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Gender Recognition from Selfie Images by Merging Convolutional Neural Networks with Genetic Algorithms

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Abstract

Human gender plays an imperative role as social construct and an essential form of an individual's personality. Gender recognition is a fundamental task for human beings. It is highly reflected in social communication, forensic science, surveillance, and target marketing. Gender recognition previously depended only on standard face images. Using the term "standard" means that the image was taken in a standard light without any background variations and without any cropped parts. But this type of image is not found in real-world. These images are called non-standard images, as they have a lot of variations, like illumination and head pose. The image may also have a lot of faces, where one of them may wear sunglasses or other accessories. Using this type of image will affect the accuracy results of gender recognition approaches. Nowadays, selfie images appear as they are unconstrained images. People take selfie images of themselves. Selfie images are very complex, as some parts of the images are cropped and damaged. This paper proposes a (CNNGA) technique for gender recognition from selfie images by merging a deep learning approach with genetic algorithms. The proposed technique achieves 90.2% accuracy in recognizing gender from the selfie dataset. The experiments use various challenge datasets, which are widely adopted in the scientific community like LFW, Data Hub, FERET, and Caltech-web Faces.

Key Words: Gender Recognition. Deep Learning. CNN. Genetic Algorithms. Selfie Images.

1. Introduction

Human face contains important visual information about gender perception. It is challenging for a machine to identify this visual information that separates male faces from female faces. Gender recognition was started with the problem in psychophysical studies to classify gender from human face; it concentrates on the efforts of perceiving human visual processing and recognizing relevant features that can be used to distinguish between female and male individuals. The gender recognition issue is always considered a two-class problem in which a standard input query face image is analyzed and assigned to a male or female class. Broadly, facial pictures are presumably the most widely utilized soft biometric to identify individuals [9]. There are intrinsic differences between human faces, both in terms of genetic traits (facial features, age, race) and occasional variations (expression) or accessories (glasses, sunglasses, scarves, hats, earrings) [3]. Often, the way humans perceive gender does not only rely upon the perception of the face region, but also on the surrounding context, such as hair, dress, and skin tone. It is a kind of motivation to do something new in the evolution of boisterous face-based gender recognition application that has extreme detection accuracy. Various methods have been proposed for classifying gender from several constrained and unconstrained dataset, as depicted in Figure 1. It is more challenging in unconstrained situations. Besides these some face images are so confusing, in most of the time a human is also failed to detect the gender from the image.

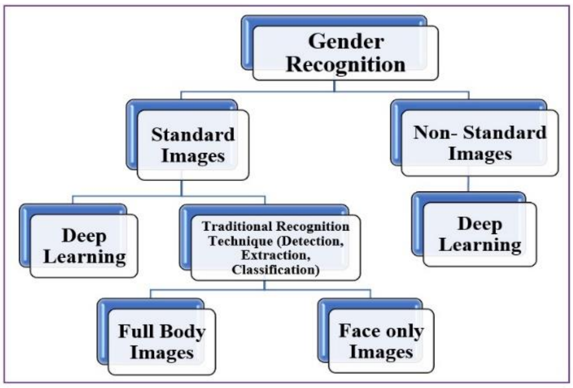

Figure 1: Gender Recognition

So, there is a wide scope for improving the performances of gender recognition approaches. Over the past few years, recognition of human gender from an unconstrained face image have become a recent trend in the research area of facial soft biometrics. This is mainly due to the need of recognizing gender from face images acquired from unconstrained sources. Gender recognition from unconstrained face images is a challenging task due to the high degree of misalignment, pose, expression, and illumination variation [2]. In previous works, the recognition of gender from an unconstrained face image are approached by utilizing image alignment, exploiting multiple samples per individual to improve the learning ability of the classifier, or learning gender based on prior knowledge about pose and demographic distributions of the dataset [6]. However, image alignment increases the complexity and time of computation, while the use of multiple samples or having prior knowledge about data distribution is unrealistic in practical applications. Recently, gender recognition deals with unconstrained real-world photos like selfie images, which are hard to analyse using facial-based approaches. These images are taken real-life situations with different resolutions and extreme occlusion. The case becomes harder when it is required to perform a specific demographic analysis of such selfie images, because they are not photographed in the best capturing conditions, i.e., neither a textured background nor a controlled lighting. Deep learning (DL) methods are used to deal with variations in selfie images. This research paper proposes a model that merges a convolutional neural network (CNN) network with a genetic algorithm. This technique achieves more accurate results in identifying human gender from a selfie image.

The remainder of this paper is structured as follows: Section 2 presents literature review. Section 3 presents a brief background. Section 4 discussed the proposed method. Section 5 presents the experiments and analysis of proposed method. Section 6 presents the performance of proposed method. Finally, section 7 concludes the paper.

2. Literature Review

Gender is the most widely studied facial demographic attribute in the computer vision field. Gender recognition determines the methods that can be used according to the type of input images. There are two types of images: standard images and non-standard images.

2.1 Gender Recognition from Standard Images

Classic gender recognition consists of three major steps: gender detection, feature extraction, and gender classification. Face detection phase, throughout literature, numerous hand-crafted features were proposed and fused in different ways as depicted in Figure 2.

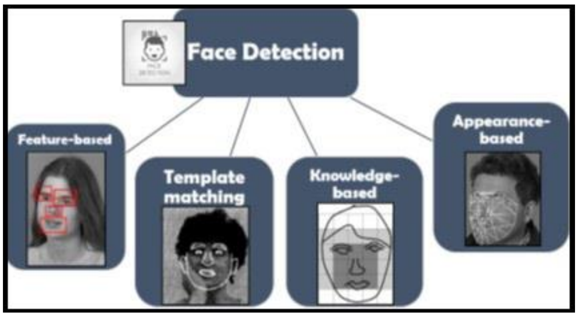

Figure 2: Face detection

Feature extraction requires identifying and describing the features that are relevant to a given problem and implementing a way to extract those features. Finally, a classification step decides whether extracted facial features represent female or male faces. Constrained datasets are mainly composed of faces usually used for biometrical application purposes. A constrained dataset is characterized by images with controlled poses of the acquired subjects and pre-defined scene conditions [18] as depicted in Figure 3.

Figure 3: Samples of Standard Images

Different modalities (e.g., the face, iris, and periocular regions) have been employed to solve the gender recognition problem. Some methods have relied on face images acquired through careful preparation and posing in a constrained environment; thus, these methods usually achieve good accuracy.

2.2 Gender recognition from non-standard images

Face recognition that uses traditional techniques achieves good accuracy by using standard images. Standard images are not found in the real-world for a lot of reasons, as follows:

• **A lot of variations appear in images, like illumination, background, head pose, scale differences, and low-resolution.**

• A single image could contain a group of faces.

• A face image may contain sunglasses, or other accessories.

• The images of a person can be very different, that can be due to some changes in the face, such as facial hair or makeup, and that faces change over time.

Gender recognition suffers from low accuracy when using images with some variations (non-standard). Non-standard images can be considered standard images, but they add some variations. People want to take images in a lot of places, which leads to a variation in the images. Some of these variations are low-resolution, head pose, illumination, make-up, and accessories as depicted in Figure 4.

Figure 4: Samples of Non-Standard Images

Gender recognition by humans is easy. However, for a computer, it is not a simple task. Like face recognition, gender classification from facial images encounters many problems due to the variant illumination, rotations, and poses present in the images. Another problem arises from the large number of features extracted by feature descriptors. To classify images for gender, many researchers have developed complex systems based on either geometrical features or appearance features. The features could be extracted from a global level from the entire face image or on a local level from a defined sub-region inside the face image [11]. The internal features are composed of the eyes, the nose, and the mouth and the external features located in the head, ears, and chin. Some research is done in the face and neck region, hair and upper body clothing, and head-shoulder-based gender recognition. There is a need to recognize gender from unconstrained face images such as online internet web pages, CCTV, webcam, and mobile devices.

3. Background

Gender recognition from facial images has garnered a lot of attention. Because of substantial advancements in the design of facial recognition systems, there is a greater need to use and improve gender recognition approaches today. A limited number of studies have been carried out on unconstrained face gender recognition. To address issues with face recognition (e.g., illumination, occlusion, noise, age, and ethnicity) and other factors that affect gender recognition accuracy, most previous studies used full faces and may be integrated with other automated systems, such as those for face recognition. However, if the person tries to conceal their gender (for example, by donning a veil, an Arabic Shemagh Scarf, any type of facial covering, or occasionally at masquerade events) or uses cosmetic tools or eye cosmetic lenses, the approach employed in existing research cannot identify such a person's gender. Women who grow beards or mustaches because of certain gynecological problems make gender identification more challenging. Another problem that appears is selfie images.

3.1 Selfie Images

SELFIE means" Self-taken Camera Picture." A SELFIE is a self-portrait photograph. They are typically taken with a digital camera or camera phone and are often posted on social media networks (like Facebook, Twitter, and Instagram). A selfie is typically taken by holding the camera at arm's length or with the help of a selfie stick, and it's become one of the most popular forms of photography in recent years. There are countless reasons why people take selfies. Some do it to capture a moment, while others use it to document their lives. Many uses it as a means of self-expression or to boost their self-esteem. Whatever the reason, selfies have become a way for people to share their experiences, emotions, and personalities with others, as depicted in Figure 5.

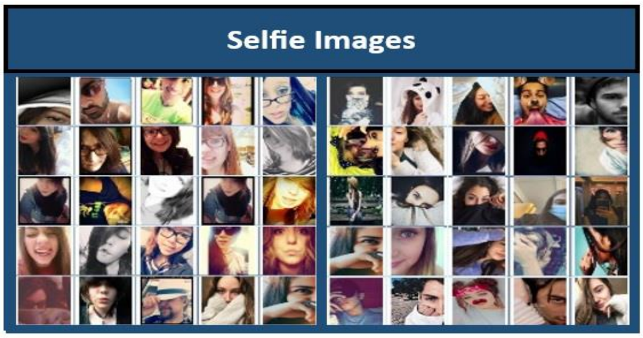

Figure 5: Samples of Selfie Images

Some selfies are extreme close-ups; others show part of an arm held straight outward and a few of the great ones even feature the subject standing in front of a mirror so that they can get a full body shot of their reflection. There are lots of selfie styles, and these are some of the most common. Selfies became a quick and easy way to convey to others a current mood, capture perfect lighting on a face with a gorgeous sunset in the background, show off muscles in the gym, or brag about an adorable haircut. Selfie is taken by oneself (and sometimes also with others), but the resulting photo usually features an unusual angle or is distorted in some way because it was created by the ultra-wide-angle lens. This effect is thought to be part of the appeal of taking selfies. A selfie is a picture that is composed of no more than head and shoulders. Selfies are frequently taken using a distinctive position and/or camera angle, rather than just a standard image of someone looking directly at the camera. The selfie's domain is nearly always digital; they are not printed, framed, and displayed on the mantelpiece, but rather shared via mobile phones, tablets, and other devices for consumption by other social media users. Arguably, this is the key to their appeal that they can use them to remind each other of what we look like or to put a face to names where acquaintance is restricted to the online universe.

3.2 Gender Recognition using CNN

Gender classification demonstrates high accuracy in many previous works. However, it does not generalize very well in unconstrained settings and environments. a Real-time system for gender recognition is based on a Convolutional neural network. A convolutional neural network is defined as a deep learning algorithm used for image recognition [24] as depicted in Figure 6.

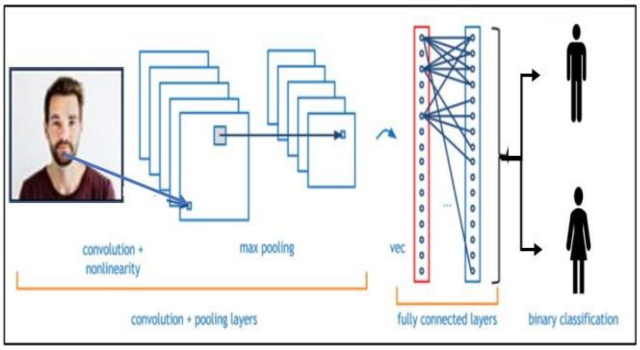

Figure 6: CNN Architecture

A real-time gender recognition system has the capability to recognize either the face of the person, whether they are male or female, even with complex face images of variations. This technology must be used for security and identity purposes in many fields. CNN (Convolutional Neural Network) architecture is a deep learning algorithm that is capable of distinguishing images from their characteristics [4]. CNN is commonly used in image analysis, image segmentation, image classification, medical image analysis, image and video recognition, and other applications. The convolutional neural network (CNN) is a neural network variant that consists of several convolutional layers alternating with subsampling layers and ends with one or more fully connected layers in the standard multilayer perceptron (MLP) [12]. A significant advantage of CNN over conventional approaches in pattern recognition is its ability to simultaneously extract features, reduce data dimensionality, and classify in one network structure.

CNN Algorithm:

- Convolutional Layer: This is the first layer. They apply the convolution effect to the input, transferring the result to the following layer. The kernel will perform the identical function everywhere it goes, converting a convolution feature matrix into a separate convolution feature matrix [1].
- RELU Layer: ReLU stands for Rectified Linear Unit. The utilization of ReLu ensures that values within the neurons that are positive are maintained, but negative values are clamped down to zero. The advantage of using ReLu is that it allows the training process to be accelerated because the gradient descent optimization occurs at a faster rate than other standard non-linearity techniques [25].
- Batch Normalization: To avoid overfitting, familiarity with a pre-data processing tool is used to bring numerical data to a standard scale without distorting its structure [14]. Batch normalization is the process of making neural networks faster and more stable by adding additional layers to a deeper neural network.
- Max Pooling: Pooling layers are worn to reduce the scale of the feature maps. MaxPooling may be a merging function that selects the highest element from the feature map region covered by the filter [16]. Therefore, the output after the max-pooling layer is a feature map that contains the most prominent features of the previous feature map.
- Flatten: Flattening converts data into a 1-dimensional array to insert it into the next layer [21]. This layer is located after the final max-pooling layer. It is the input to the first Fully Connected (FC) layer. Flattening greatly reduces the number of learnable parameters and results in a lower computational cost.
- Dropout Layer. Following the first two layers (FC and RELU), dropout is a technique that is utilized to reduce a model's potential to overfit [7]. It is a technique where randomly chosen nodes are ignored in the network during the training phase at each stage. A dropout is a form of regularization that aims to prevent overfitting by increasing testing accuracy, perhaps at the expense of training accuracy.
- Fully Connected Layers. They are a basic part of convolutional neural networks (CNNs), which have been demonstrated to be fruitful in perceiving and arranging images [20]. The target of a fully connected layer is to take the consequences of the convolution or pooling cycle and use them to order the image into a name (in a straightforward arrangement model).
- SoftMax: It is an activation function in the output layer. The SoftMax activation function generates the outputs in the range of 0 and 1. The output of the SoftMax function is equivalent to a categorical probability distribution [8], it tells you the probability that any of the classes are true.
- CNN has demonstrated exceptional performance in a variety of computational intelligence challenges. Finding a systematic, automatic, and optimal set of hyperparameters for developing an efficient CNN for complicated tasks, on the other hand, remains difficult. Moreover, due to the advancement of technology, data is collected at sparse locations, and hence the accumulation of data from such a diverse and sparse location poses a challenge.

3.3Gender recognition using genetic algorithms

Genetic algorithms in machine learning are mainly adaptive heuristics or search engine algorithms that provide solutions for search and optimization problems. It is a methodology that solves unconstrained and constrained optimization problems based on natural selection. A genetic algorithm is an adaptive heuristic search algorithm inspired by" Darwin's theory of evolution in Nature [23]. It is one of the most important algorithms as it helps solve complex problems that would take a long time to solve. They are a single search optimization algorithm that aids in the discovery of the best potential solution by taking all restrictions into account. Furthermore, unlike other algorithms, it makes use of directed random search. It refers to finding the optimal solution by initiating the process with a random initial cost function and then searching for the one with the least cost in the space. It comes in handy when you are discovering solutions for huge and complex datasets.

Genetic algorithms are adaptive heuristic search algorithms based on the evolutionary ideas of natural selection and genetics [17]. As such, they represent an intelligent exploitation of a random search used to solve optimization problems. Genetic algorithms, while randomized, are by no means random; instead, they use historical information to direct the search into the region of better performance within the search space. Genetic algorithms are commonly used to generate high quality solutions to optimization and search problems by performing bio-inspired operators such as mutation, crossover, and selection. A standard genetic algorithm requires two prerequisites, i.e., a genetic representation of the solution domain and a fitness function to evaluate everyone [13]. Genetic algorithms were invented to mimic some of the processes observed in natural evolution. Many people, biologists included, are astonished that life at the level of complexity that is observed could have evolved in the relatively short time suggested by the fossil record. The goal of GA is to utilize this ability of evolution to address optimization issues. Genetic algorithms are a metaheuristic search technique based on the mechanisms of natural selection, genetics, and evolution. Previous works showed that metaheuristic methods are effective tools for solving complex search problems with large solution spaces, as depicted in Figure 7.

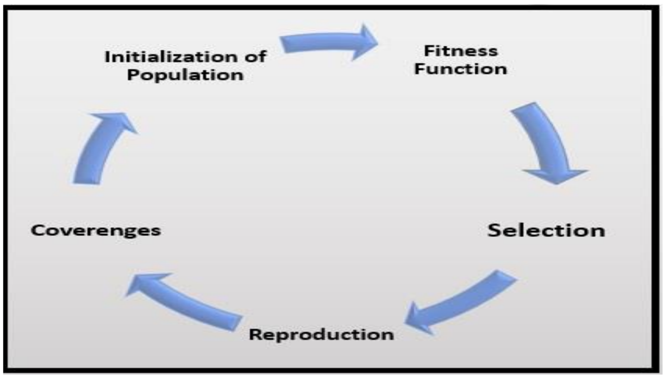

Figure 7: GA architecture

A genetic operator is an operator used in genetic algorithms to guide the algorithm towards a solution to a given problem.

There are three main types of operators:

1. Selection: Selection operators give preference to better solutions (chromosomes) allowing them to pass on their 'genes' to the next generation of the algorithm [5]. In genetic algorithms, the objective function is also referred to as the" fitness function" and it is used to choose the best solutions before passing them to the crossover operator. Different methods for choosing the best solutions exist, for example, Roulette wheel selection and tournament selection; different methods may choose different solutions as being 'best'. The selection operator may also simply pass the best solutions from the current generation directly to the next generation; this is known as elitism or elitist selection.

Algorithm 1: Fitness Function

```
Individual : individual Set images;
∀image ∈ imagesdo;
reconstructed ← individual(image);
fitness ← 0;
for ∀individual(image)do ;
fitness = Accuracy(individual);
for end;
return fitness;
```

2. Crossover: Crossover is the process of taking more than one parent solution (chromosomes) and producing a child solution from them. By recombining portions of good solutions, the genetic

algorithm is more likely to create a better solution [5]. As with selection, there are several different methods for combining the parent solutions, for example, single-point crossover and two-point crossover.

Algorithm 2: Crossover Algorithm

Individual parent1 , parent2;
Require: both parents are matrices of size m by n;
child $\leftarrow$ 0;
i $\leftarrow$ randomrange1..(m $\times$ n);
j $\leftarrow$ randomrange1..(m $\times$ n);
for $\forall parent_{(x,y)} do$;
if $(x \times m) + y$ *and* $(x \times m) + y$ **then**
    result $\leftarrow$ Feature Found;
    else
        result $\leftarrow$ Feature Not Found;
    end
end
for end;
return result;

3. Mutation: The mutation operator encourages genetic diversity amongst chromosomes and attempts to prevent the genetic algorithm from converging to a local minimum by stopping the chromosomes from becoming too close to one another. In mutating the current pool of chromosomes, a given chromosome may change entirely from the previous chromosome. By mutating the chromosomes, a genetic algorithm can reach an improved solution solely through the mutation operator [22]. Again, different methods of mutation may be used; these range from a simple bit mutation (flipping random bits in a binary string chromosome with some low probability) to more complicated mutation algorithms, which may replace genes in chromosomes with random values drawn from the uniform or Gaussian distributions.

Algorithm 3: Mutation Algorithm

Individual parent;
Require: parent is a matrix of size m by n;
child $\leftarrow$ parent;
i $\leftarrow$ randomrange1..(m);
j $\leftarrow$ randomrange1..(n);
k $\leftarrow$ randomgaussian;
$child_{(i,j)} \leftarrow$ k;
return child;

4. Proposed Method

Convolutional Neural Network (CNN) is a Deep Learning algorithm, which is used to distinguished if an input image is male or female. Genetic Algorithm are optimization techniques which are not guaranteed to produce better results than the search methodology they rely on, in this case an exhaustive search, but commonly outperform naive search methods [10]. Heuristics employ assumptions on the structure of the underlying data to attempt to shortcut the underlying search methods they are based on. Genetic Algorithms postulate that the search space contains gradients between poor solutions and good solutions. Convolutional neural network and genetic algorithms are two techniques for learning, each with its own strengths and weaknesses. The two have generally evolved along separate paths. When neural networks are coupled with genetic algorithms, the learning process can be really accelerated to solve a certain problem [19]. The deep neural network model is a nonlinear computational method for learning information from data and predicting complicated trends, regardless of the distributions to which errors are subjected or how complex the relationships hidden in the data are. It has been successfully applied to numerous areas such as speech recognition, human face recognition, crop yield prediction, crop type classification, weather forecasting, environmental monitoring, and image fusion. However, neural networks tend to get trapped in local extreme values during the training [15]. Therefore, this problem is solved by combining the neural network approach with optimization methods, such as genetic algorithms (GA) and have achieved a better performance and improved result, consequently. A genetic algorithm is used to solve some complex problems quickly that would have taken a much longer time when done manually. CNNGA technique depends on merging deep learning and genetic algorithms.

Algorithm 4: CNNGA Algorithm

Generate n (size of dataset) individuals) as chromosomes
Input dataset to convolutional neural network (CNN) Take the ouput of CNN as chromosomes Compute accuracy of each chromosomes as fitness function
$[Parent_i, Parent_j] \leftarrow Selectrandomlytwochromosomes(usingRoulettewheel)$
$[Offspring_i, Offspring_j] \leftarrow crossover(Parent_i, Parent_j)$
$[Offspring1_i, Offspring1_j] \leftarrow mutation([Offspring_i, Offspring_j])$
$[Parent_i, Parent_j] \leftarrow replacewith([Offspring1_i, Offspring1_j])$ $computefitnessvalueof([Offspring_i 1, Offspring1_j])$
If optimal solution found, then end If optimal solution is not found, then input the new population to CNN

GA parameters in the gender recognition are defined as follows:

4. Chromosome: An image from the dataset.
5. Gene: A feature in the image.
6. Population: A dataset.
7. Fitness: An accuracy value.
8. Fitness function: An activation function.
9. Selection, Crossover, Mutation: Three steps to reproduce a better dataset.

4.1 CNNGA Method Architecture

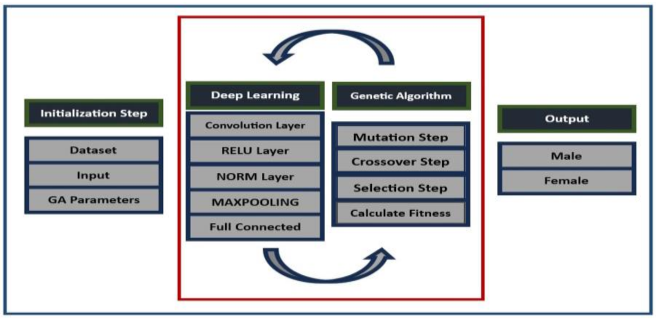

Figure 8: CNNGA Architecture

Figure.8 shows the steps of the CNNGA technique as follows:

1. Determine the input dataset.
2. Initialization: In this step, all the parameters that are related to the genetic algorithm are initialized.
3. Number of Population: It is initialized randomly.
4. Size of Population: It is the number of chromosomes in a population, which in this proposed work equals the size of the dataset.
5. Fitness Function: In this proposed work, the accuracy of the solution (chromosome) is used as the fitness function.
6. Deep Learning Step: Several convolutional layers and fully connected layers are designed. But the input and classification layers are deleted.
7. The condition to evaluate the solutions is when the fitness value is the most accurate value for a solution.

8. Genetic Algorithm Step:

A. Selection operator: Roulette-wheel selection is used to select two chromosomes with high fitness value (accuracy). The larger the fitness of an individual, the more likely its selection as depicted in Figure 9.

B. Crossover Operator: A Two-Point crossover is used to exchange the genes between the selected chromosomes to get the best new ones. It is equivalent to performing two single-point crossovers with different crossover points as depicted in Figure10.

C. Mutation Operator: Inversion Mutation is used. It selects two positions within a chromosome or tour at random and then inverts the cities in the substring between these two positions as depicted in Figure 11.

At the initialization stage, there are five parameters that should be considered, such as population size (n), generation size (iteration process), probabilities of crossover and mutation, and the length of chromosomes. After the initialization step, the dataset is used in a deep learning (CNN) step as input. The output will be the result of a fully connected layer. The fitness function (accuracy) of individuals is calculated and checked for an optimal solution. If the optimal solution is found, go to the classification layer. If there is no optimal solution, the individuals pass to genetic algorithms as follows:

1. Selection operator: Roulette-Wheel Selection
2. Crossover Operator: A Two-Point Crossover
3. Mutation Operator: Inversion Mutation is used.

The new offspring, resulting from the previous three steps, are replaced by their parents in the new population, and then this population is passed to deep learning as an input.

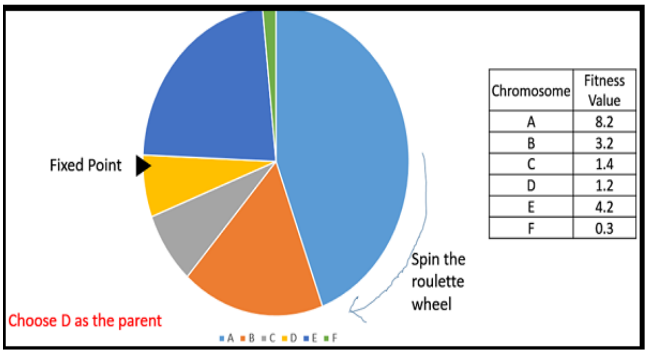

Figure 9: Selection Operator

Chromosome1	11011|00100|110110
Chromosome2	10101|11000|011110
Offspring1	11011|11000|110110
Offspring2	10101|00100|011110

Figure 10: Crossover Operator

Parent	11001 11010	11100	111110
Offspring	11001 11010	00111	111110

Figure 11: Mutation Operator

Figure.12 represents CNNGA technique that is used to develop the way to recognize the gender from selfie images by merging deep learning with genetic algorithms.

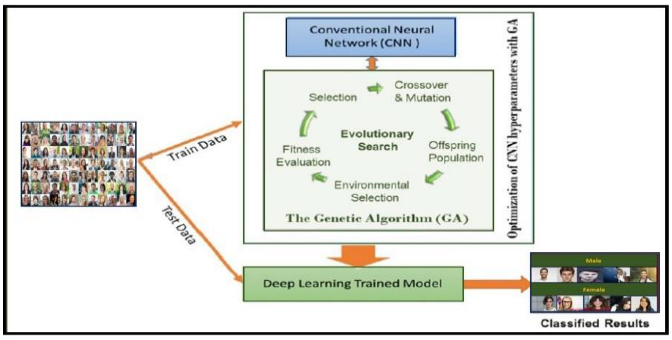

Figure 12: CNNGA Technique

5. Experiments and Results

5.1 Dataset

This paper makes use of a variety of challenging and benchmark datasets. These datasets are usually required to properly test and measure the performances, as depicted in Figure. 13.

Figure 13: Benchmark Datasets

Gender image datasets can be grouped into two main categories: constrained and unconstrained. The first is the LFW dataset, a public face verification benchmark composed of 13233 images for 5749 people. The second dataset is the FERET dataset, which is a standard facial recognition dataset with 14126 images, 1199 individuals, and 365 duplicate image sets. The third is the CaltechWebFaces dataset, which has a total of 10524 faces in 7092 images gathered from the internet. The fourth is the Data Hub dataset, which is composed of 214 images and a common facial analysis dataset. The fifth dataset is a selective group of 500 images that were chosen at random from the internet, called DS1. The sixth is the OriginalPics dataset, which is a common facial analysis dataset that is composed of 28035 images. The seventh is the Selfie dataset, which is composed of 12709 images, and the common facial analysis dataset. All datasets are very challenging and depict various resolutions and in different settings, e.g., portrait images.

5.2 Deep Learning Step

Deep learning is used to extract relevant features that differentiate between males and females. The input to the deep learning step, for the first time, is one of the previous datasets for the gender recognition problem. This dataset is a group of label images that contain categories of the problem (male, female). This dataset is passed to the input layer of a convolutional neural network (CNN). The result of the last layer (the fully connected layer) is a set of labelled images with a probability for each image.

5.3 Optimal Solution Step

The output of deep learning is a set of individuals with a probability of being the solution. The first step is to check the accuracy of everyone by using the fitness function:

1. If one of the individuals (chromosomes) accuracy is equal to or approximates the optimal solution accuracy, this will be the output (male or female) of the technique.
2. If there is no individual equal to the optimal solution, go to the genetic algorithm step.

5.4 Genetic Algorithm Step

The input of the genetic algorithm is the set of individuals resulting from the deep learning step. The genetic algorithm consists of three steps:

1. Selection Operator: It is Roulette-Wheel selection. This technique is used to select two chromosomes with a high fitness value (accuracy). With it, the larger the fitness of an individual is, the more likely its selection is.
2. Crossover Operator: A Two-Point crossover is used to exchange the genes between the selected chromosomes to get the best new ones. It is equivalent to performing two single-point crossovers with different crossover points.
3. Mutation Operator: Inversion Mutation is used. It selects two positions within a chromosome or tour at random and then inverts the cities in the substring between these two positions. The output of the genetic algorithm is the input to the deep learning step.

6. Performance of CNNGA Technique

According to the standard experimental design, all datasets were randomly split by assigning 70% of the images to training and 30% to validation. Furthermore, the accuracy measure is used, as it reviews the percentage of successfully recognized images with respect to the total dataset. The following equation Eq.1 depicts the accuracy metric's formula.

$$\textbf{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Where TP are the retrieved relevant-matches, FP are the retrieved irrelevant matches, FN are the missed relevant matches and TN are the not retrieved relevant matches.

6.1 Accuracy of Deep Learning Stage

The first step is to use the benchmark datasets to test the performance of the model that use deep learning only. Figure.14 presents samples of the output of using deep learning in recognizing the gender.

Figure 14. Samples of Gender Recognition of using CNN

In the final, deep learning model alone achieves 98.2% using LFW dataset, but it achieves 89.5% using Selfie dataset.

6.2 Accuracy of CNNGA Technique

CNNGA technique used in this work depends on merging deep learning and genetic algorithms in gender recognition by using benchmark datasets. Figure.15 present samples of the output of using CNNGA technique in recognizing the gender.

Figure 15. Samples of Gender Recognition using CNNGA Technique

To ensure that CNNGA technique achieves high accuracy, it is compared with deep learning method using different dataset, as shown in Table 1.

Table 1: Comparison Between DL and (CNNGA) Models Using Different Datasets

Baseline	DS1	LFW	Data-Hub	FERET	Caltech Web Faces	Original Pics	Selfie
CNNGA Technique	92.5%	99.1%	94.2%	90.5%	97 %	89%	90.2%
Deep Learning	92.3%	98.2%	92.2%	90.5%	86.3%	91.7%	89.5%

In the final, the CNNGA technique achieves 99.1% using LFW dataset, but it achieves 90.2% using Selfie dataset.

6.3 Biometric Metric for (CNNGA) Model

The performance of this thesis is evaluated by using the accuracy measure, as it reviews the percent of successfully recognized images to the total dataset as depicted in Table.2 and Chart1. Another performance measure is biometric metrics that are used to evaluate the effectiveness of the CNNGA technique, as FRR refers to the false rejection ratio, which measures the percentage of valid inputs that are incorrectly rejected. FAR refers to the false acceptance ratio, which measures the percentage of invalid inputs that are incorrectly accepted. EER refers to an equal error rate, which is the rate at which both acceptance and rejection errors are equal.

Table 2: Performance of Two Approaches

Method	Accuracy	CNNGA-Accuracy	FRR	FAR	EER
Deep Learning	98.2%	89%	3%	4.5 %	6.5 %
CNNGA	99.1%	90.2%	4.8 %	5%	6%

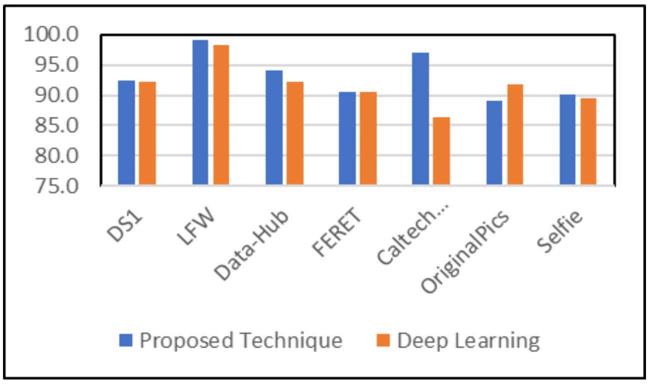

Chart -1: Comparison Between DL and (CNNGA) Models

7. Conclusion

Previous studies depended on conventional neural networks (CNN) in gender recognition. In this research, there is an effective technique for recognizing gender from selfie images by optimizing a CNN model with a genetic algorithm. The CNNGA technique achieves 99.1% accuracy on the common benchmark dataset, LFW. This work applies to selfie images, which are a recent type of unconstrained image. This type of image has become very popular with humans and their applications, so there is a need to deal with selfie images.

Future work is on how to increase the accuracy of recognizing gender from selfie images. Another work is how to determine the best way to deal with a lot of complicated selfie datasets.

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