A Group Decision-Making for Selecting Multi-Deep Face Recognition Models

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***Abstract*— Deep face recognition is a significant area of biometric authentication that addresses challenges such as low resolution, varying facial expressions, and inconsistent lighting. This paper presents a robust deep-learning approach to tackle these challenges. The study aims to employ multi-criteria decision-making techniques and verify the influence of individual and group expert opinions in decision-making. However, balancing criteria such as accuracy, sensitivity, specificity, precision, and recall remain challenging across different models. To fill this gap, the study utilized a decision-support framework that included the fuzzy analytical hierarchical process to set criteria weights based on expert input and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to select the optimal model. JAFEE3 in the LDN+DB model emerged as the best option, while LWF4 in the LDN+AB model proved to be the least effective. These results are valuable for researchers engaged in image processing, machine learning, and decision-making techniques.**

***Keywords*— Deep face recognition, Fuzzy system, AHP method, TOPSIS method, Conflict of Criteria**

I. INTRODUCTION

Nowadays, deep learning algorithms are widely used in various sectors such as public security and daily life. Various studies have used these algorithms to solve various problems within the field of facial recognition, skin detection, and so on. However, deep face recognition technology is uncomplicated and can recognize faces without pause and ad interaction. In our knowledge, human beings can be recognized by face or voice, so many applications are designed to recognize people based on similar methods [1]. Deep facial recognition technology has become a popular and easy-to-use method in many studies. This technology provides many facilities for facial recognition, despite the presence of images suffering from distortions, roughness, or partial obstruction. It also helps build a programming ID for any image using facial recognition technology based on machine learning algorithms [2]. And helps overcome the real challenges of a computer-programmed face predicting behavior according to different shooting conditions such as changing lighting direction and perspective caused by object evolution. Whereas, analysts work through computer vision, image investigation and preparation, design recognition, and machine learning, inspired by various real-world applications[3].

On the other hand, a significant challenge identified by analyzing the face image is to describe the appearance of the face, depending on the accuracy of the face descriptor during the extraction of features and the representation method. Two basic strategies were adopted to extract facial features: the first is based on geometric inclusion and the second is based on the appearance description [4]. Therefore, the engineering includes a strategy based on the components of the face image according to the reliability and accuracy of the site. Thus, it is often difficult to perform any modifications to it. Whereas, an appearance-based strategy depends on one of the components, the general facial highlights or facial channels that can be used to create the field [5]. Executing a strategy based on appearance is great under controlled conditions. Recently, some important strategies, used to enhance score accuracy, have been proposed. Thus, most recent studies focused on analyzing the vital parts of the face image, which constitute an essential element for recognizing the face and its external appearance. Therefore, many applications have achieved the required results to highlight the external appearance of the face image and obtain an effective appearance, such as applications of augmented reality, communications, virtual conferences, client verification files, and so on. Thus, the deep learning algorithms of face recognition and facial expressions are growing steadily nowadays [6].

In this study, several limitations that arise from reliance on a specific set of facial recognition algorithms and data sets were identified. This study focused only on a select group of facial recognition models. While these models are widely used and well-established, they represent a subset of algorithms available within this domain. There are some factors that may affect algorithm performance such as lighting conditions, position differences, occlusions, or image quality are not explored extensively in this paper. Thus, the results obtained from these specific models may not be generalizable to other algorithms that were not considered in this study. Future research could explore a broader range of facial recognition models to provide a more comprehensive analysis.

The study aims to address the conflict problem between criteria, which posed a significant challenge [7]. Thus, decision support techniques presented the best solutions for multi-criteria according to experts' preferences [8]. The group of decision-makers was adopted for the evaluation and selection of facial recognition models according to the proposed methodology.

According to the proposed methodology, the FAHP method was used to calculate the weights of the criteria according to the pairwise principle [9]. Whereas, the process of selecting the best alternative among facial recognition models is carried out according to the conditions of the TOPSIS method [10].

The paper is organized as follows; the introduction is presented in section 1. Section 2 discusses significant related works to deep learning models. Section 3 presents the methods and materials used in this study. Section 4 discusses and analyzes the results. Section 5 presents the conclusion and future works.

II. Literature Review

The related works to deep learning models for facial recognition according to decision support methods are presented. Several studies have addressed this issue and proposed various approaches to solve such a problem.

Salama Abd ELminaam, Diaa, et al.[11] proposed a face recognition approach according to fuzzy computing and cloud computing based on three deep learning algorithms. A deep convolutional neural network was applied to samples according to specific conditions such as blockages, type of lighting, and location. The DCNN algorithm can extract facial features, which allows for comparing different facial images effectively. This system helps to identify a group of faces on the Internet by comparing the new images with the images stored in the system physically.

Soni, N., Sharma, E. K., & Kapoor, A. [12] proposed a simple and effective system using the Viola-Jones algorithm deep learning based on facial recognition. The system was applied based on four basic stages such as pre-processing, successive feature extraction, feature optimization, and recognition. This system is characterized by extracting four basic outputs which are the local extreme diagonal number pattern (LDENP) feature, gradient-based directional features, and gradient-based wave features for cascading feature extraction.

Zeng, J., Qiu, X., & Shi, S. [13] introduced a deep learning-based face recognition system using a MXNet system architecture through quantitative analysis of forensic face images that suffer from noise. Therefore, the use of Gaussian filtering has been proven to be better than using the image optimization method based on the self-snake model for face image recognition. Thus, it has been proven that image noise removal helps to improve system performance for deep face recognition instead of using the image enhancement method.

Serengil, S.I. and Ozpinar, A.,[14] proposed a lightweight and hybrid framework for facial recognition to reach a high level of performance. A hybrid framework features working to disable the facial recognition models for the state-of-the-art models. The framework was designed to make a pipeline through four stages such as detection, alignment, representation, and verification during face recognition.

Ling, Hefei, et al.[15] proposed attention using a convolutional neural network (ACNN) to discriminate face recognition that aims to reduce redundancies in information and focus on image spatial maps. The proposed attention module focused on the spatial attention channels and block comprising the feature maps of the image. Feature maps multiply the matrix according to the relationship between the channels and the matrix of the spatial relationship to obtain a smooth and strong face image.

Zhu, Zheng, et al.,[16] introduced a new face benchmark consisting of noisy 4M/260M faces (WebFace260M) and clean 2M/42M faces (WebFace42M) training data relying on a high-accuracy time-constrained evaluation protocol. This protocol was designed for face recognition under inference time constraint and is efficient and scalable. This study reduced the relative failure rate by 40% on the challenging IJB-C group and ranked third among 430 entries in the NIST-FRVT based on WebFace42M dataset.

Boutros, Fadi, et al., [17] proposed an Elastic Face penalty loss system that would allow flexibility of payment in order to ease fixed penalty margin restrictions when separating categories. This system is a state-of-the-art face recognition solution proposed to incorporate a fixed penalty margin over a commonly used classification loss function, softmax loss, into the supernormal envelope to increase the discriminatory power of face recognition models, by minimizing interclass variance and maximizing interclass variance. The system is implemented using random margin values derived from a normal distribution at each training iteration.

Giral, D., Hernández, C., and Salgado, C .,[18] proposed evaluating the performance of the spectral decision model of CRN using deep learning technology based on three basic decision-making techniques Vise Kriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Simple Additive Weighting (SAW). To achieve this, the applied model, Support Vector Machine (SVM) algorithm based on deep learning, is to extract features within three levels of traffic (high, medium, and low). An experimental power matrix was created to measure the spectrum level for the primary user.

Al-Bander, Baidaa, et al.,[8] presented a multi-criteria decision-making framework for evaluating and selecting the optimal deep learning model for skin cancer detection by integrating the entropy method with the VIse Kriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method. A deep convolutional neural network (CNN) algorithm was applied, to implement optimization, transfer learning, class balancing, transfer learning, data augmentation, and network complexity, according to multiple evaluation criteria. The values of the evaluation criteria weights are calculated by applying entropy, while VIKOR is used to select the optimal alternative.

III. Materials and Methods

In this section, the proposed research direction is discussed to solve the conflicting problems between the multiple criteria of the face recognition approach using a hybrid decision-making technique. According to the literature, many studies have applied these techniques to solve problems in various sectors such as education, industry, and healthcare centers [19]. The proposed methodology was applied in three phases; the first phase was implemented based on the four datasets within eleven deep learning models for face recognition. The second phase implements the training and evaluation process for eleven models according to five parameters using a deep learning algorithm. In the final phase, the selection process is carried out based on the MCDM techniques. Whereas, the AHP method was applied to calculate the weights of five main criteria based on the fuzzy triangular numbers approach. In contrast, the TOPSIS technique is used to select the ideal alternative from eleven face recognition models. Figure 1, shows a framework for the decision-making approach proposed.

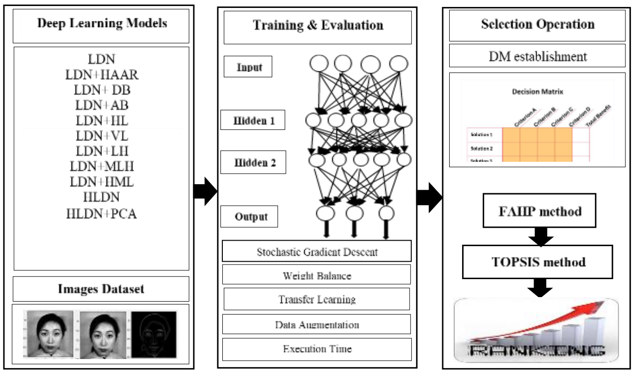

Fig 1. Framework for decision-making approach proposed

A. Materials

In the proposed system, four public databases were adopted for training and validation using the deep learning algorithm for face recognition models as in Figure 1. These databases are discussed according to each set's name, number of images, and category as shown below:

Data set

The study utilizes four major facial recognition datasets: JAFFE, LFW, CK, and CAS-PEAL. Below are the key details:

JAFFE: 213 digital images of 10 Japanese woman specialties with six facial expressions.

LFW: 13,000digital images gathering from websites sources, indicating 1,680 individuals.

CK: 486digtal images of facial texture frequently utilizing in sentiment recognition purpose.

CAS-PEAL: 99,594 digital images from 1,040 dealing with fluctuating environments such as lighting changing, occlusion occurring, and facial term.

1) JAFFE Database

Japanese Facial Expression Database (JAFFE): The database includes 213 images of 7 appearances (6 main appearances + 1 gallery) taken from 10 Japanese women models. Each photo has been evaluated on 6 feeling spellbinding words by 60 Japanese subjects. The database was organized and amassed by Michael Lyons, Miyuki Kamachi, and Jiro Gyoba. A database of outward appearance images was gathered. Ten expressers postured 3 or 4 cases of each of the six essential outward appearances (bliss, trouble, amaze, outrage, sicken, fear) and a nonpartisan face for a sum of 219 images of outward appearances. For the straightforwardness of the test plan, just Japanese female articulations are considered. Every feeling took photos of her while looking through a semi-intelligent plastic sheet towards the camera. Hair was tied far from the face to uncover every expressive zone of the face. Tungsten lights were situated to facilitate even brightening of the face. A case encased the district amongst camera and plastic sheets to lessen back-reflection. The images were imprinted in monochrome and digitized utilizing a flatbed scanner [20].

2) LFW Database

A dataset of Labeled Faces in the Wild has been categorized according to the environment from which it was collected. A facial recognition issue has been resolved for an unrestricted set of images in this dataset. The dataset includes a total of 13,000 face images that are collected online from 1680 subjects [21].

3) CK Database

The dataset includes images of facial expressions called Cohn-Kanade. This type of dataset contains several images of facial expressions that are widely used in academic studies for automatic analysis. CK Dataset has two versions so far. This type of dataset contains a total of 486 diverse facial images taken from 97 subjects. Therefore, this type of data set is not subject to censorship because it is environmental data [22].

4) CAS-PEAL Database

The face image dataset is a tough and unrestricted data set called CAS-PEAL. The sponsoring organization of the National High-Technology Program and IS VISION created a data set that includes several facial recognition images. Currently, the total number of facial images in this data set is 99,594 taken from 595 images of males and 445 of females in various situations, including facial expressions, accessories, and lighting [23].

B. Methods

This section discusses the structure of the ANN algorithm applied according to selected criteria based on decision-making methods [24]. Figure 2 shows artificial neural network structure.

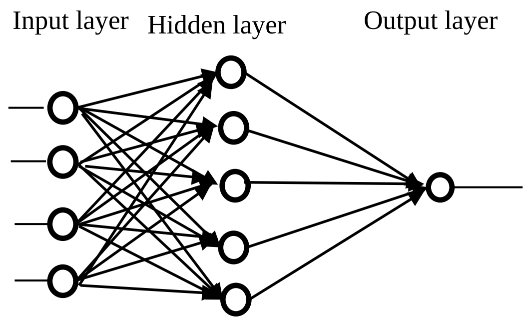

Fig 2. Artificial neural network structure

1) LDN

In the local direction number pattern (LDN) model, each pixel in the input image is assigned a binary code. Thus, all regulatory elements in the image that determine the proportion of texture and its density changes will be encoded. Edge magnitudes are mainly unaffected by variations in lighting. Edge magnitudes are mainly unaffected by variations in lighting. In this pattern, the values of the neighborhood's edge responses are calculated based on the higher or more positive and negative direction values using the compass mask.

2) LDN +HAAR and LDN+DB

This method helps to extract the face components' level features. Wavelet transform appears to give a decent match to the space-recurrence qualities of common images. Subsequently, it is substantially simpler to fabricate a reasonable image demonstrate in the wavelet area than, say, in the pixel space. The DWT is utilized for the most part attributable to its great confined recurrence qualities and its capacity to manage unexpected changes, spikes, floats, and patterns. Therefore, 2-D haar and duchies wavelet transforms are used to generate DWT features from the input LDN code.

3) LDN+LH LDN ,HML HLDN and LDN+MLH

It is composed of two histograms HLDN Histogram (HLH) and Multi-Feature HLDN Histogram (HMLH). The HLH takes the HLDN code of the input face image and generates the histogram features. In LHL, the histogram just encodes the event of certain miniaturized scale designs without area data, to total the area data to the descriptor, to partition the face picture into little districts, {R1, . . . , RN }, and separate a histogram Hi from every locale Ri. Therefore, a histogram Hi uses each code of the data as a container to gather all codes. At long last, the LH is registered by linking those histograms:

$$LH = \prod_{i=1}^{N} H^{i} \qquad (1)$$

Where the HMLH model is created by combining features with varying resolutions. This combination of resolutions of the multi-histogram is called HLDN (HMLH) as in the formula:

$$MLH_{\sigma_1,\ldots,\sigma_n} = \prod_{j=1}^{N} \prod_{i=1}^{n} H_{\sigma_i}^{j} \qquad (2)$$

4) HLDN+PCA

- Algorithm 1, depicted a hybrid local directional number (HLDN) based on the proposed facial recognition approach
- Algorithm 1: HLDN
- Input: test face image I and
- Tk // Kirsch operator threshold value
- Output: face descriptor HLDN
- 1. Perform DoG to the test face image as:
- I' = DoG (I) // Algorithm 2
- 2. Apply Kirsch compass mask to extract 8 directions of pre-processed image (I')
- K [i] = kirsch (I'); i = 1….8 masks
- 3. Generation HLDN face descriptor using threshold value (Tk)
- [m, n] =size (I')
- for i=1:m
- for j=1:n
- for k =1:8
- out (k) = Kk(i,j)
- end for
- if(max(out)> Tk) then
- HLDN(i,j)=max(out);
- end if
- end for
- end for
- Return (HLDN)
- Apply PCA algorithm based on HLDN

a) Deep neural network models (DNNs)

In this paper, deep neural networks (DNNs) are used which is one important type of the neural networks approach, and are applied to the models of image filters. This type of algorithm is used mainly in classification or prediction, and it was implemented in this study to extract the basic characteristics of facial images. Figure 3 shows the DNN structure.

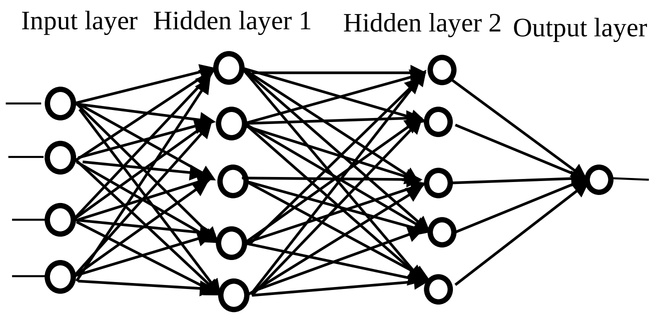

Fig 3. Deep neural network stricture

b) DNN factors

In this study, five main parameters affecting the performance and selection of multi-depth face recognition models were determined based on the DNN algorithm. According to these parameters, decision-making methods are used to evaluate the most appropriate models for face recognition tasks. Five basic parameters are discussed in details as follows:

- Random Gradient Ratios [25]: Random gradient ratios refer to a technique used in deep neural networks (DNNs) during the training process. It involves adjusting the learning rate for each parameter in the network using a random ratio. This technique helps in optimizing the training process and improving the convergence of the model.
- Weight Balance [26]: Weight balance refers to the distribution of weights assigned to different layers or nodes in a DNN. Balancing the weights ensures that the network learns effectively and avoids any bias toward specific features or patterns. It plays a crucial role in achieving accurate and robust face recognition models.
- Transfer learning scheme [27]: Transfer learning is a technique where pre-trained models are used as a starting point for a new task. In the context of face recognition, transfer learning involves using pre-trained DNN models that have been trained on large datasets, such as ImageNet, and fine-tuning them for the specific face recognition task. This approach helps in leveraging the knowledge learned from a large dataset to improve the performance of the model on a smaller face recognition dataset.
- Data augmentation strategy [28]: Data augmentation involves applying various transformations or modifications to the original training data to increase its diversity. In the context of face recognition, data augmentation techniques can include random rotations, scaling, cropping, or adding noise to the face images. By augmenting the training data, the model becomes more robust and generalizes better to unseen faces.

- Time complexity of the computational network [29]: Time complexity refers to the amount of time required for a computational network, such as a DNN, to process and analyze input data. In the context of face recognition, time complexity is an important consideration as it affects the efficiency and real-time performance of the model. It involves analyzing the computational requirements of the network, such as the number of layers, nodes, and operations performed, to understand the time it takes for the network to process face images.

c) Fuzzy Analytic Hierarchy Process method

In the last century, the fuzzy theory was invented to establish a new concept that distributes values in a probabilistic way based on fuzzy variables by L. Zadeh [29]. Fuzzy theory is based on elastic constraints for fuzzy values assigned to specific variables. This theory has been used in various sectors such as education, healthcare, industry, and so on [30].

A triangular fuzzy number (TFN) is adopted which represents the membership function of three basic elements adopted $\tilde{\alpha} = (a^l, a^m, a^u)$ for more detail as in the following formula [31]:

$$\text{Triangular Fuzzy Numbers } \tilde{\alpha} = (a^l, a^m, a^u) \tag{3}$$

$$\mu\, \tilde{a}\,(x) = \begin{cases} (x - a_l)\ /\ (a_m - a_l) & \text{if } a_l \le x \le a_m \\ (a_u - x)\ /\ (a_u - a_m) & \text{if } a_m \le x \le a_u \\ 0, & \text{Otherwise.} \end{cases}$$

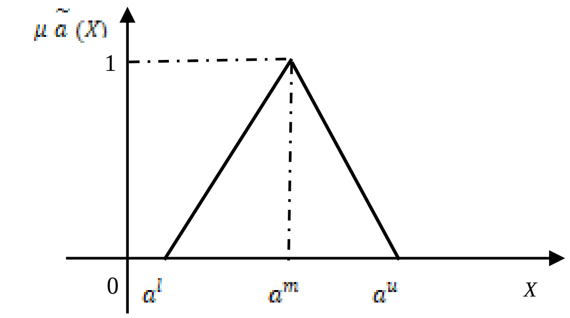

Fig 4. Represents the TFN scheme

Figure 4 illustrates the TFN scheme that consists of three basic values. Usually, triple numbers consist of the lowest value as a^l, the middle value as a^m, and the upper value as a^u then $a^l \le a^m \le a^u$, where the $a^l = a^m = a^u$ to be $\tilde{a}$ a crisp number. Table 1 depicts the TFN measurements.

Table 1. Triangular fuzzy number measurements

TFN Formulas	Measurements of TFN
Addition operation	$\tilde{a} + \tilde{b} = (a^l + b^l,\ a^m + b^m,\ a^u + b^u)$
Subtraction operation	$\tilde{a} - \tilde{b} = (a^l - b^l,\ a^m - b^m,\ a^u - b^u)$
Multiplication operation	$\tilde{a} * \tilde{b} = (a^l * b^l,\ a^m * b^m,\ a^u * b^u)$
Division operation	$\tilde{a} / \tilde{b} = (a^l / b^U,\ a^m / b^m,\ a^u / b^l)$

The AHP method is an important method of decision support which is widely used to calculate criteria weights. The fuzzy triangular number approach was combined with the AHP method applied to evaluate the different criteria in this study. According to [32], the pairwise comparisons using triangular fuzzy numbers presented a fuzzy number that takes into consideration the interdependencies between the decision criteria. However, it is computationally exceedingly challenging to compute fuzzy eigenvalues and fuzzy eigenvectors using the direct approach. The AHP technique structure is depicted in Figure 5.

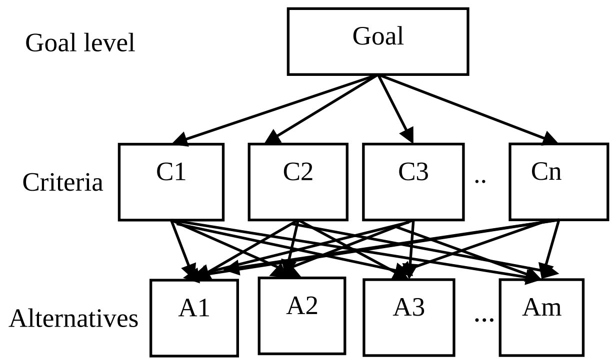

Fig 5. AHP technique structure

The methodology relied on the concept of triangular fuzzy numbers to calculate the correlation between the criteria based on the pairwise comparison. However, computing fuzzy eigenvalues and fuzzy eigenvectors via the direct method is computationally exceedingly challenging. Figure 3 illustrates the AHP technique structure. Basically, the decision matrix can be represented according to the rules of the analytical hierarchy process method as $\hat{A}$ = (m × n). In addition, the decision matrix can also be represented using the concept of triangular fuzzy numbers as follows:

$$\hat{A} = (a^l, a^m, a^u)$$

The DM consists of triple values:

$$\hat{A} = \begin{bmatrix} a^l_{11}, a^m_{11}, a^u_{11} & \cdots & a^l_{1n}, a^m_{1n}, a^u_{1n} \\ \vdots & \ddots & \vdots \\ a^l_{m1}, a^m_{m1}, a^u_{m1} & \cdots & a^l_{mn}, a^m_{mn}, a^u_{mn} \end{bmatrix} \tag{4}$$

where the matrix $(\hat{A})$ can be converted to the reciprocal form when achieving the required conditions:

$$\tilde{a}_{ij} = (a^l_{ij}, a^m_{ij}, a^u_{ij}) \tag{5}$$

$$\tilde{a}_{ij} = \left(\frac{1}{a^l_{ij}}, \frac{1}{a^m_{ij}}, \frac{1}{a^u_{ij}}\right) \tag{6}$$

Where the i,j = 1,2,……, n

$$\hat{A}=\begin{bmatrix} (1,\ 1,\ 1) & (a_{ij}^{l}, a_{ij}^{m}, a_{ij}^{u}) & \cdots & (a_{ij}^{l}, a_{ij}^{m}, a_{ij}^{u}) \\ \left(\frac{1}{a_{ij}^{l}}, \frac{1}{a_{ij}^{m}}, \frac{1}{a_{ij}^{u}}\right) \vdots & (1,\ 1,\ 1) & \ddots & (a_{ij}^{l}, a_{ij}^{m}, a_{ij}^{u}) \vdots \\ \left(\frac{1}{a_{ij}^{l}}, \frac{1}{a_{ij}^{m}}, \frac{1}{a_{ij}^{u}}\right) & \left(\frac{1}{a_{ij}^{l}}, \frac{1}{a_{ij}^{m}}, \frac{1}{a_{ij}^{u}}\right) & \cdots & (1,\ 1,\ 1) \end{bmatrix} \tag{7}$$

Where $0 < a_{ij}^{l} < a_{ij}^{m} < a_{ij}^{u}$, i,j = 1,2,….., n.

In this stage, various criteria are compared based on the proposed measures. Therefore, the fuzzy logic approach is best suited for dealing with uncertainties. Thus, in arithmetic operations, it is possible to use linguistic terms to be easily converted into triangular fuzzy numbers. Table 2 includes the formula for converting the decision matrix values into TFN based on the rules of the AHP method.

Table 2.Linguist scale converted to TFN

Linguist scales	Triangular Fuzzy number	Reciprocal triangular fuzzy number
Equal significance	(1,1,1)	(1,1,1)
Slightly significance	(2,3,4)	(0.25,0.33,0.5)
Strong significance	(4,5,6)	(0.167,0.20,0.25)
Very strong significance	(6,7,8)	(0.125,0.43,0.167)
Extremely significance	(9,9,9)	(0.111,0.111,0.111)

Table 3 shows a Likert scale that consists of five basic language values to create a decision matrix [33] . These metrics have been applied to the values obtained by the FAHP method based on the pair-wise concept.

According to Table 3, the decision matrix was created to evaluate the various deep face recognition dataset based on multiple criteria. The criteria were evaluated based on expert opinions using pairwise comparison. The outputs of the decision matrix will be adopted as the basic inputs of the TOPSIS method in the next stage.

Table 3.Decision matrix structure

	Accuracy	**Sensitivity**	**Specificity**	**Precision**	**Recall**
Alternative 1	Acc.v (A1/Ts)	Se.v (A1/ Ts)	Sp.v (A1/ Ts)	.Prv(A 1/Ts)	Re.v (A1/Ts)
Alternative 2	Acc.v (A2/Ts)	Se.v (A2/ Ts)	Sp.v (A2/ Ts)	Pr.v(A 2/ Ts)	Re.v (A2/Ts)
Alternative 3	Acc.v (A3/Ts)	Se.v (A3/ Ts)	Se.v (A3/ Ts)	Pr.v(A 3/ Ts)	Re.v (A3/Ts)
⋮	⋮	⋮	⋮	⋮	⋮
Alternative n	Acc. v (An/Ts)	Se.v (An/ Ts)	Sp.v (An/ Ts)	Pr.v(A n/Ts)	Re.v (An/Ts)

Acc. v: Accuracy value, Se. v: Sensitivity value, Sp. v: Specificity value, Pr. v:
Precision value, Re.v: Recall value, A: Alternatives, Ts: Test sample, n: Number of Alternatives.

d) Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) technique

The TOPSIS technique is a similarity-to-ideal solution technique developed by Hwang and Yoon (1981). The TOPSIS technique selects alternatives based on the distance between the positive ideal solution which gives the best values and the negative ideal solution which gives the worst values. This technique is the most widely used and popular because of its ease of use and clarity, as it can be applied to solve various problems that consist of a large number of criteria and alternatives. This technique is based on mathematical and statistical models that give verifiable and quantitatively comparable results, which enhances the reliability of the results it provides. Therefore, these factors make this technique the ideal choice for many researchers and decision-making specialists, and more popular than others. This technique includes several rules that must be applied to ensure an ideal selection among the other options, as follows:

1. The normalization stage of the decision matrix

In this step, different attributes are compared to be converted the dimensioned attributes to non-dimensional attributes. The normalization process in matrix $(x_{ij})_{m*n}$ which is converted to the form, $R = (r_{ij})_{m*n}$:

$$r_{ij} = x_{ij} / \sqrt{\sum_{i=1}^{m} x_{ij}^{2}} \tag{8}$$

The new matrix R is represented below:

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \tag{9}$$

2. Creating a weighted normalized decision matrix

In this step, the decision makers collect the weights as $w = w_1, w_2, w_3, \cdots, w_j, \cdots, w_n$, in the normalized decision matrix. In the resulting matrix, the values of the matrix column (*V*) are multiplied by the values of the corresponding weights w_j. Therefore, the decision matrix weights must be equal to 1.

$$\sum_{j=1}^{m} w_j = 1 \tag{10}$$

The resulting matrix (V) can be represented as follows:

$$V = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} =$$

$$\begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \cdots & w_n r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_1 r_{m1} & w_2 r_{m2} & \cdots & w_n r_{mn} \end{bmatrix} \tag{11}$$

3- Determine the ideal positive and negative solutions

In this step, two types of alternatives are selected A^* (positive ideal alternative) and, A^- (negative ideal alternative) as follows:

$$A^* = \left\{ \left(\left(\max_i v_{ij} \middle| j \in J \right), \left(\min_i v_{ij} \middle| j \in J^- \right) \middle| i = 1,2,\dots,m \right) \right\} \quad (12)$$

$$= \{ v_1^*, v_2^*, \dots, v_j^*, \cdots v_n^* \} \quad (13)$$

$$A^- = \left\{ \left(\left(\min_i v_{ij} \middle| j \in J \right), \left(\max_i v_{ij} \middle| j \in J^- \right) \middle| i = 1,2,\dots,m \right) \right\} \quad (14)$$

$$= \{ v_1^-, v_2^-, \dots, v_j^-, \cdots v_n^- \} \quad (15)$$

Therefore, the J represents a subset of the $\{i = 1,2,\dots,m\}$, that included the beneficial attributes as in J^- to be a complement set of J, while other subset included non-beneficial attributes (J^n), to be cost set of J.

4- Computing the separation scale based on the Euclidean distance

In this step, the distance between the alternatives as in V is calculated based on the positive ideal vector A^* using the Euclidean distance as follows:

$$S_{i^*} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^* \right)^2}, \ i = (1,2,\cdots m) \quad (16)$$

In contrast, the separation values for all alternatives as in V are calculated based on the negative ideal vector A^- as follows:

$$S_{i^-} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^- \right)^2}, \ i = (1,2,\cdots m) \quad (17)$$

5- Calculating the closeness of the ideal solution

In this step, the value of closeness of A_i to the ideal solution A^* is calculated depending on the separation values calculated in the previous step as in the following formula:

$$C_{i^*} = S_{i^-} / (S_{i^-} + S_{i^*}), \ 0 < C_{i^*} < 1, \ i = (1,2,\cdots m) \quad (18)$$

Finally, $C_{i^*} = 1$ when only ($A_i = A^*$), whereas, $C_{i^*} = 0$ when only ($A_i = A^-$)

e) Group decision maker

Individual and group decision-makers are the two fundamental principles on which Multiple Criteria Decision Making (MCDM) approaches are based [35]. In the context of selecting a specific option, the individual decision-making process involves each person presenting their own viewpoint or preferences. However, when multiple decision-makers are involved, the decision is no longer made by a single member as in the individual decision-making process as shown in Figure 7. Instead, it becomes a collective effort where the choice is determined through group decision-making.

Group decision-making involves gathering decision-makers from various domains or areas of expertise [36], [37], [38], [39]. This approach ensures that the decision-making process benefits from the diverse knowledge and perspectives of multiple experts as in Figure 6. The collective judgment of these experts is considered to be more comprehensive and informed compared to a decision made by a single individual.

To facilitate the group decision-making process, certain steps are followed. First, the decision group identifies and defines the criteria that will be used to evaluate the face recognition models. The process of assigning weights to criteria involves careful consideration of the expertise and opinions of the decision group members. Various techniques, such as the Analytic Hierarchy Process (AHP) or the Analytic Network Process (ANP), can be used to calculate these weights.

Once the criteria weights are determined, each expert in the decision group provides their individual recommendations for the selection of face recognition models based on their own assessment of the criteria. These individual recommendations are then aggregated to reach a final group recommendation. The final group recommendation represents the collective judgment and consensus of the decision group.

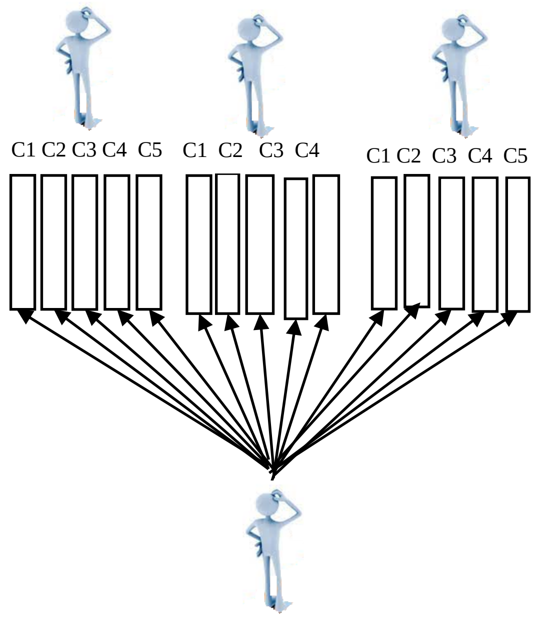

Fig 6.Group decision maker

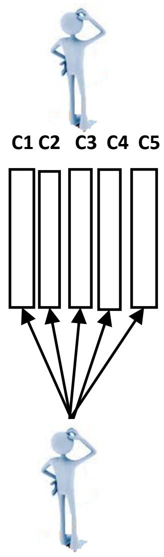

Fig 7. Individual decision maker

IV. Result and Discussion

The proposed methodology provided two different types of outcomes. First, the outcomes of integrating the fuzzy system with the AHP method to determine the criteria weights according to the opinion of the decision-makers group are discussed. Secondly, the TOPSIS technique was used to determine the results of internal and external aggregation by selecting the ideal alternative that is closest to the positive ideal solution and furthest to the negative ideal solution.

1) *Criteria weights calculated*

In this section, the results of the first type are discussed after calculating the values of the criteria selected in this study. Five basic criteria have been adopted and their weights calculated according to the integration of the fuzzy system with the analytic hierarchy process (AHP) method based on the principle of the pairwise. Table 4 shows the values of the criteria weights that were calculated in the FAHP method for six experts in the field of computer science.

Table 4. Criteria weights-based FAHP method

Criteria	Accuracy	Sensitivity	Specificity	Precision	Recall
EX-1	0.398	0.089	0.093	0.028	0.392
EX-2	0.412	0.068	0.111	0.027	0.383
EX-3	0.470	0.064	0.077	0.029	0.361
EX-4	0.418	0.114	0.098	0.030	0.340
EX-5	0.421	0.062	0.093	0.032	0.392
EX-6	0.466	0.065	0.087	0.025	0.358

The process of calculating the weights is an important stage in completing the solution by applying the FAHP method. Basically, the weight values calculated in the previous stage will be the main inputs for the TOPSIS method. In detail the preferences of the experts are discussed as follows:

- *First Expert*

Figure 8 shows the results according to the internal aggregation depending on computing the weight of the criteria according to the judgment of the first expert. The percentage of the first criterion, accuracy was 40%, while the percentage of the sensitivity criterion was 9%, as well as the percentage of the specificity criterion, is 9%, in contrast, the percentage of the precision criterion is 3%. Finally, the percentage of the recall criterion is 39%. The internal aggregation value according to the results of the TOPSIS method for the first expert for selecting the best alternative is 0.919080, while the worst alternative was 0.071001, and the calculation of the mean values was 0.777687- SD± was 0.146420, respectively.

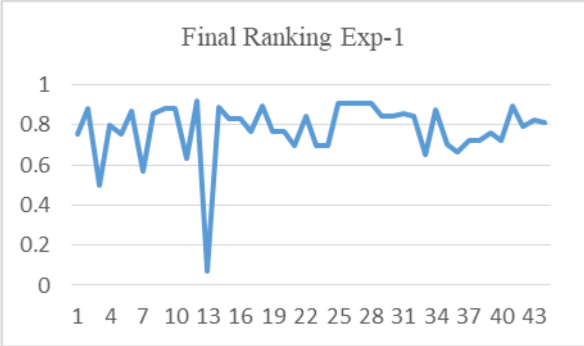

Fig 8.Ranking for the first expert

- *Second Expert*

Figure 9 shows the results according to the internal aggregation depending on computing the weight of the criteria according to the judgment of the second expert. The percentage of the first criterion, accuracy was 41%, while the percentage of the sensitivity criterion was 7%, as well as the percentage of the specificity criterion, is 11%, in contrast, the percentage of the precision criterion is 3%. Finally, the percentage of the recall criterion is 38%. The internal aggregation value according to the results of the TOPSIS method for the second expert for selecting the best alternative is 0.900922, while the worst alternative was 0.111928, the calculation of the mean values was 0.781784- SD± was 0.136433, respectively.

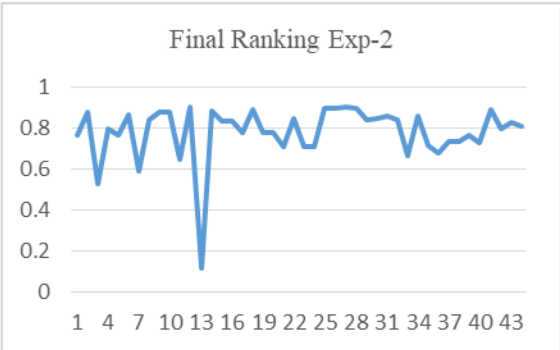

Fig 9. Ranking for the second expert

- *Third Expert*

Figure 10 shows the results according to the internal aggregation depending on computing the weight of the criteria according to the judgment of the third expert. The percentage of the first criterion, accuracy was 47%, while the percentage of the sensitivity criterion was 6%, as well as the percentage of the specificity criterion, is 8%, in contrast, the percentage of the precision criterion is 3%. Finally, the percentage of the recall criterion is 36%. The internal aggregation value according to the results of the TOPSIS method for the third expert for selecting the best alternative is 0.941695, while the worst alternative was 0.058460, the calculation of the mean values was 0.815714- SD± was 0.145186, respectively.

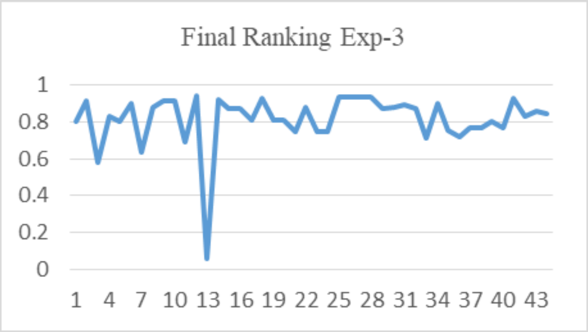

Fig 10. Ranking for the third expert

- *Fourth Expert*

Figure 11 shows the results according to the internal aggregation depending on computing the weight of the criteria according to the judgment of the fourth expert. The percentage of the first criterion, accuracy was 47%, while the percentage of the sensitivity criterion was 6%, as well as the percentage of the specificity criterion, is 8%, in contrast, the percentage of the precision criterion is 3%. Finally, the percentage of the recall criterion is 36%. The internal aggregation value according to the results of the TOPSIS method for the fourth expert for selecting the best alternative is 0.903867, while the worst alternative was 0.074911, the calculation of the mean values was 0.773660- SD± was 0.135270, respectively.

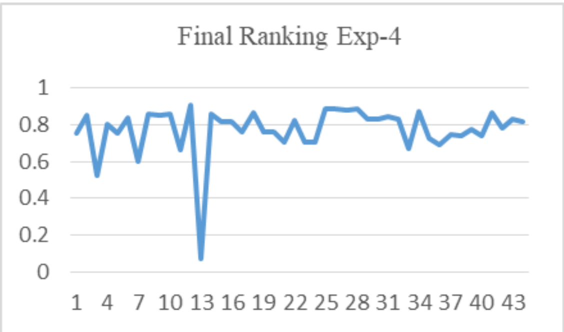

Fig 11.Ranking for the fourth expert

- *Fifth Expert*

Figure 12 displays the outcomes of the internal aggregation based on computing the weights of the criteria under the fifth expert's assessment. The percentage of the first criterion accuracy as a percentage of the first criterion was 42 percent, whereas sensitivity as a percentage of the criteria was 6 percent, specificity as a percentage of the criteria was 9 percent, and precision as a percentage of the criteria was 3 percent. The recall criterion's percentage is 39 percent in the end. The internal aggregation value for the fifth expert for choosing the best alternative is 0.926550, while the worst option was 0.086290, according to the TOPSIS technique results. The computation of the mean values was 0.795150-SD was 0.145230, respectively.

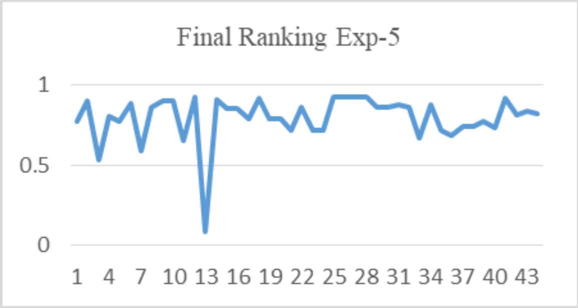

Fig 12. Ranking for the fifth expert

- *Sixth Expert*

Figure 13 shows the results according to the internal aggregation based on computing the criteria's weights following the sixth expert's assessment. The percentage of the first criterion, accuracy was 47%, while the percentage of the sensitivity criterion was 6%, as well as the percentage of the specificity criterion, is 9%, in contrast, the percentage of the precision criterion is 3%. Finally, the percentage of the recall criterion is 36%. The internal aggregation value according to the results of the TOPSIS approach for the sixth expert for choosing the accurate alternative is 0.903867, while the worst alternative was 0.074911, the calculation of the mean values was 0.773660- SD± was 0.135270, respectively.

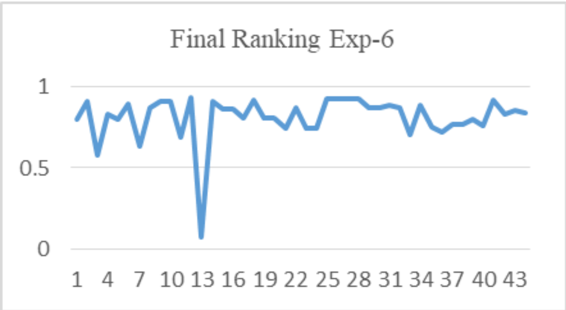

Fig 13.Ranking for the sixth expert

- *Internal and external aggregation calculated:*

The values of the internal and external grouping were determined based on the conditions of the TOPSIS technique based on the opinions of the experts. As a result, these results can be assessed based on how closely the values of the experts' results match those of the first section. The results of the internal aggregation in Table 5 show there was a large match between the results of the six experts. According to the literature, the equation is used to calculate the internal aggregation values as follows:

Internal Aggregation= S-/(S- + S+)

Table 5. Results of Internal aggregation

EX1		EX2		EX3		EX4		EX5		EX6		SUM (S+)	SUM (S-)	Internal agg
S+	S-	S+	S-	S+	S-	S+	S-	S+	S-	S+	S-			
0.0158	0.0494	0.016	0.0521	0.014	0.0567	0.015	0.0458	0.0154	0.0537	0.0142	0.0563	0.0904	0.314	0.7764
0.0077	0.0578	0.0083	0.0598	0.0059	0.063	0.009	0.0526	0.0067	0.0614	0.0064	0.0626	0.044	0.3573	0.8903
0.0386	0.038	0.0377	0.042	0.0353	0.0489	0.0338	0.0373	0.0383	0.0436	0.0351	0.0484	0.2188	0.2582	0.5412
0.0134	0.0528	0.014	0.0549	0.012	0.0593	0.0124	0.0496	0.0133	0.0564	0.0122	0.0589	0.0773	0.3319	0.811
0.0158	0.0494	0.016	0.0521	0.014	0.0567	0.015	0.0458	0.0154	0.0537	0.0142	0.0563	0.0904	0.314	0.7764
0.0086	0.0568	0.0092	0.0588	0.0067	0.0622	0.0098	0.0516	0.0076	0.0605	0.0073	0.0618	0.0491	0.3517	0.8774
0.0333	0.0439	0.0327	0.0467	0.0306	0.0531	0.029	0.0441	0.0333	0.048	0.0304	0.0526	0.1894	0.2883	0.6035
0.0097	0.057	0.0109	0.0585	0.0086	0.0626	0.0091	0.0538	0.0098	0.06	0.009	0.0622	0.0571	0.3541	0.8611
0.0077	0.0578	0.0083	0.0598	0.0059	0.063	0.009	0.0526	0.0067	0.0614	0.0064	0.0626	0.044	0.3573	0.8903
0.0076	0.0578	0.0081	0.0598	0.0058	0.063	0.0089	0.0525	0.0065	0.0614	0.0063	0.0626	0.0433	0.3571	0.8918
0.027	0.0466	0.0265	0.049	0.0248	0.0549	0.0234	0.0462	0.0269	0.0503	0.0246	0.0545	0.1533	0.3016	0.6629
0.0054	0.0613	0.0069	0.0628	0.0041	0.0659	0.006	0.0565	0.0051	0.0644	0.0048	0.0655	0.0324	0.3764	0.9208
0.0631	0.0048	0.0642	0.0081	0.0673	0.0042	0.059	0.0048	0.0657	0.0062	0.0669	0.0054	0.3863	0.0335	0.0798
0.0074	0.0579	0.0079	0.0599	0.0056	0.0631	0.0087	0.0527	0.0063	0.0615	0.0062	0.0627	0.042	0.3578	0.8949
0.0107	0.0536	0.011	0.0559	0.009	0.0598	0.011	0.0492	0.01	0.0575	0.0094	0.0594	0.061	0.3355	0.8461
0.0107	0.0536	0.011	0.0559	0.009	0.0598	0.011	0.0492	0.01	0.0575	0.0094	0.0594	0.061	0.3355	0.8461
0.0151	0.0495	0.0149	0.0521	0.0133	0.0567	0.0144	0.0457	0.0145	0.0538	0.0135	0.0563	0.0856	0.3141	0.7857
0.007	0.0589	0.0075	0.0608	0.0052	0.0639	0.0083	0.0535	0.0059	0.0624	0.0058	0.0635	0.0396	0.363	0.9016
0.0151	0.0495	0.0149	0.0521	0.0133	0.0567	0.0144	0.0457	0.0145	0.0538	0.0135	0.0563	0.0856	0.3141	0.7857
0.0151	0.0495	0.0149	0.0521	0.0133	0.0567	0.0144	0.0457	0.0145	0.0538	0.0135	0.0563	0.0856	0.3141	0.7857
0.0201	0.0463	0.0199	0.0492	0.0182	0.0545	0.0183	0.0435	0.0198	0.0508	0.0182	0.054	0.1145	0.2983	0.7225
0.0061	0.0587	0.0068	0.0605	0.0046	0.0638	0.0071	0.0537	0.0052	0.0621	0.0051	0.0634	0.0349	0.3623	0.912
0.0061	0.0587	0.0068	0.0605	0.0045	0.0638	0.007	0.0537	0.0052	0.0622	0.0051	0.0634	0.0347	0.3623	0.9126
0.0061	0.0596	0.0067	0.0613	0.0044	0.0644	0.0073	0.0543	0.005	0.063	0.005	0.064	0.0345	0.3666	0.914
0.0061	0.0587	0.0068	0.0605	0.0046	0.0638	0.0071	0.0537	0.0052	0.0621	0.0051	0.0634	0.0349	0.3623	0.912
0.0102	0.0542	0.0105	0.0564	0.0086	0.0603	0.0103	0.0499	0.0096	0.058	0.009	0.0599	0.058	0.3387	0.8536
0.0099	0.0543	0.01	0.0565	0.0084	0.0603	0.01	0.05	0.0092	0.058	0.0087	0.0599	0.0562	0.339	0.8577
0.0091	0.0552	0.0094	0.0573	0.0075	0.0611	0.0095	0.0507	0.0083	0.0589	0.0079	0.0606	0.0517	0.3439	0.8693
0.0102	0.0542	0.0105	0.0564	0.0086	0.0603	0.0103	0.0499	0.0096	0.058	0.009	0.0599	0.058	0.3387	0.8536
0.0242	0.0452	0.0241	0.0481	0.022	0.0538	0.0215	0.0433	0.0241	0.0496	0.022	0.0534	0.138	0.2933	0.68
0.0085	0.0583	0.0099	0.0598	0.0073	0.0636	0.0081	0.055	0.0086	0.0612	0.0078	0.0632	0.0502	0.3612	0.878
0.0206	0.0495	0.0207	0.0517	0.0188	0.057	0.0181	0.0481	0.0206	0.053	0.0188	0.0566	0.1177	0.316	0.7286
0.024	0.048	0.024	0.0503	0.0219	0.056	0.0211	0.0471	0.024	0.0516	0.0219	0.0555	0.1368	0.3085	0.6928
0.0192	0.0507	0.0194	0.0527	0.0175	0.0579	0.0168	0.0492	0.0192	0.0541	0.0175	0.0575	0.1096	0.3221	0.746
0.019	0.0498	0.019	0.052	0.0174	0.0573	0.0166	0.0481	0.019	0.0535	0.0173	0.0568	0.1083	0.3175	0.7456
0.016	0.0517	0.0164	0.0538	0.0145	0.0587	0.0142	0.0495	0.016	0.0552	0.0146	0.0582	0.0917	0.3272	0.781
0.0192	0.0498	0.0194	0.052	0.0175	0.0572	0.0169	0.048	0.0192	0.0534	0.0176	0.0568	0.1098	0.3172	0.7428
0.0071	0.0593	0.0076	0.0612	0.0052	0.0642	0.0085	0.0537	0.0059	0.0629	0.0057	0.0637	0.04	0.365	0.9012
0.0135	0.0508	0.0136	0.0534	0.0118	0.0578	0.0132	0.0468	0.0129	0.0551	0.0119	0.0573	0.0769	0.3212	0.8067
0.0112	0.0539	0.0117	0.0559	0.01	0.0602	0.0103	0.0505	0.0111	0.0575	0.0102	0.0598	0.0645	0.3377	0.8396
0.0124	0.0532	0.0129	0.0553	0.0112	0.0597	0.0113	0.0501	0.0124	0.0568	0.0113	0.0593	0.0716	0.3344	0.8235

Whereas, calculating the values of the external aggregation by averaging the rank of the six experts. Therefore, the results of the external aggregation values for selecting the ideal alternative were proven to be 0.920481, while the value for the worst alternative was 0.079632 and the average values were 0.792634 and SD± 0.141425, respectively. Table 6, shows the ranking of the face recognition models using the TOPSIS method.

Table 6.TOPSIS ranking to select the ideal alternative

Models	Dataset	Final Ranking-1	Final Ranking-2	Final Ranking-3	Final Ranking-4	Final Ranking-5	Final Ranking-6	External aggr	Internal aggr
LDN	LWF1	0.7573	0.7653	0.8018	0.7537	0.7771	0.7986	0.7756	0.7765
	CK1	0.8822	0.8781	0.9148	0.8540	0.9022	0.9067	0.8897	0.8904
	CAS1	0.4965	0.5271	0.5805	0.5243	0.5323	0.5795	0.5400	0.5412
	JAFEE1	0.7974	0.7963	0.8322	0.8001	0.8089	0.8284	0.8106	0.8110
LDN +HAAR	LWF2	0.7573	0.7653	0.8018	0.7537	0.7771	0.7986	0.7756	0.7765
	CK2	0.8685	0.8650	0.9026	0.8406	0.8885	0.8949	0.8767	0.8774
	CAS2	0.5684	0.5879	0.6340	0.6035	0.5904	0.6335	0.6030	0.6036
	JAFEE2	0.8539	0.8427	0.8796	0.8557	0.8594	0.8739	0.8609	0.8611
LDN+DB	LWF3	0.8822	0.8781	0.9148	0.8540	0.9022	0.9067	0.8897	0.8904
	CK3	0.8834	0.8803	0.9159	0.8552	0.9039	0.9079	0.8911	0.8918
	CAS3	0.6331	0.6492	0.6890	0.6634	0.6513	0.6887	0.6625	0.6630
	JAFEE3	0.9191	0.9004	0.9417	0.9039	0.9266	0.9313	0.9205	0.9208
LDN+AB	LWF4	0.0710	0.1119	0.0585	0.0749	0.0863	0.0752	0.0796	0.0798
	CK4	0.8865	0.8840	0.9184	0.8588	0.9070	0.9106	0.8942	0.8949
	CAS4	0.8337	0.8358	0.8690	0.8174	0.8523	0.8640	0.8454	0.8461
	JAFEE4	0.8337	0.8358	0.8690	0.8174	0.8523	0.8640	0.8454	0.8461
LDN+HL	LWF5	0.7660	0.7780	0.8096	0.7609	0.7876	0.8071	0.7849	0.7857
	CK5	0.8940	0.8898	0.9251	0.8661	0.9141	0.9167	0.9010	0.9017
	CAS5	0.7660	0.7780	0.8096	0.7609	0.7876	0.8071	0.7849	0.7857
	JAFEE5	0.7660	0.7780	0.8096	0.7609	0.7876	0.8071	0.7849	0.7857
LDN+VL	LWF6	0.6967	0.7118	0.7499	0.7040	0.7196	0.7481	0.7217	0.7226
	CK6	0.8436	0.8455	0.8778	0.8266	0.8623	0.8727	0.8547	0.8555
	CAS6	0.6967	0.7118	0.7499	0.7040	0.7196	0.7481	0.7217	0.7226
	JAFEE6	0.6967	0.7118	0.7499	0.7040	0.7196	0.7481	0.7217	0.7226
LDN+LH	LWF7	0.9058	0.8984	0.9333	0.8840	0.9221	0.9251	0.9114	0.9120
	CK7	0.9064	0.8993	0.9338	0.8846	0.9229	0.9257	0.9121	0.9127
	CAS7	0.9074	0.9009	0.9362	0.8820	0.9259	0.9279	0.9134	0.9140
	JAFEE7	0.9058	0.8984	0.9333	0.8840	0.9221	0.9251	0.9114	0.9120
LDN+MLH	LWF8	0.8421	0.8436	0.8746	0.8294	0.8585	0.8699	0.8530	0.8537
	CK8	0.8456	0.8496	0.8775	0.8335	0.8628	0.8732	0.8570	0.8577
	CAS8	0.8591	0.8590	0.8904	0.8426	0.8760	0.8849	0.8687	0.8694
	JAFEE8	0.8421	0.8436	0.8746	0.8294	0.8585	0.8699	0.8530	0.8537
LDN+HML	LWF9	0.6511	0.6656	0.7095	0.6682	0.6731	0.7077	0.6792	0.6800
	CK9	0.8731	0.8582	0.8966	0.8720	0.8773	0.8898	0.8778	0.8781
	CAS9	0.7061	0.7138	0.7520	0.7264	0.7202	0.7503	0.7281	0.7286
	JAFEE9	0.6671	0.6768	0.7189	0.6911	0.6829	0.7172	0.6923	0.6928

HLDN	LWF10	0.7254	0.7313	0.7678	0.7452	0.7378	0.7663	0.7456	0.7460
	CK10	0.7240	0.7327	0.7671	0.7432	0.7378	0.7662	0.7452	0.7456
	CAS10	0.7638	0.7669	0.8013	0.7778	0.7751	0.7993	0.7807	0.7811
	JAFFE10	0.7215	0.7285	0.7655	0.7398	0.7353	0.7638	0.7424	0.7429
HLDN+PCA	LWF11	0.8935	0.8899	0.9246	0.8628	0.9140	0.9182	0.9005	0.9012
	CK11	0.7901	0.7974	0.8301	0.7808	0.8096	0.8275	0.8059	0.8068
	CAS11	0.8279	0.8267	0.8575	0.8302	0.8381	0.8548	0.8392	0.8396
	JAFFE11	0.8105	0.8102	0.8421	0.8158	0.8208	0.8397	0.8232	0.8236

ccording to Rachel, Jenisha, et al.,[] they used the same techniques applied in our study. However, this study focused solely on the selection process without addressing the relationship between collective and individual expert opinions. In contrast, our study detailed the individual and group expert opinions and their impact on making the appropriate decision in selecting the optimal alternative. Therefore, our study offers a more accurate comparison of these two types of opinions that must be considered. Consequently, the results obtained in our study are more reliable compared to previous studies.

The results demonstrated consistency with the study's objective. They established the relationship between the values of individual and group expert opinions and their impact on decision-making. Thus, the study concluded that there is a strong alignment between external and internal aggregation, as shown in Figure 14.

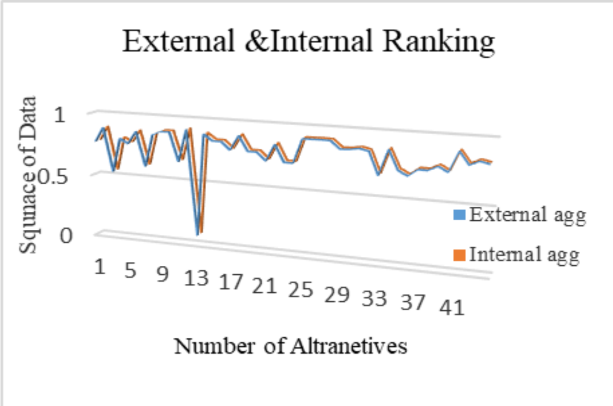

Fig 14.Group ranking based TOPSIS method

V. Conclusion

In this study, the proposed methodology based on decision-making methods was used to evaluate and select the ideal model. Eleven models for deep facial recognition, comprising four basic datasets were adapted as alternatives based on five specific criteria. A decision matrix (DM) was created, incorporating various face recognition models, which were then evaluated using multiple criteria. To calculate the criteria weights, the fuzzy system was combined with the hierarchical analysis process using the wise pair principle, which is considered one of the best methods according to the literature. The TOPSIS method was employed to select the ideal alternative by determining the closest positive geometric distance and the farthest negative geometric distance from the ideal solution. However, the study acknowledges a limitation in terms of missing some essential criteria that could have a significant impact on the final results. The findings indicate that the LDN+DB model using the JAFFE dataset is the best and is the recommended choice among all the models, while the LDN+AB model using the LWF dataset performed the worst. In contrast, the results showed the relationship between the values of external and internal aggregation and their impact on decision-making. Thus, the results proved that there is a great deal of consistency between them. Therefore, future studies should focus on considering the time complexity factor and defining objective procedures for evaluating facial recognition models in real-time.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Each author provided their contributions to complete this paper. The author Abdulbasit AL AZZAWI conducted the data analysis and dataset preparation in addition to writing the background of the study. The author Qahtan M . Yas conducted the practical aspect of the research methodology and discussed the results. In addition, author Zainab Mohamed Ali conducted the references' literature review, conclusion, and typesetting of the references.

ACKNOWLEDGMENT

I would like to thank all the authors who contributed to the completion of this great work. I would also like to thank the scientific committee in our college for their continuous support and encouragement in completing this work.

REFERENCES

[1] M. Wang and W. Deng, "Deep face recognition: A survey," *Neurocomputing*, vol. 429, pp. 215–244, 2021, doi: 10.1016/j.neucom.2020.10.081.

[2] H. Du, H. Shi, D. Zeng, X. P. Zhang, and T. Mei, "The Elements of End-to-end Deep Face Recognition: A Survey of Recent Advances," *ACM Comput. Surv.*, vol. 54, no. 10, 2022, doi: 10.1145/3507902.

[3] A. Voulodimos, N. Doulamis, A. Doulamis, and E. Protopapadakis, "Deep Learning for Computer Vision: A Brief Review," *Comput. Intell. Neurosci.*, pp. 1–14, 2018, doi: 10.1155/2018/7068349.

[4] Y. Li, Z. Wang, Y. Li, X. Zhao, and H. Huang, "Design of face recognition system based on CNN," *J. Phys. Conf. Ser.*, vol. 1601, no. 5, 2020, doi: 10.1088/1742-6596/1601/5/052011.

[5] Y. Makhija and R. S. Sharma, *Face recognition: Novel comparison of various feature extraction techniques*, vol. 741. Springer Singapore, 2019. doi: 10.1007/978-981-13-0761-4_110.

[6] E. M. Onyema, P. K. Shukla, S. Dalal, M. N. Mathur, M. Zakariah, and B. Tiwari, "Enhancement of Patient Facial Recognition through Deep Learning Algorithm: ConvNet," *J. Healthc. Eng.*, vol. 2021, pp. 1–8, 2021, doi: 10.1155/2021/5196000.

[7] A. A. Zaidan, B. B. Zaidan, M. A. Alsalem, O. S. Albahri, A. S. Albahri, and M. Y. Qahtan, *Multi-agent learning neural network and Bayesian model for real-time IoT skin detectors: a new evaluation and benchmarking methodology*, vol. 32, no. 12. Springer London, 2020. doi: 10.1007/s00521-019-04325-3.

[8] B. Al-bander, Q. M. Yas, H. Mahdi, and R. K. H. S. Al-hamd, "Benchmarking of deep learning algorithms for skin cancer detection based on a hybrid framework of entropy and VIKOR techniques," *Turkish J. Electr. Eng. Comput. Sci.*, vol. 29, pp. 2634–2648, 2021, doi: 10.3906/elk-2103-65.

[9] Q. M. Yas and G. K. Ouda, "Toward on Develop a Framework for Diagnosing Novel-COVID-19 Symptoms Using Decision Support Methods," *Commun. Comput. Inf. Sci.*, vol. 1548 CCIS, pp. 93–107, 2022, doi: 10.1007/978-3-030-97255-4_7.

[10] F. M. Jumaah, A. A. Zaidan, B. B. Zaidan, R. Bahbibi, M. Y. Qahtan, and A. Sali, "Technique for order performance by similarity to ideal solution for solving complex situations in multi-criteria optimization of the tracking channels of GPS baseband telecommunication receivers," *Telecommun. Syst.*, pp. 1–19, 2017, doi: 10.1007/s11235-017-0401-5.

[11] D. S. AbdELminaam, A. M. Almansori, M. Taha, and E. Badr, "A deep facial recognition system using computational intelligent algorithms," *PLoS One*, vol. 15, no. 12 December, pp. 1–27, 2020, doi: 10.1371/journal.pone.0242269.

[12] N. Soni, E. K. Sharma, and A. Kapoor, "Hybrid meta-heuristic algorithm based deep neural network for face recognition," *J. Comput. Sci.*, vol. 51, no. February, p. 101352, 2021, doi: 10.1016/j.jocs.2021.101352.

[13] J. Zeng, X. Qiu, and S. Shi, "Image processing effects on the deep face recognition system," *Math. Biosci. Eng.*, vol. 18, no. 2, pp. 1187–1200, 2021, doi: 10.3934/MBE.2021064.

[14] S. I. Serengil and A. Ozpinar, "LightFace: A Hybrid Deep Face Recognition Framework," in *Proceedings - 2020 Innovations in Intelligent Systems and Applications Conference, ASYU 2020*, 2020, pp. 1–5. doi: 10.1109/ASYU50717.2020.9259802.

[15] H. Ling, J. Wu, L. Wu, J. Huang, J. Chen, and P. Li, "Self residual attention network for deep face recognition," *IEEE Access*, vol. 7, pp. 55159–55168, 2019, doi: 10.1109/ACCESS.2019.2913205.

[16] Z. Zhu *et al.*, "WebFace260M: A Benchmark Unveiling the Power of Million-Scale Deep Face Recognition," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2021, pp. 10487–10497. doi: 10.1109/CVPR46437.2021.01035.

[17] F. Boutros, N. Damer, F. Kirchbuchner, and A. Kuijper, "ElasticFace: Elastic Margin Loss for Deep Face Recognition," in *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, 2022, pp. 1577–1586. doi: 10.1109/CVPRW56347.2022.00164.

[18] D. Giral, C. Hernández, and C. Salgado, "Spectral decision in cognitive radio networks based on deep learning," *Expert Syst. Appl.*, vol. 180, no. April, 2021, doi: 10.1016/j.eswa.2021.115080.

[19] T. M. RF Mahmood, ASMJ Ismael, QM Yas, "A Survey for Promising COVID-19 Vaccines: Issues, Advantages, and new Research Directions," *HIV Nurs.*, vol. 22, no. 2, pp. 2017-2028., 2022.

[20] H. S. Lee and B. Y. Kang, "Continuous emotion estimation of facial expressions on JAFFE and CK+ datasets for human–robot interaction," *Intell. Serv. Robot.*, vol. 13, no. 1, pp. 15–27, 2020, doi: 10.1007/s11370-019-00301-x.

[21] I. Medvedev, F. Shadmand, and N. Gonçalves, "Young Labeled Faces in the Wild (YLFW): A Dataset for Children Faces Recognition," *arXiv Prepr. arXiv*, p. 2301.05776, 2023, [Online]. Available: http://arxiv.org/abs/2301.05776

[22] V. B. Suneeta, P. Purushottam, K. Prashantkumar, S. Sachin, and M. Supreet, "Facial expression recognition using supervised learning," *Adv. Intell. Syst. Comput.*, vol. 1108 AISC, no. May, pp. 275–285, 2020, doi: 10.1007/978-3-030-37218-7_32.

[23] S. S. Rajput and K. V. Arya, "A robust face super-resolution algorithm and its application in low-resolution face recognition system," *Multimed. Tools Appl.*, vol. 79, no. 33–34, pp. 23909–23934, 2020, doi: 10.1007/s11042-020-09072-5.

[24] M. Soni, M. A. Shnan, and Y. Bengio, "Scalable Neural Network Algorithms for High Dimensional Data," *Mesopotamian J. Big Data*, pp. 1–12, 2023, doi: 10.58496/mjbd/2023/001.

[25] B. McDanel, H. Dinh, and J. Magallanes, "Accelerating DNN Training with Structured Data Gradient Pruning," in *Proceedings - International Conference on Pattern Recognition*, 2022, pp. 2293–2299. doi: 10.1109/ICPR56361.2022.9956574.

[26] W. Xu, Y. Zhang, and X. Tang, "Parallelizing DNN Training on GPUs: Challenges and Opportunities," in *The Web Conference 2021 - Companion of the World Wide Web Conference, WWW 2021*, 2021, pp. 174–178. doi: 10.1145/3442442.3452055.

[27] Y. Kim, Y. Kim, C. Yang, K. Park, G. X. Gu, and S. Ryu, "Deep learning framework for material design space exploration using active transfer learning and data augmentation," *npj Comput. Mater.*, vol. 7, no. 1, pp. 1–7, 2021, doi: 10.1038/s41524-021-00609-2.

[28] K. Zhang *et al.*, "Data augmentation for motor imagery signal classification based on a hybrid neural network," *Sensors (Switzerland)*, vol. 20, no. 16, pp. 1–20, 2020, doi: 10.3390/s20164485.

[29] N. Khare *et al.*, "SMO-DNN: Spider monkey optimization and deep neural network hybrid classifier model for intrusion detection," *Electron.*, vol. 9, no. 4, pp. 1–18, 2020, doi: 10.3390/electronics9040692.

[30] Y. I. Daradkeh, I. Tvoroshenko, V. Gorokhovatskyi, L. A. Latiff, and N. Ahmad, "Development of effective methods for structural image recognition using the principles of data granulation and apparatus of fuzzy logic," *IEEE Access*, vol. 9, pp. 13417–13428, 2021, doi: 10.1109/ACCESS.2021.3051625.

[31] K. G. Yas, Q.M., Ibrahim, D.S. and Mohammed, "Academic Ranking of Diyala University Using Hybrid Decision-Making Approach," in *In AIP Conference Proceedings*, 2023, pp. 1–13.

[32] T. Ma and F. Xiao, "An Improved Method to Transform Triangular Fuzzy Number into Basic Belief Assignment in Evidence Theory," *IEEE Access*, vol. 7, pp. 25308–25322, 2019, doi: 10.1109/ACCESS.2019.2900362.

[33] Q. Yas, E. M. Hameed, A. Badr, and B. Al-bander, "Multi Risk

Factors Evaluation for Lung Cancer Incidence Based Decision Support Systems," *Turkish J. Comput. Math. Educ.*, vol. 12, no. 13, pp. 3409–3419, 2021.
[34] Q. M.Yas, "A NEW METHODOLOGY FOR EVALUATION AND BENCHMARKING OF," 2018.
[35] A. K. Jassim Al-Shamary, Q. M. Yas, A. M. Badr, R. Al Shalabi, and S. H. Aldulaimi, "Multi Criteria Decision Making Technique for Evaluation and Selection performance Large Scale Data of Composite Materials," in *2022 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems, ICETSIS 2022*, IEEE, 2022, pp. 96–103. doi: 10.1109/ICETSIS55481.2022.9888862.
[36] A. U. Rehman, A. Shekhovtsov, N. Rehman, S. Faizi, and W. Sałabun, "On the analytic hierarchy process structure in group decision-making using incomplete fuzzy information with applications," *Symmetry (Basel).*, vol. 13, no. 4, pp. 1–15, 2021, doi: 10.3390/sym13040609.
[37] Q. M. Yas and F. K. Zaidan, "A NEW HYBRID MULTI-CRITERIA DECISION APPROACH FOR EVALUATING AND BENCHMARKING VACCINES," *Int. J. Tech. Phys. Probl. Eng.*, vol. 15, no. 54, pp. 33–38, 2023.
[38] A. A. M. Al-Azzawi, M. L. Talal, B. J. Khadhim, and Q. M. Yas, "Selecting Optimal Educational Boards Based on a Decision Support Approach," *Int. J. Tech. Phys. Probl. Eng.*, vol. 15, no. 1, pp. 345–351, 2023.
[39] M. Tang and H. Liao, "From conventional group decision making to large-scale group decision making: What are the challenges and how to meet them in big data era? A state-of-the-art survey," *Omega (United Kingdom)*, vol. 100, p. 102141, 2021, doi: 10.1016/j.omega.2019.102141.