NEURAL NETWORK WITH AGNOSTIC META-LEARNING MODEL FOR FACE-AGING RECOGNITION

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ABSTRACT

Face recognition is one of the most approachable and accessible authentication methods. It is also accepted by users, as it is non-invasive. However, aging results in changes in the texture and shape of a face. Hence, age is one of the factors that decreases the accuracy of face recognition. Face aging, or age progression, is thus a significant challenge in face recognition methods. This paper presents the use of artificial neural network with model-agnostic meta-learning (ANN-MAML) for face-aging recognition. Model-agnostic meta-learning (MAML) is a meta-learning method used to train a model using parameters obtained from identical tasks with certain updates. This study aims to design and model a framework to recognize face aging based on artificial neural network. In addition, the face-aging recognition framework is evaluated against previous frameworks. Furthermore, the performance and the accuracy of ANN-MAML was evaluated using the CALFW (Cross-Age LFW) dataset. A comparison with other methods showed superior performance by ANN-MAML.

Keywords: Face Aging, Face Recognition, Artificial Neural Network, Meta Learning, CALFW

1.0 INTRODUCTION

A neural network is a technique that uses non-linear functions to reach the required level of accuracy [1][2]. Recently, neural networks techniques have been used in several identification- and modeling-based models [1][3][4]. They include face recognition, age estimation, and security applications [1]. Face detection is required in various fields such as security, entertainment [5], surveillance, lost child location, and shape prediction [1]. However, faces do not remain the same over time. The face-aging process makes a face appear older by applying certain age-related properties [6]. Face aging progression is a face rendering application that uses face synthesis on the image of a particular person of a given age to present the effects of age [7].

To function in real time, face recognition models face many difficulties and challenges. There are many issues still under development and improvement. One of these issues is image availability, which means a lack of availability of various images at different ages for the same person [8].

This uncontrolled process leads to different facial changes from one person to another, despite the people being the same age [1]. Thus, this problem has become the focus of much research attention. Moreover, the age process differs from person to person; thus, it is has become the focus of much research attention[9].

Aging is hard to model because it depends on genes and the environment. Different methods have been produced to solve aging modeling problems. However, many approaches completely discard personalized information and apply the same aging pattern to all people.

Many algorithms and techniques based on neural networks have been proposed for human face recognition. And these techniques have their strengths and weaknesses[10].

This paper focuses on Artificial Neural Networks (ANN) models. We use the meta-learning approach to handle problems with diverse techniques and architectures, as well as regression, classification, and policy gradient reinforcement learning.

The ANN approach requires minimal modification. The goal of using the meta-learning approach is to train ANNs, as meta-learning can extract local and global features. This increases the probability of recognizing a person at different ages. Moreover, a meta-learning–trained model is equipped with the ability to learn from many different tasks.

The core contribution is to suggest an effective face-aging recognition framework that adopts an ANN with model-agnostic meta-learning. The proposed framework improved the accuracy of face aging detection as shown in the results.

The significance of the ANN-MAML framework is in its ability to detect the face of the same person at a different age, where there can be more than 10 years between the first image and the second. The main goal of this paper is to improve the Artificial Neural Network (ANN) technique by adding Adaptation Model-Agnostic Meta-Learning (MAML) for face-aging recognition [11].

The strengths of MAML are to solve the face ageing recognition based on ANN as a classifier. ANN is used because it achieved high detection accuracy. The scope is limited to enhance the recognition ageing rate. Nevertheless, MAML shortcomings are the lowest age in the dataset is 18 years , also MAML can deal with image extension PGM only .

The proposed framework ANN-MAML is a model for face ageing recognition with acceptance accuracy, which can detect the same person face with different more than ten years.

The remainder of this paper is structured as follows: Section 2 contains the literature review, section 3 introduces the ANN-MAML methodology for face-aging recognition, and Section 4 describes the results. The final section will highlight the conclusions of this paper.2.

2.0 REVIEW OF RELATED LITERATURE

2.1 Face-aging recognition

There are two important face-aging recognition techniques: prototype-based approaches [13] and physical model–based approaches [14]. However, these methods neglect personal differences such as wrinkles, which leads to the generation of unrealistic faces.

In 2016, a model based on local pattern selection (LPS) was used to match and compare the same person at different ages[15]. The LPS model was evaluated using two databases: MORPH and FGNET. The accuracy of the LPS model reached 94.87% for MORPH dataset [25]. In addition, RNNs have been used in proposed models for a smooth face-aging process [19].

In 2017, a fuzzy c-means clustering algorithm, which is essentially a statistical technique, was used for age estimation [16]. Moreover, a deep convolution neural network model has been used to recognize newborn faces. The model was tested on the IIT dataset, which has 220 faces, each with 10 images in various poses [17].

In 2018, a model based on probabilistic linear discriminant analysis was used to detect face-aging features; it was evaluated using three datasets: CACD, MORPH, and FGNET [18]. In addition, a model based on identity preserving conditional generative adversarial networks has been used to detect the transformation of different facial aging patterns [19].

2.2 Artificial Neural Networks

In 2015, a framework was used for recognizing the face expressions using Artificial Neural Network. The system evaluated by Cohn-Kanade dataset with average accuracy of 65%. The systm was tested using 60 images. However, the number of the images that was used is low and the system didn't use images that exhibit aging of the same person[26].

In 2017, a system was established to extract the facial expression recognition built with Gabor filters, and after that the system uses artificial neural network to classify a person's facial expressions.
In the system tested by the JAFFE dataset, the accuracy was 85.7%. This dataset contains images for 10 Japanese female models which means there are no images from different countries, and no diversity in the facial features. As every country has specific facial features.

In 2019, a model was created based on artificial neural network to identify the human face. The framework was developed to improve the accuracy of the face recognition process. The performance for the system reached and accuracy of 82%. The dataset that was used contained 100 images collected by the authors, and no images from different countries were used. Thus again, there was no diversity in the facial features.
In 2020, a framework was produced for classifying face emotions based on neural network. The framework used the JAFFE dataset to evaluate the system with 99% accuracy performance. Nevertheless, only 213 images of 10 Japanese female models were used. This dataset contains images for 10 Japanese female models which means again here there was diversity in the facial features that were used.

3.0 THE METHODOLOGY OF ANN-MAML FOR FACE-AGING RECOGNITION

This section shows the methodology applied in this paper. The stages of the paper's methodology are shown in figure 1. The literature is reviewed in Stage 1. Stage 2 explains the proposed model. Stage 3 shows the experiments and results. Finally, Stage 4contains the evaluation, and also presents the analyses and evaluation.

3.1 ANN-MAML Stages:

3.1.1 Stage 1: Literature Review

This paper aimed to develop a model for face aging recognition. Consequently, the undertaken literature review focused on the following related works:

- Review of current ageing systems: During the paper, studying the various systems used for human face ageing and age progression.

- After that, extract the challenges and open issues for face recognition to be identified from the literature review.

- Finally, the core goal of this paper is to increase the effectiveness of face ageing recognition. The objectives determined are methodically followed until the main objective is reached.

3.1.2 Stage 2 Proposed Model

This stage presents the whole design and implementation for the proposed model based on ANN combined with modified MAML.

The proposed model has 4 phases pre-processing, feature selection using wavelet transforms, training based on modified MAML technique, and finally, the classifier phase based on ANN.

3.1.3 Stage 3: Experiments and Result

The third stage presents the experiments and the results. The model was experimented with three datasets Cross-Age LFW (CALFW, AT&T, own collected dataset).

3.1.4 Stage 4: Evaluation

The outcomes from the experiments are shown and analysed in the evaluation section that calculated the performance of the new proposed model. Evaluation of the various models are determined from previous studies, such as Recall, Accuracy, F-measure, False Positive Rate and Precision.

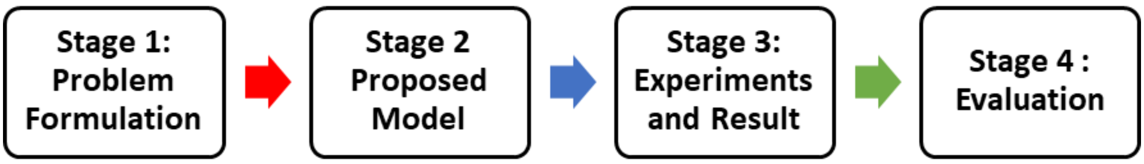

Fig. 1: Show the research methodology stages. It has 4 stages.

3.2 The Recognition model

Recently, ANN become one of the common techniques used for prediction and classification and recognition [20]. The extraordinary capability of ANN is one of the high-speed parallel processing and has improved the results in general [21]. Currently, ANNs are mostly used in numerical models because ANN has good properties of self-learning, advancement in input to an output mapping, adaptively, and nonlinearity [12]. ANNs are successful, efficient, and effective techniques during the implementation; it gives a great level of ability in dealing with either complex or non-complex issues in many different domains [21].

ANNs are efficient in solving various issues in different domains such as security, finance, computer science, prediction, weather, art and education. Despite these common applications in different fields based on ANN, there is still a need to improve its performance. ANN is built from 3 layers, the input layer is the first layer for initial data, the second layer is hidden layers where all computation is done, and the last is the output layer which is used to produce the results [22][27].

The ANN architecture is developed with two hidden layers and initial weights set the default value[26]. Therefore, this is done to avoid over-fitting and reduce the probability of wrong detection [32]. On the other side, adding more hidden layers and nodes leads to an increase in training time [33].

3.3 Case study ANN_MAML:

The paper's target is to build an artificial neural network that could recognize a face after aging. In order to achieve this, we need to:

1. Prepare the image.
2. Extract the features.
3. Train the system.
4. Select the features.
5. Recognize the face.

Consequently, we could design the hierarchy of the ANN-MAML model according to this analysis.

3.4 Hierarchy design:

The purpose of designing the hierarchy is to build the small functions separately for every stage. This means every layer has a particular function, and we can choose the hierarchy according to the function split. The goal for this ANN-MAML framework is to recognize the face. The hierarchy of the framework is shown in figure 2.

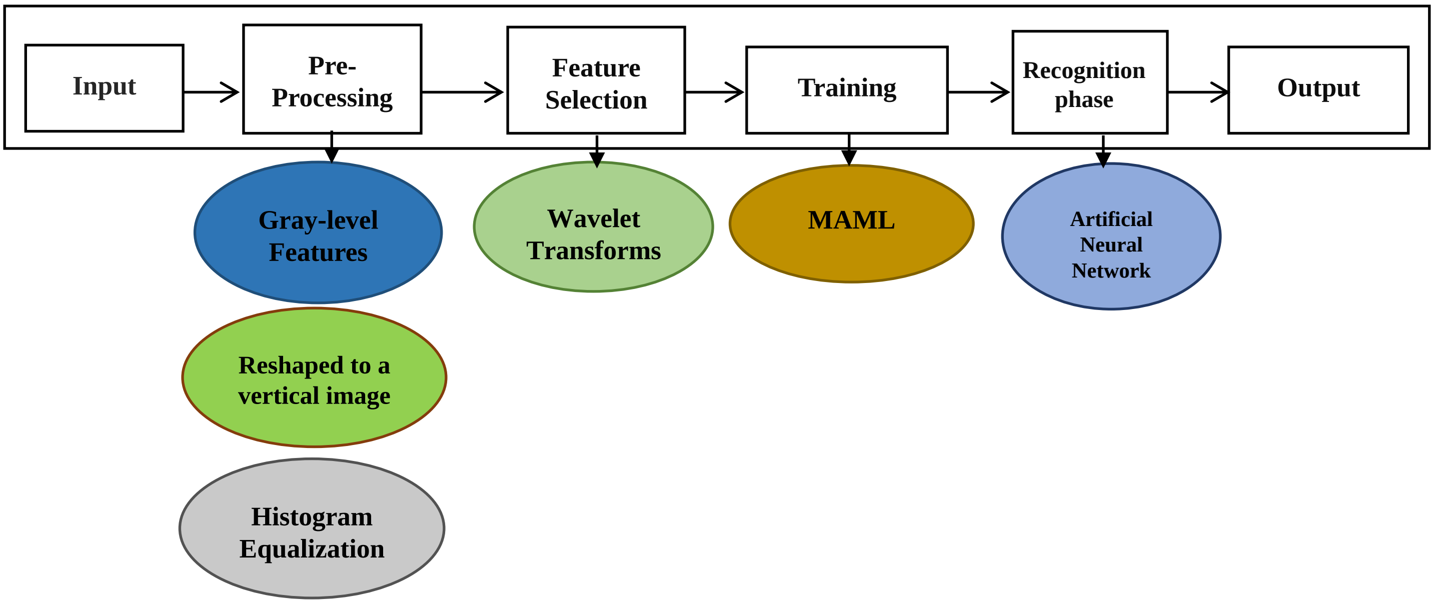

Fig. 2: The Design for face-aging recognition framework ANN-MAML

3.5 Module Design

This section represents the different stages of the framework as follows:

- **Pre-processing stage:** The first step is the image pre-processing stage, which include gray level features, reshaping to a vertical image and histogram equalization.

- **Feature Selection stage:** Feature extraction is important in image recognition, as well as in face recognition. This stage explain wavelet transforms algorithm; wavelet transforms used to extract the features from the images. The function φ(r) and ϕ(r) are used to refer for scaling function and corresponding wavelet function, and both of them satisfy the dilation equations, with ϕ mn (r) and with φmn (r) being their dilations and translations respectively.

$$\phi^{m}_{n}(r) = 2^{-m/2}\ \phi(2^{-m/2} t - n),\ n \in Z \quad (1)$$

$$\varphi^{m}_{n}(r) = 2^{-m/2}\ \varphi(2^{-m/2} t - n),\ n \in Z \quad (2)$$

The steps for feature extraction from the image can be clarified as follows:

First, normalize the images W (x1, x2); second, deduct the image's average value from the normalization. This leads to focusing perfectly on the main pixels of the image. Multi-sized wavelets take the images apart. This is done by extracting the individual signal features that have high frequency[28].

Next, rebuild wavelet decomposition factors to extract the signals on the different frequency. D_0, D_1, ….., D_M used to express the decomposed reconstructed signals from low frequency coefficient and high frequency coefficient. D can be referred to signal as

$$D = D_0 + D_1 + \ldots\ldots + D_M \quad (3)$$

3.4 Training Stage

The second step is training of the network using MAML, which is one of the most common algorithms in meta-learning. MAML determines the best initial weights of the network so that the network can learn new tasks rapidly, even if the training involves only a few labeled samples. The algorithm can be used to train any model, so that the model can rapidly become familiar with any new function using a few datasets. Meta-learning considers existent functions as training examples[29].

Consider that in a model f, the input x maps to outputs a. Assume a meta-model f define the parameters by meta-parameters θ. By meta-learning, the model can be trained with different dataset sizes. Figure 3 shows the Model-agnostic meta-learning algorithm procedure that improves for a representation θ so it rapidly adjusts to different functions.

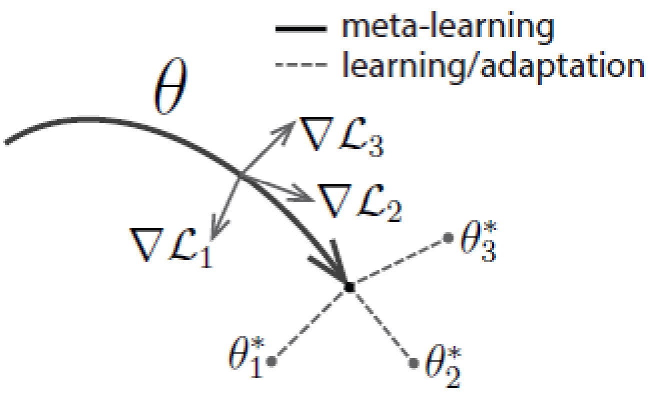

Fig. 3: Model-agnostic meta-learning algorithm (MAML)

A task T can be presented as $T = \{ L(X_1, a_1,..., X_H, a_H), q(X_1), q(X_{t+1}| Xt, a_t), H \}$. L is the loss function, $q(X_1)$ is the initial observation, $q(X_{t+1}| Xt, at)$ is the transition distribution, and H is the episode length. The framework creates different samples of length H by select the output a_t at each time t. The loss $L(X_1, a_1,..., X_H, a_H) \rightarrow \mathbb{R}$ offers specific feedback, that can lead for misclassification loss or cost function[30].

Such minor modifications in parameters will create improvements in the loss function of any task drawn from p(T) when changed in the direction of the gradient of that loss[31].

The model used the parameterized function f_θ with parameters θ. When the model is modified to a new task T_i, the parameter θ becomes θ'_I. This parameter uses the gradient descent

$$\theta'_i = \theta - \alpha . \quad (4)$$

$$\theta'_i = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta). \quad (5)$$

where α is a hyper parameter. The parameters are trained by improving the performance of f_θ', θ through task samples from p(T), as shown in Algorithm 1. The meta-aim is:

$$\min_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta'_i}) = \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)}) \quad (6)$$

It is observed that meta-optimization is achieved over the parameters θ, whereas the aim is calculated using the modified parameters θ′. The proposed model aims to improve the model parameters. A small number of gradient steps on a new task will produce maximally effective behavior in that task.

Algorithm 1: Model-agnostic meta-learning
Require: p(T): distribution over tasks
Require: α, ß: step size hyper parameters
1: randomly initialize θ
2: while not done do
3: Sample batch of tasks $T_i \sim p(T)$
4: for all T_i do
5: Evaluate $\nabla_\theta L_{Ti}(f_\theta)$ with respect to K examples
6: Compute adapted parameters with gradient descent : $\theta'_i = \theta - \alpha \nabla_\theta L_{Ti}(f_\theta)$
7: End for
8: Update $\theta \leftarrow \theta - \beta \nabla_\theta \Sigma_{Ti \sim p(T)} L_{Ti}(f_{\theta'})$
9: end while

Algorithm 2: Adaptation MAML
1: function ADAPT (f, ϴ, D_a; ϕ)
2: $\Theta_0 \leftarrow \Theta$
3: for j ϵ { 1 … adaptation steps } do
4: $L_j \leftarrow L(Y_a, f(X_a; \Theta_{j-1}))$
5: $\Theta_j \leftarrow \Theta_{j-1} - \phi \nabla_{\Theta j-1} L_j$
6: return $\Theta_{\text{adaptation steps}}$

3.5 Classifier stage

ANN consists of either single layer or multiple layers. Commonly, ANN contain three layers: input images, hidden (responsible for extracting patterns), and output (shows last outputs) [2]. Every layer have number of neuron, the neuron is initiated by the sum weight inputs it obtains and the beginning send the signal over a transfer function to produce a single output. At the transfer functions, the learning procedures define the performance of the neural network [3].

3.6 Data collection

- **<u>CALFW</u>**

CALFW is a set of images of people from the LFW (Labeled Faces in the Wild). The age gaps in the CALFW dataset are as large as possible so researchers can use it for age intra-class variation [23].

The CALFW dataset [23] was built to evaluate face verification algorithms over a large age gap. This dataset has 4,025 individuals, with 2–4 images of each one. Like the original LFW dataset, CALFW defines 10 individual categories of image pairs. Each category has 300 positive pairs (an age difference of less than 10 years between the images in each pair) and 300 negative pairs (an age difference of more than 10 years between the images in each pair) [24].

Many different techniques use the CALFW dataset for face-aging recognition, such as convolutional neural networks and generative adversarial network[34] .

- **THE OWN DATA SET (MIDDLE EAST DATA SET MEDS)**

The researcher collects a data set from different people with different ages from the Middle East. The condition in this picture collection is that a person should be more than 15 years old. Moreover, there should be a difference of 10 years or more for the same person. The collection contains pictures of 100 people, every person at least has 2 pictures. The researcher has therefore collected 200 pictures.

- **AT&T**

The AT&T is a dataset that contains400 face images. All the images are greyscale. The images are 92 by 112 pixels in size with PGM format.

4.0 RESULT AND ANALYSIS

The purpose of this section is to verify the proposed model, which is programmed using MATLAB. This study evaluates the accuracy of the model in face-aging recognition using the Cross-Age Labeled Faces in the Wild database and my own data set (Middle East data set meds).

The novelty of this study is the framework that recognizes the face after aging. This evaluation section presents the achievements of the proposed framework. The evaluation phase highlights the performance of the proposed framework.

The dataset is either CALFW or AT&T or Middle East datasets and each of this dataset has a unique feature. The descriptions of the datasets used in this evaluation stage are as follows:

1. Dataset 1: CALFW Database

Cross-Age LFW (CALFW) is a dataset which was purposely built by collecting 3,000 positive face pairs with age gaps to add aging process intra-class variation and negative pairs with same gender and race are also selected to reduce the influence of attribute difference between positive/negative pairs and achieve face verification instead of attributes classification. As shown in figure 4 the aging progression is clearer at CALFW dataset.

Figure 4: The aging progression is clearer at CALFW dataset.

CALFW is founded to create a real-life face recognition situation. As Well CALFW is applied to reach the face verification. At this dataset a different image of the same person have been added. As shown in figure 5 and figure 6 it is shown the Positive Pairs and negative pairs. The Age difference at the positive pairs is less than 10 years and the negative pairs are more than 10 years.

The procedure of building CALFW dataset can be divided into the following subsequent stages:

1. Collecting raw images from the Internet.
   Google, Getty Images, and Bing are used to search for different face images with different ages. The images were for different celebrities with different ages.

2. Running a face detector and manually correcting the results when there is more than one person in the picture.
3. Trim and resize the detected faces. The images were resized to 250 × 250 using the Matlab function imresize. Finally, the images were saved in JPEG format.
4. Removing the repeat images. Firstly, the definition of repeated image is that the two images are numerically equivalent at each pixel. Secondly, the repeated images have been deleted.

5. Assessing if the labels are correct or not correct.
6. Finding landmarks images
7. Estimating the age of each image. Determine the largest age gap pairs as positive pairs and the people with same gender and race as negative pairs.

Figure 5: Positive Pairs in CALFW

Figure 6: Negative Pairs in CALFW

2. <u>Dataset 2: AT&T Database of faces:</u>

AT&T database covers 10 various images of 40 different subjects, so the total images are 400 images. These different subjects can be images with varying facial details (e.g., glasses / no glasses), facial expressions (e.g., open / closed eyes, smiling / not smiling), different times and varying the lighting of the face. The images were with a different grayscale background, also these images were with the subjects in a vertical, forward position of the face. In this database there are 10 images for each person. The database contain 400 sample images, the image size is 92 x112 pixels, with 256 grey level per pixels that is clear in figure7.

AT&T has a mount of faces captured between April 1992 and April 1994 at Cambridge University Engineering Department lab. This dataset used in the context of a face recognition project carried out in coRobotics Group at the same university.

Figure7: AT&T images

3. <u>The Own Data set (Middle east Data set MEDS)</u>
   - Collecting raw images from the different people in middle east, by asking people to provide me with their images with different ages.
   - Running a face detector and manually correcting the results when there is more than one person in the picture.

- Trim and resize the detected faces. The images were resized to 250 × 250 using the Matlab function imresize. Finally, the images were saved in pgm format as shown in figure8.
- Finding landmarks images
- Determine the age of each image. Determine the largest age gap pairs as positive pairs and the people with same gender and race as negative pairs.

Fig. 8: Middle East dataset

4.1 Processing Time

Different Sizes of Dataset has been used to evaluate our framework ANN –MAML: As shown in figure9 and table1 the relation between size of dataset and time needed for training. It is approved that when the size of the images increases the time of training correspondingly increases. The datasets was divided into 70% of the data for training and 30% for testing .The data size was 180 images and the training time was 83.518 seconds. Also, when the data size was 220 images, the training time was 180.532 seconds. Similarly, the time increased to 346.129 seconds when the data size became 440 images. Finally, the time became 2146.492 seconds when this size images become 500.

Table 1: Face recognition rates at CALFW dataset

No. Images	Time
180	83.518
220	180.532
440	346.129
500	2146.492

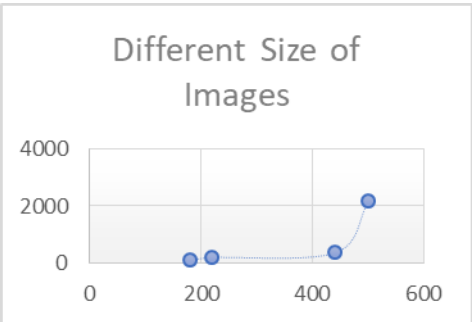

Fig. 9: Relation between size of dataset and time need to training.

4.2 Calculated the Accuracy for the three datasets

The second experiment calculates the proposed framework's accuracy using three datasets CALFW, AT&T, MEDS as shown in table 2.

Table 2: Accuracy for the framework using the three datasets

Algorithm	CALFW	AT&T	MEDS
Deep Metric Learning (Ni et al., 2019)	87.57%	91%	85%
AA-CNN(Y. Huang & Hu, 2020)	90%	92%	87%
KISSME(Koestinger, Hirzer, Wohlhart, Roth, & Bischof, 2012)	84.46%	89%	80%
Noisy Softmax(Chen, Deng, & Du, 2017)	82.52%	88%	81%
Linear Discriminant Analysis (Zangeneh et al.)	82%	95%	79%
Kernel Fischer Discriminant Analysis (KFDA)	83.40%	96%	80%
Kernel Principal Component Analysis (KPCA	30.50%	50.83%	30%
Principal Component Analysis (PCA)	71.60%	79.11%	70%
Artificial Neural Network	85%	92%	75%
Proposed framework (ANN-MAML)	90.40%	96.20%	86.95%

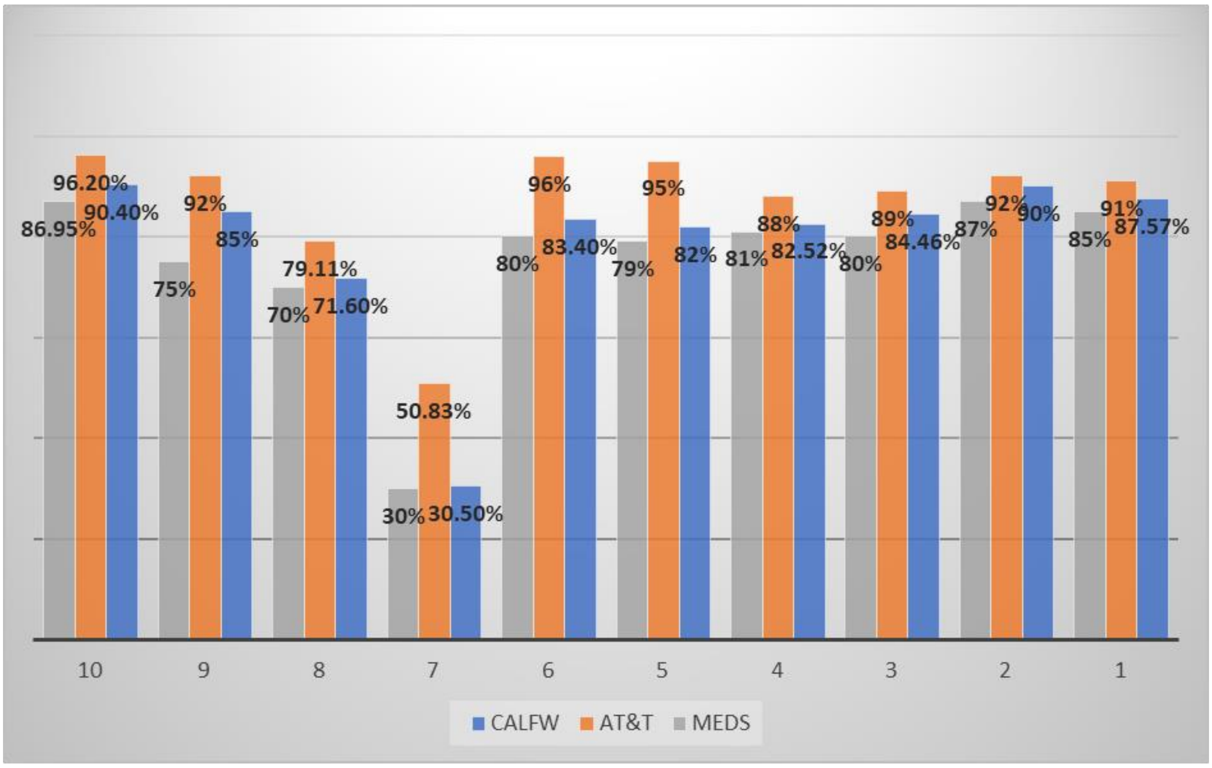

Fig. 10: Accuracy for the framework using the three datasets

As shown from table 2 that the proposed framework gives the best accuracy comparing with previous studies. AT&T give 96.20%, CALFW give 90.40% and MEDS give 75%.

4.3 Confusion Matrices Calculating

- Calculate the Confusion Matrices for CALFW:

1. Specificity (True Negative Rate) = TN / (TN + FP) =490 / (490+35)=0.9333.

2. Sensitivity (recall or true positive rate) = TP / (TP + FN) = 500/(500+70)=0.87719.
3. False Positive Rate (FPR) = FP / (FP + TN) == 35/(35+490)= 0.6666.
4. Precision = TP / (TP + FP) = 500/(500+35) = 0.9345.
5. F1- Score (F- measure) = 2* ((precision * sensitivity)/(precision + sensitivity)) = 2*((.81973)/(1.81169)) = .45246.
6. Fales Negative Rate (FNR) = FN/ (TP + FN) = 70/(500+70)= 0.12280.

Accuracy = (TP+TN) / (TP+TN+FP+FN) = (500+490)/ (500+490+70+35) = 0.9041.

Table 3: Calculate the Confusion Matrices for CALFW:

Actual **PC**	**Same person**	**Not the same person**
Same person	**500**	**70**
Not the same person	**35**	**490**

- Confusion Matrices for AT&T:
  1. Specificity (True Negative Rate) = TN / (TN + FP) = 76 / (76+3) = 0.9620
  2. Sensitivity (recall or true positive rate) = TP / (TP + FN) = 76 / (76+3) =0.9620
  3. False Positive Rate (FPR) = FP / (FP + TN) == 3 / (3+76) = 0.03797
  4. Precision = TP / (TP + FP) = 76 / (76+3) = 0.9620
  5. F1- Score (F- measure) = 2* ((precision * sensitivity)/(precision + sensitivity))= 2
  6. False Negative Rate (FNR) = FN/ (TP + FN)= 1 – Sensitivity= 0.03797
  7. Accuracy = (TP+TN) / (TP+TN+FP+FN) = 152/158 = 0.9620

Table 4: Confusion Matrices for AT&T:

Actual	**Same person**	**Not the same person**
Same person	TP = 76	FN = 3
Not the same person	FP = 3	TN = 76

- Confusion Matrices for MEDS:

1. Specificity (True Negative Rate) = TN / (TN + FP) = 30 / (30+3) = 30 / 33 = 0.9090
2. Sensitivity (recall or true positive rate) = TP / (TP + FN) = 30 /(30+6) = 30/36=0.8333
3. False Positive Rate (FPR) = FP / (FP + TN) =3/ (33) = 1- Specificity= 1- 0.9090
4. Precision = TP / (TP + FP) = 30 / (30+3) = 0.83
5. F1- Score (F- measure) = 2* ((precision * sensitivity) / (precision + sensitivity)) = 2*(0.83* 0.83)/(0.83+ 0.83)= 2

6. False Negative Rate (FNR) = FN/ (TP + FN)= 1 – Sensitivity= 1-0.86= 0.14
7. Accuracy = (TP+TN) / (TP+TN+FP+FN) = (30+30) / 69 = 0.8695 = 86.95%

Table 5 : Confusion Matrices for MEDS :

Actual / **PC**	**Same person**	**Not the same person**
Same person	TP = 30	FN= 6
Not the same person	FP= 3	TN = 30

5.0 CONCLUSIONS

The authors developed a framework for face-aging recognition based on meta-learning and ANNs. The proposed face-ageing recognition framework ANN-MAML based on ANN collaborate with model-agnostic meta-learning (MAML). The worth of this ANN-MAML framework is to detect the images for the same person with different more than 10 years. This detection is one of the face detection challenges. The model was evaluated by three datasets CALFW, AT&T and, the Middle east. The model is implemented by MATLAB. For each dataset, the accuracy has been calculated, the Confusion Matrices have been analysed, then the Error Analysis have been extracting. In the end, a comparison has been made between the model and previous works. The performance was for CALFW 90.40%, for AT&T 96.20%, and MIDDLEVEASEV86.95%

In the future, the proposed framework can use a graphics processing unit (GPU), which would increase the training speed. This can help in increasing the number of images processed. The proposed model can also be tested and evaluated on different datasets.

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