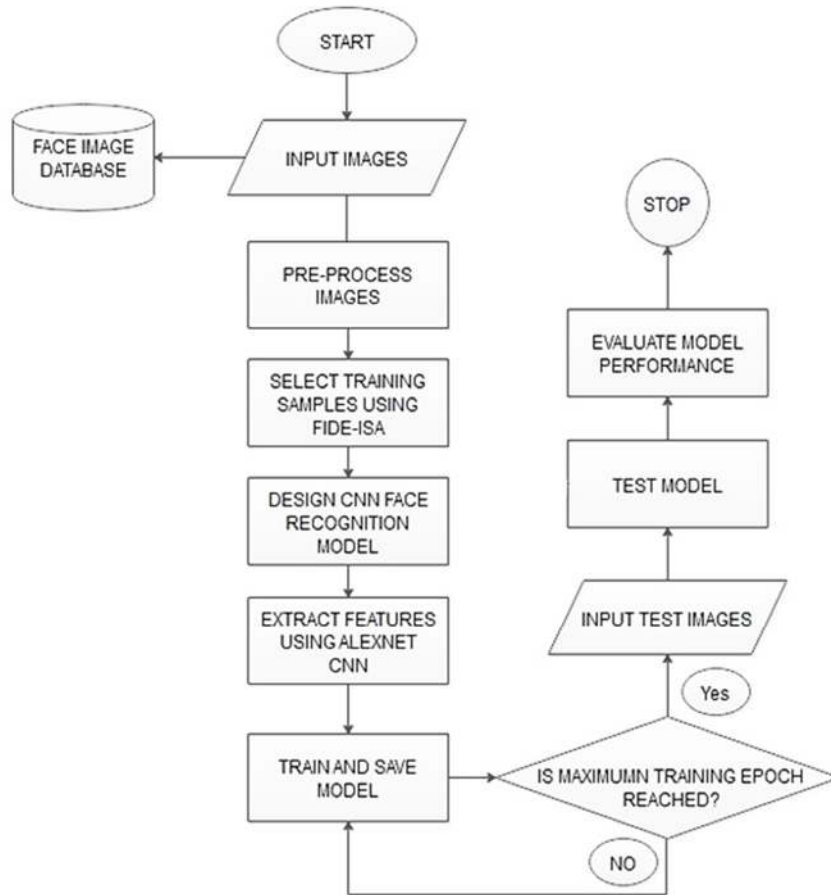


Figure 4: Flow chart of CNN Model Development Process adapted from [15]

The results obtained as shown in Table 1 shows the systems training convergence time and accuracy obtained for seven different image sizes. For 36 images, the time of convergence is 108s, with 54 images, the convergence time increases to 149s, with 90 images, the convergence time is 154s, and with 126 images, it converges at 169s. Training with 162, 198 and 234, converges at 331s, 455s and 484s

respectively. The accuracy obtained for the model trained with 36 images is 94.44%, while the accuracy obtained for other are 100% respectively. The results show an increase in the convergence time as the number of training images increases. In terms of accuracy however, the results shows a maximum accuracy of 100% for training samples from 54 images and above as shown in Figure 5.



**Table 1:** Model Performance Results

Experiments	Number of Training Images	Images per Person	Convergence Time (m)	Accuracy (%)
1	36	2	1.48	94.44
2	54	3	2.29	100
3	90	5	2.34	100
4	126	7	2.49	100
5	162	9	5.31	100
6	198	11	7.35	100
7	234	13	8.40	100

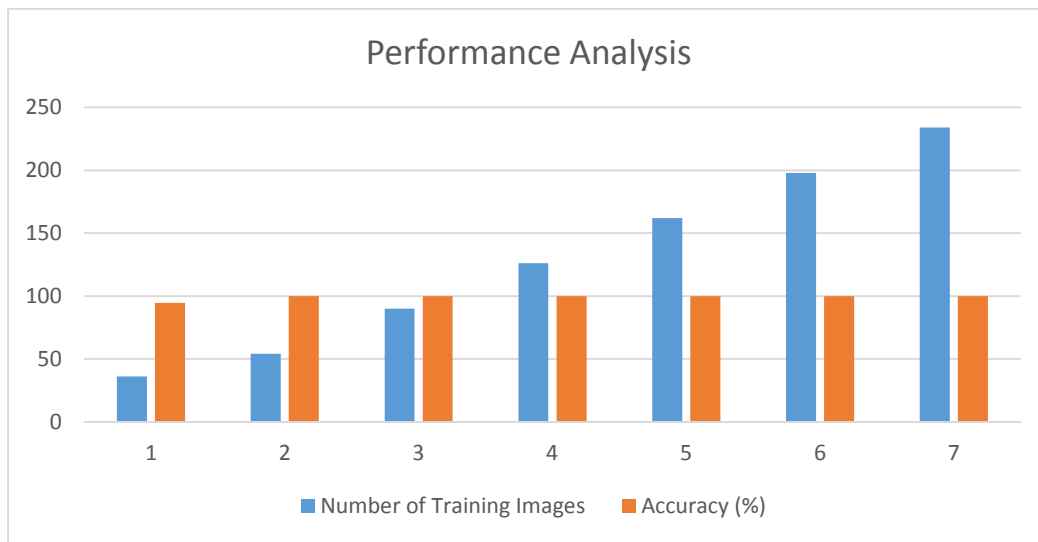


Figure 5: Training size performance analysis

**Performance Validation**

The developed model was validated with four existing facial recognition systems where

face94 datasets were used and the result is shown in Table 2.

**Table 2:** Model Performance Validation

Author	Method	Accuracy
Alhayani and Rane, (2014)	Radon Transform	94
Alhayani and Rane, (2014)	Wavelet Transform	92.79
Alhayani and Rane, (2014)	Radon Wavelet Transform	94.48
Vinay <i>et al.</i> , (2018)	Deep Learning with Binary Patterns	93.6
Tuncer <i>et al.</i> , (2020)	Quintet Triple Binary Pattern (QTBP) with KNN	97.30
Tuncer <i>et al.</i> , (2020)	Quintet Triple Binary Pattern (QTBP) with SVM	100
Proposed Research	FIDE-ISA CNN Model with Softmax	100

The results show that the proposed model out-performed existing models in terms of accuracy of detection except in Tuncer *et al.*,

(2020) where the proposed model obtained similar results. However, Quintet Triple Binary Pattern (QTBP) with SVM model is highly complex and

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thus, Tuncer et al., recommended the adoption of a light weight deep learning model such as the one developed in this research.

## CONCLUSION

In this paper, the mathematical models and algorithm of the proposed facial image deviation estimation and selection algorithm was presented. Facial landmarks such as: left eye, right eye, nose, left mouth and right mouth were detected and used to estimate the deviation between the reference image and other images. The deviation measured serve as a basis for selection of the images for training a deep learning model. This will reduce the complexities experienced with deep learning models and reduce the over reliance on huge dataset for training such models. In terms of testing the developed trained system, the results obtained indicated that models trained with 54 images and above produces 100% accurate authentication of faces. Only the model trained with less than 54 images produces less than 100% accurate authentication. This is an indication that training a facial recognition system with few images can produced better results in-terms of accuracy and time of convergence. The effectiveness of the algorithm will further be tested with more image datasets and other deep learning models.

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