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Facial Race and Gender Recognition Based on Convolutional Neural Network Models

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ABSTRACT: Facial recognition is important due to its broad implications for fairness, ethics, social justice, legal adherence, technological advancement, and public confidence. By pushing forward research efforts in this domain and crafting more precise and impartial systems, we can contribute to fostering a fairer and more inclusive society. Researchers and developers have widely adopted deep learning and computer vision techniques across various domains, particularly in addressing issues of bias and representation, demonstrating notable and swift progress. To distinguish individuals based on gender and race, developers often focus on analyzing colours and facial features. This thesis presents a unique convolutional neural network model that identifies facial race and gender. The model underwent training, validation, testing and evaluation on datasets encompassing four racial categories (African, Asian, Indian, and Caucasian) and both genders. We curated these datasets from various sources, such as "beautiful face," "SCUT-FBP5500_v2," also known as the AFD dataset, "cnsifd_faces_bmp," "Indian_actors_faces," and "img_align_celeba." The combined datasets for the four racial groups comprise 2,400 publicly identifiable images, evenly divided into 1,200 males and 1,200 females. Each racial category includes 600 randomly selected samples, with 300 from each gender. This study compares the performance of Race Gender Convolution Neural Network (RGCNN) to three pre-trained CNN models such as Microsoft Residual Network 50 layers ResNet50, Google Net InceptionV3 and Visual Geometry Group VGG19. Analysis of the experimental outcomes reveals that the Race Gender Convolution Neural Network (RGCNN) outcomes outperform the other models in terms of accuracy in both racial and gender classification. Following in racial classification, ResNet50 is in second place, InceptionV3 is in third place and VGG19 trails behind. The RGCNN model stands out for its lightweight design and reduced parameter count. On the other hand, the VGG19 model comes in second. Regarding parameter count, InceptionV3 is third, followed by ResNet50, which has the highest parameter count. The system's predictive capabilities, encompassing race and gender classifications across a sample size of 40 individuals, achieve an impressive 98% accuracy rate.

Keywords *- Facial Race and Gender Recognition, Race Determination, Gender Determination, Security Systems with Deep Learning.*

ÖZET: Yüz tanıma, adalet, etik, sosyal adalet, yasal uyum, teknolojik ilerleme ve kamu güveni üzerindeki geniş etkileri nedeniyle önemli bir öneme sahiptir. Bu alandaki araştırma çabalarını ilerletmek ve daha hassas ve tarafsız sistemler oluşturmak suretiyle, daha adil ve daha kapsayıcı bir toplumun gelişmesine katkıda bulunabiliriz. Derin öğrenme ve bilgisayarlı görme teknikleri, özellikle önyargı ve temsil sorunlarını ele almak üzere çeşitli alanlardaki araştırmacılar ve geliştiriciler tarafından yaygın bir şekilde benimsenmiş ve kayda değer ve hızlı bir ilerleme göstermiştir. Bireyleri cinsiyet ve ırka göre ayırt etmek için, geliştiriciler genellikle renkleri ve yüz özelliklerini analiz etmeye odaklanır. Bu tez, yüz ırkını ve cinsiyeti tanımlayan benzersiz bir evrişimli sinir ağı modeli sunmaktadır. Model, dört ırk kategorisini (Afrikalı, Asyalı, Hintli ve Kafkasyalı) ve her iki cinsiyeti kapsayan veri kümeleri üzerinde eğitim, doğrulama, test ve değerlendirmeye tabi tutulmuştur. Bu veri kümelerini "beautiful face", "SCUT-FBP5500_v2", AFD veri kümesi olarak da bilinir, "cnsifd_faces_bmp", "Indian_actors_faces" ve "img_align_celeba" gibi çeşitli kaynaklardan derledik. Dört ırk grubu için birleştirilmiş veri kümeleri, 1.200 erkek ve 1.200 kadın olmak üzere eşit şekilde bölünmüş 2.400 adet genel olarak tanımlanabilir görüntüden oluşur. Her ırk kategorisi, her cinsiyetten 300 olmak üzere 600 rastgele seçilmiş örnek içerir. Bu çalışma, Irk Cinsiyet Evrişim Sinir Ağı'nın (RGCNN) performansını Microsoft Residual Network 50 katmanları ResNet50, Google Net InceptionV3 ve Visual Geometry Group VGG19 gibi üç önceden eğitilmiş CNN modeliyle karşılaştırır. Deneysel sonuçların analizi, Irk Cinsiyet Evrişimli Sinir Ağı (RGCNN) sonuçlarının hem ırk hem de cinsiyet sınıflandırmasında doğruluk açısından diğer modellerden daha iyi performans gösterdiğini ortaya koymaktadır. Irk sınıflandırmasında ResNet50 ikinci, InceptionV3 üçüncü sırada yer alırken, VGG19 geride kalmaktadır. Özellikle, RGCNN modeli hafif tasarımı ve azaltılmış parametre sayısıyla öne çıkmaktadır. Öte yandan, VGG19 modeli ikinci sırada yer almaktadır. Parametre sayısı açısından, InceptionV3 üçüncü sırada yer alırken, onu en yüksek parametre sayısına sahip olan ResNet50 takip etmektedir. Sistemin, 40 kişilik bir örneklem büyüklüğünde ırk ve cinsiyet sınıflandırmalarını kapsayan öngörü yetenekleri etkileyici bir %98 doğruluk oranına ulaşmaktadır.

Anahtar Kelimeler *- Yüz Irkı ve Cinsiyet Tanıma, Irk Belirleme, Cinsiyet Belirleme, Derin Öğrenme ile Güvenlik Sistemleri.*

1. Introduction

The automatic detection of a person's race based on facial features is becoming an increasingly significant problem [1]. In numerous applications, including the access control of security systems and the indexing of video retrieval systems based on content, like the content-based audiovisual archives network multiagent system [2], That offers helpful illumination for deciphering other intricate patterns. Human biometric recognition is ongoing and impartial due to the disciplines of deep learning and computer vision that remain incrementally growing [3]. The automatic detection of a person's race based on facial features is becoming an increasingly significant problem in numerous applications, including the access control of security systems and the indexing of video retrieval systems based on content, like the content-based audiovisual archives network multiagent system [4]. That offers helpful illumination for deciphering other intricate patterns. Human biometric recognition is ongoing and impartial due to the disciplines of deep learning and computer vision that remain incrementally growing [5]. The researchers' investigations showed that facial recognition highly depends on the human race. From this vantage point, it has emerged as an important investigation based on the Sunnah algorithms for facial recognition through race. Nowadays, biometric identification is a more accurate way of categorizing people according to their physical characteristics and assigning them a specific identity [6]. Every person of a given culture will likely share similar racial characteristics. This concept is useful to researchers in various sectors, including archaeology and biomedicine, who identify ancient and ancestor humans and use images of people to pinpoint them on a continent [7]. Face recognition is the technology that is most commonly used in areas where people are always on guard, such as stadiums, trade centres, and airports worldwide. It enables passive identification without the suspect noticing it. It is accurate and non-intrusive. Images of human faces can be used to determine demographic details like gender, age, and ethnicity. When wearing a disguise, it is easy to conceal age and gender. Age-based classification would be difficult to implement strategically; therefore, it can't be standardized. Identification will perform effectively. And effectively reduce the search scope if the suspect's race is known in advance [8]. Most of the time, it's just an afterthought experiment where people use their images to recognize faces. There have been considerations of four major races: African, Asian, Caucasoid, and Indian. The four races' most notable characteristics are examined and explored. This efficiently streamlines the algorithm, resulting in quicker outcomes. Convolutional neural networks, or CNNs, have been achieving amazing things. Identification will function better. It has become one of the most representative neural networks in deep learning. CNN-based computer vision has enabled individuals to perform tasks that were previously considered impossible, like intelligent medical interventions, self-driving cars, self-serve grocery stores, and facial recognition. In this article, we discuss traditional models and applications, provide an overview of convolutions, and suggest future directions for CNN to understand contemporary CNN better and help it better serve people [9]. A certain kind of feedforward neural network called a CNN can derive features from data using convolution structures [10]. CNN does not require manual feature extraction, in contrast to conventional feature extraction techniques. CNN's architecture draws inspiration from visual perception. Constant progress in deep learning and computer vision has made comprehending human face recognition patterns an important objective. A wealth of evidence suggests that the human race significantly impacts face recognition [11]. This research uses a new lightweight CNN model, dubbed RGCNN, to classify faces based on gender and race. RGCNN reduces the number of parameters while maintaining a high rate of performance. The remainder of the document is structured as follows: In section 2, the letteral review. The methodology is section 3. Section 4 is the result and discussion. Finally, the conclusion is in section 5.

2. Letteral Review

Katti H et al. [12] presented an analysis that examined how well humans and machines performed on the difficult task of classifying Indian faces based on ethnicity. They also established and collected the Centre for Neuroscience Indian Face Dataset (CNSIFC), which consists of 1650 faces labelled with ethnicity (South vs North Indian). For this binary ethnic classification task, they trained several classifiers using CNN-based features, local form features, or spatial intensity features. The classifiers achieved the highest accuracy of 62% using CNN-based features.

Puc A. [13] systematically analyzed the performances of two commercially available deep age estimation algorithms using facial image data from the public datasets APPA-REAL and UTKFace. They estimated ages for pertinent demographic subcategories to investigate racial and gender prejudice in more detail. The existing datasets used to represent gender and ethnicity in the training and testing age estimation algorithms are not comprehensive enough. They also observed that the tested models performed better on male than female subjects. However, they could not identify overt or ongoing bias against one race. Particularly for uncontrolled face photographs, test dataset variables such as image quality, position, illumination, occlusion, and so on appear to have a stronger impact on age estimate performance than race. More research is necessary to understand the factors influencing age estimation accuracy properly. This situation seems unique in that there are no distinct quality borders among different demographic groups, making it hard to evaluate the effectiveness of the existing models equitably.

Wang M et al. [14], The 4K Racial Faces in the Wild (RFW) dataset was constructed and collected, consisting of pictures representing the four ethnic groupings of African, Asian, Indian, and Caucasian faces. We chose the ethnic group based on data from a list of celebrities. The database consists of pictures from MS-Celeb-1M labelled using the Face++ API. The study validated the racial bias of the most advanced facial recognition system using this standard. The authors suggested a deep information maximization adaptation network that uses Caucasians as the source domain and other races as the target domains to address racial bias. They used to validate four commercial APIs rigorously' and four state-of-the-art (SOTA) algorithms' racial bias. Then, by employing Caucasian as the source domain and other races as target domains, further describe the solution utilizing deep unsupervised domain adaptation and suggest a deep information maximization adaptation network (IMAN) to mitigate this bias. At the cluster level, this unsupervised method learns the discriminative target representations. At the same time, it aligns the global distribution to lower the racial disparity at the domain level. We suggest a new mutual information loss to improve network output discrimination without labelling information further. Long-term tests on the RFW, GBU, and IJB-A databases show that IMAN learns features that work well in various racial and database settings.

Narang N et al. [15] proposed a deep network for recognizing visible and multi-distance infrared images for Asian or Caucasian racial groupings and male and female groups. After training and testing on images related to a modest 203 classes, the model performs well and achieves a 95% success rate in classifying races.

Muhammad G et al. [16] proposed a method for recognizing race from face images using Weber local descriptors (WLD). Initially, the algorithm extracts the WLD histogram from photos of normalized faces. Next, the algorithm selects the optimal bins using the Kruskal-Wallis feature selection technique. They perform testing using chi-square, Euclidean, and city block minimum distance classifiers. The FERET database utilized in the studies represents the five main racial groupings: Asian, African, American Black, Hispanic, Middle Eastern, and White. According to experimental data, the proposed system employing a city block distance classifier, WLD histogram, and feature selection obtains the following accuracy rates: Asian: 97.74%, Black: 96.89%, Hispanic: 92.06%, Middle: 98.33%, and White: 99.53%. Comparing these accuracies to principal component analyses, they are noticeably greater.

Roomi SM et al. [17] proposed a method that can easily be incorporated into any facial recognition system to recognize humans into three major races: Caucasoid, Negroid, and Mongoloid. The suggested classification technique first extracts the unique principal facial feature, skin colour model, and other secondary aspects like the supplied face's lip and forehead to classify the races properly. Comprehensive simulations using photos from Yale, FERET, and other sources demonstrate how well the suggested approach performs.

3. Methodology

3.1 The datasets

The proposed model's dataset includes images of individuals displaying all the mentioned races. In this study, we utilized the dataset from various sources:

1. Samples of Asian face images were collected from three data sets: the first dataset, Pretty Face, contains 3318 images. The number of samples selected from this dataset is 497; the second dataset is SCUT-FBP5500_v2.1, which consists of 5500 images and randomly selected (1005) images. The third dataset is referred to as the AFD dataset. We arrange the images in 135 directories, each name representing the actor's present facial image. The total number of images for each actor is different. There are 598 images of randomly selected samples. This translates to 2100 randomly selected Asian face-race samples, as illustrated in Table 3.1.

Table 3.1. The Asian Face Race Samples

Race	Datasets Name	Dataset samples	Selected samples
Asian face	pretty-face [18]	3318	497
	SCUT-FBP5500_v2.1[19]	5500	1005
	CASIA-FaceV5[20]	135 directories	598
Total			2100

The Asian face race random samples that are collected from the three datasets shown in Figure 3.1

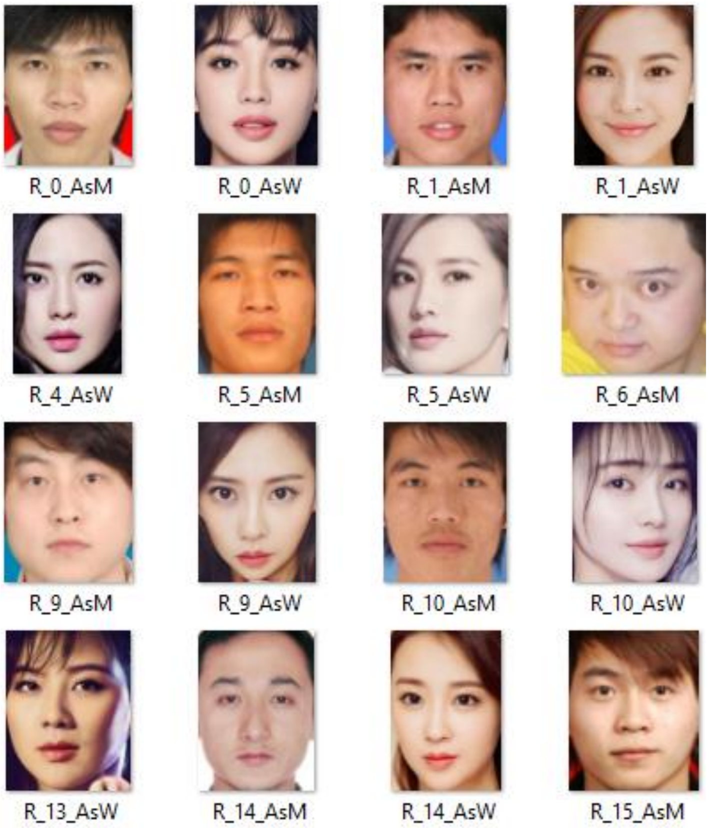

Figure 3.1. The Asian Face Race Samples

2. The collected images of Indian faces came from two datasets. The first dataset, cnsifd_faces_bmp, consists of 1647 images. We selected 804 samples from this dataset, called the second dataset, Indian_actors_faces. We arrange the images in 135 directories, each name representing the actor's facial image. The total number of images for each actor is not exactly equal. The total number of randomly selected samples is 906. Table 3.2 shows that there are 1710 randomly selected Indian face-race samples.

Table 3.2. The Indian Face Race Samples

Race	Datasets name	Dataset samples	Selected samples
India face	cnsifd_faces_bmp [21]	1647	804
	Indian_actors_faces [22].	135 directories	906
Total			1710

The Indian face race random samples that are collected from the two datasets shown in Figure 3.2

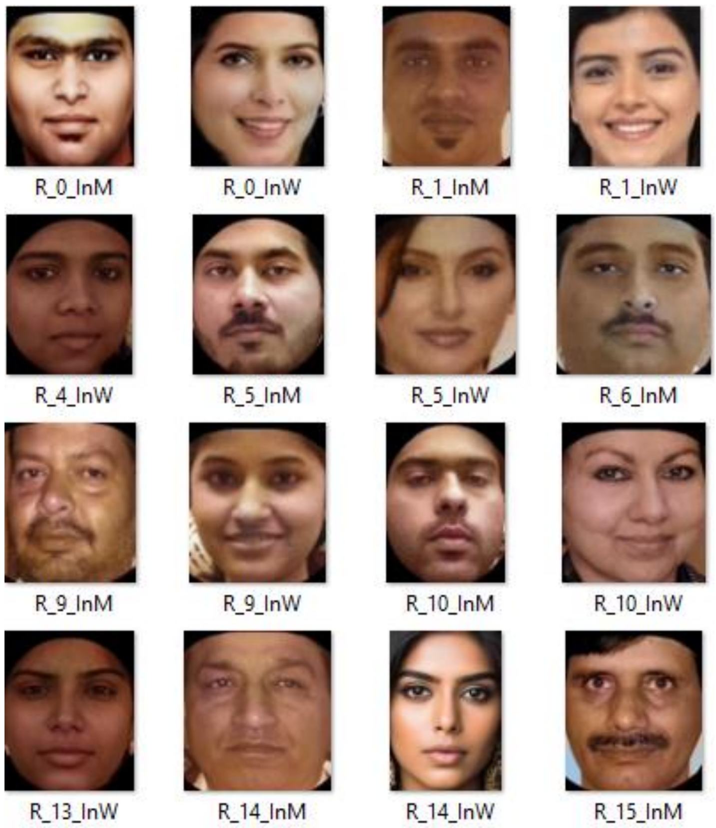

Figure 3.2. The Indian Face Race Samples

3. The Caucasian faces are samples collected from the img_align_celeba dataset, which consists of 202599 images. As illustrated in Table 3.3, 1785 images were selected randomly for the samples.

Table 3.3. The Caucasian Face Race Samples

Race	Dataset name	Dataset samples	Selected samples
Caucasian face	img_align_ celeba [23].	202,599	1785
Total			1785

The Caucasian face race random samples that are collected from the one dataset shown in Figure 3.3

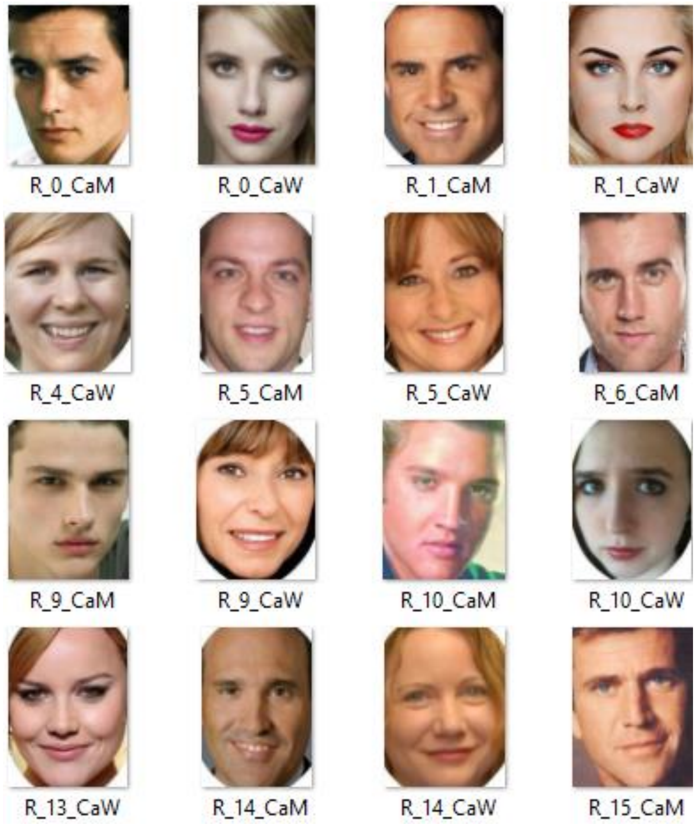

Figure 3.3. The Caucasian Face Race Samples

4. The 38546 images of African faces collected in the CASIA-Face-Africa dataset are illustrated in Table 3.4. The total number of samples selected randomly from this dataset is 1286 images.

Table 3.4. The African Face Race Samples

Race	Dataset name	Dataset samples	Selected samples
African face	CASIA-Face-Africa [24].	38,546	1286
Total			1286

The African face race random samples that are collected from the one dataset shown in Figure 3.4

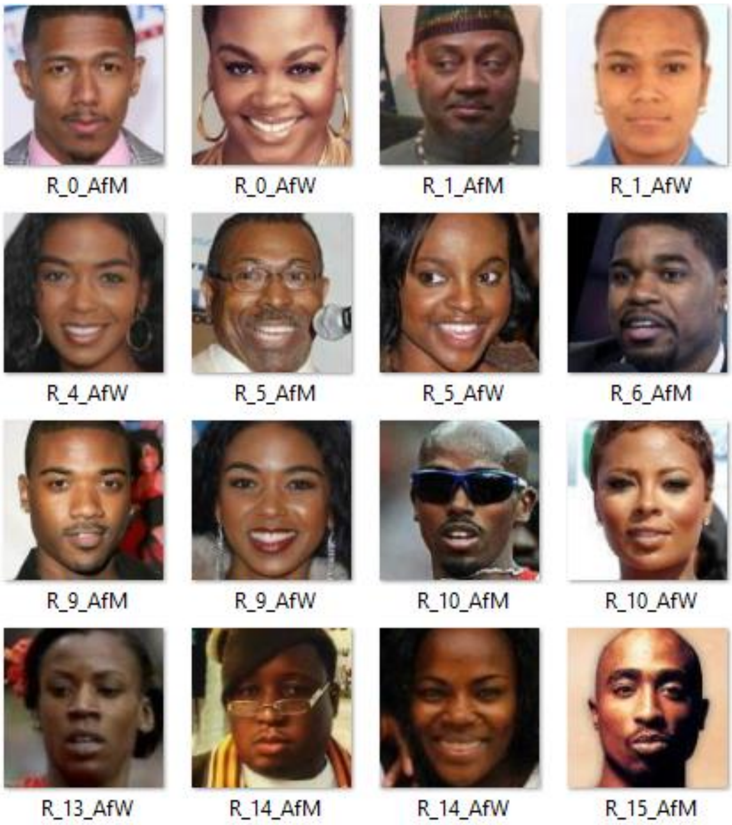

Figure 3.4. The African Face Race Samples

3.2. Preprocessing of the dataset

In the four race datasets, the total number of selected images is 6881, separated between males and females. The number of female images is 3200, and the number of male images is 3681. From each race, we randomly selected 300 females and 300 males, as illustrated in

Tables 3.5 and 3.6. The sum of 300 images from each race and gender will be 1200 female and 1200 male images, as illustrated in Tables 3.5 and 3.6.

Table 3.5. The race datasets samples used in this study

Race	Sample dataset	Selected Dataset
Asia	2100	600
Africain	1286	600
Caucasian	1785	600
India	1710	600

Table 3.6. The gender datasets samples used in this study

Gender	Sample dataset	Selected Dataset
Female	3200	1200
Male	3681	1200

3.3 CNN Models

This new model, called RGCNN, has a minimum number of parameters to recognize four races (African, Asian, Caucasian, and Indian) and their genders. The RGCNN model has several convolutional layers followed by dense layers, as Table 3.7 illustrates:

Table 3.7. RGCNN model

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 150, 150, 16)	784
max_pooling2d (MaxPooling2D)	(None, 75, 75, 16)	0
conv2d_1 (Conv2D)	(None, 75, 75, 32)	8224
max_pooling2d_1 (MaxPooling2	(None, 37, 37, 32)	0
conv2d_2 (Conv2D)	(None, 37, 37, 64)	32832
max_pooling2d_2 (MaxPooling2	(None, 18, 18, 64)	0
conv2d_3 (Conv2D)	(None, 18, 18, 128)	131200
max_pooling2d_3 (MaxPooling2	(None, 9, 9, 128)	0
flatten (Flatten)	(None, 10368)	0
dense (Dense)	(None, 128)	1327232
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 2)	258

Total params: 1,500,530
Trainable params: 1,500,530
Non-trainable params: 0

a. Visual Geometry Group (VGG-19)

The 1.3 million ImageNet ILSVRC dataset, including 10,000 classes, 100,000 training photos, and 50,000 validation images, was used as the Visual Geometry Group (VGG) training set. VGG-19, a variant of the VGG architecture with 19 highly connected layers, has consistently surpassed another cutting-edge model in terms of performance [25]. Before using the SoftMax activation function to classify the data, the VGG19 model uses completely connected and highly connected convolutional layers to improve feature extraction and reduce sample size. MaxPooling is utilized instead of average pooling [26].

b. Google Net InceptionV3

InceptionV3 is one of the deep CNN architectures that is widely used. One of the most sophisticated deep learning models for image recognition is Google's InceptionV3, utilized for computer vision applications such as object identification, image segmentation, and facial recognition [27]. Based on the Inception module, its architecture allows the network to handle a wide range of complex and diverse picture datasets by learning and extracting features from a wide range of input image scales and resolutions [28]. The InceptionV3 architecture's usage of asymmetric convolutions was one of the many improvements over its predecessors. The idea was to divide the standard 3x3 convolution kernel into asymmetric kernels of different sizes, such as 1x3 and 3x1, to compare the amount of processing. Splitting the 3x3 convolution into 1x3 and 3x1 convolution layers reduced the computation quantity by 33%, whereas splitting it into two 2x2 convolutional layers only reduced it by 11% [29].

c. Microsoft Residual Network 50 layers ResNet50

The ResNet-50 (residual neural network), a version of the Microsoft ResNet architecture with 50 deep layers, has been trained using at least one million images from the ImageNet database [30]. Triple-layer skips with nonlinearities, or TDouble, and batch normalization are the two methods most frequently used in ResNet models. Highway Net is a model that is commonly employed in ResNet models. It determines the skip weights by using an additional weight matrix. Average pooling is used in the ResNet-50 architecture's convolutional block sequences [31]. The last layer of classification is SoftMax. They elucidated the core idea of ResNet50 in greater detail in their study on diagnosing macular diseases from optical coherency tomography photos [32]. The ResNet-50 consists of conv1, conv2_x, conv3_x, conv4_x, and conv5_x, which are five convolutional layers. Following loading, the input image is sent via a 64-bit convolutional layer (conv1 layer) with a kernel size of 7. This is a following maximum by a maximum x pooling layer with a stride length of two in both situations. Next, the layers in $conv2\_x$ are grown according of use to the residual networks' connectivity. A third layer of $kerbeme = 3\ x\ 3$, $numf\ iltee = 64$, repeated three times, corresponds to the lev between $ponl$ and $*2$. Similarly, the process continued until the fifth convolutional layer was classified, where the average pooling at the fully connected layer and SoftMax were used for classification [33].

d. The Race and Gender Methodology.

Figures 3.5 and 3.6 illustrate that the race and gender model has two primary components: the training phase and the testing phase. The dataset is split 70% for training and 30% for testing. Every model underwent training and testing on all four races and genders.

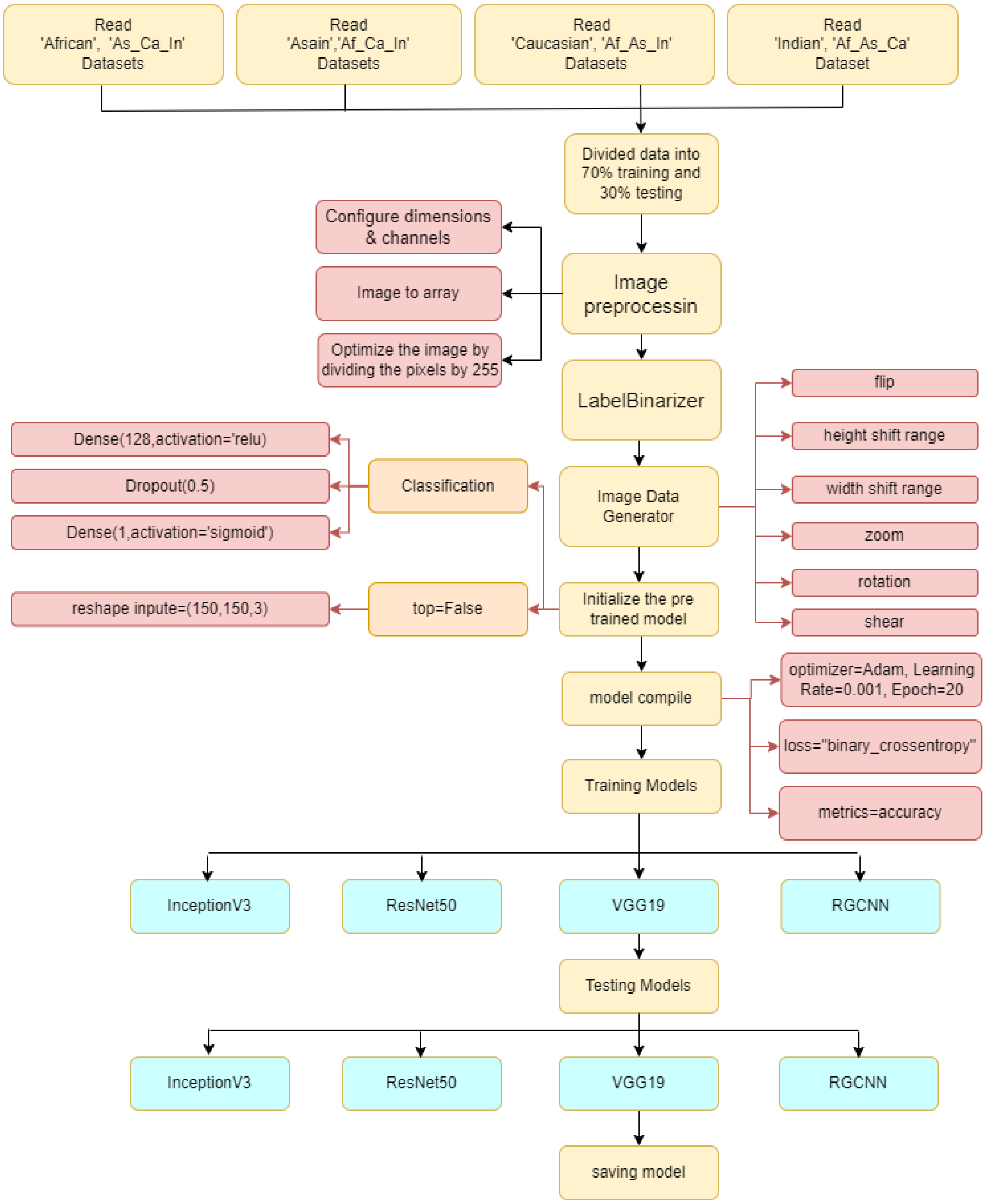

Figure 3.5. The race training and testing process based on four models

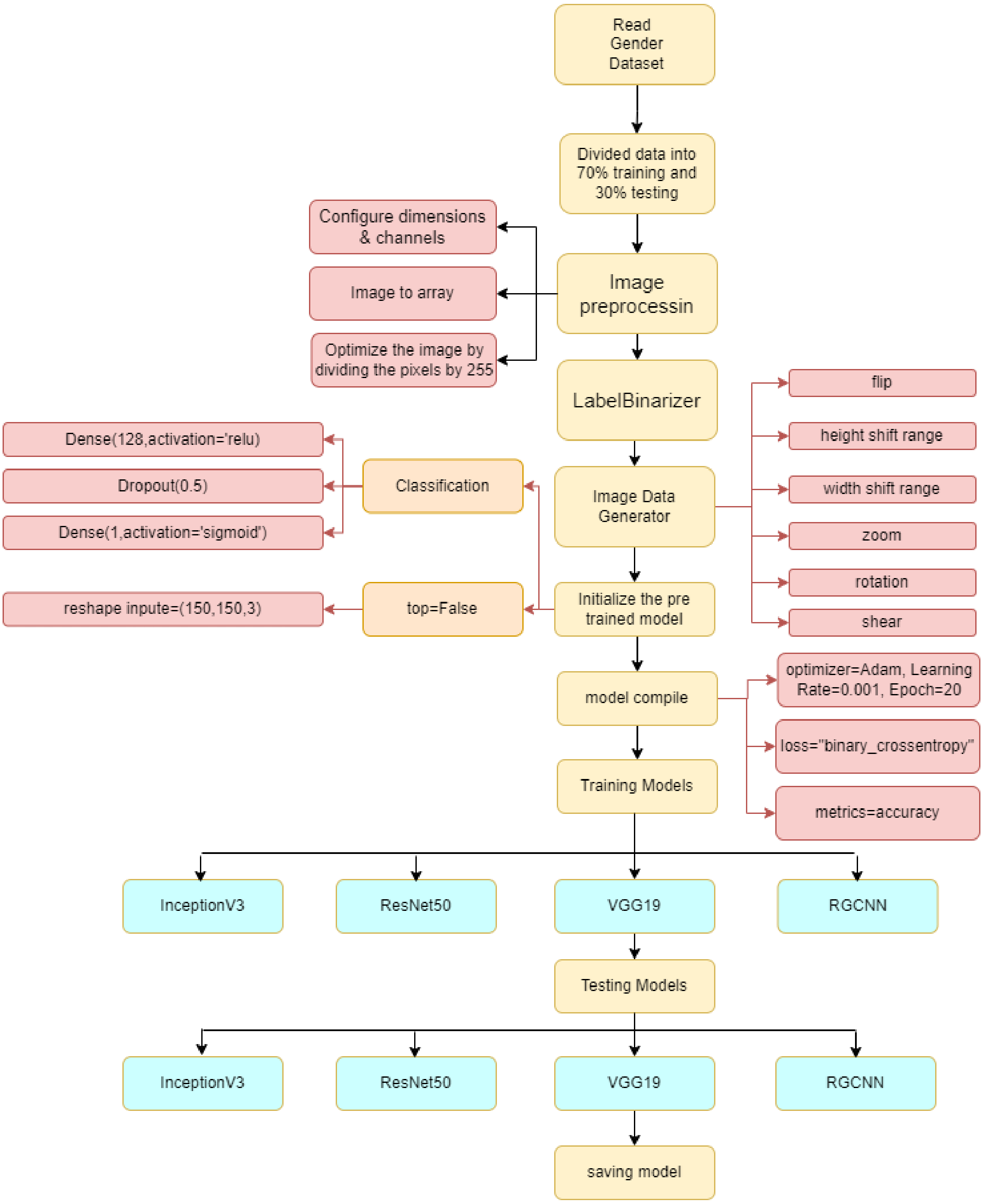

Figure 3.6. The gender training and testing process based on four models

3.3 The Performance Measures and Validation.

In this section, we discuss the critical performance evaluation metrics to assess the effectiveness of the proposed model. The row values, including True positive (TP), Tue Negative (TN), False Positive (FP), and False Negative (FN), are used to calculate important metrics like Accuracy, Precision, Recall and F1-Score [34]. As illustrated in the below functions:

1. Accuracy = (TP+TN) / (TP+TN+FP+FN) (1)

2. Precision =(TP) / (TP+FP) (2)

3. Recall =(TP) / (TP + FN) (3)

4. Specificity = (TN) / (TN + FP) (4)

5. F1− score =2 x (Precision x Recall) / (Precision + Recall) (5)

All models were trained and tested for 20 epochs using the ADAM optimizer, with a (0.001) learning rate and a batch size of (420) for both race and gender datasets.

4. Result and Discussion

This section displays the performance evaluation of the CNN models for each race and gender. For this work, we utilized Python on a computer with an Intel® CoreTMi7-4700MQ CPU running at 2.40 GHz with 64 bits. The four models were evaluated using 70% of the race and gender pictures for training and validation, while the remaining 30% was used for testing. The accuracy rate serves as a criterion for evaluating each model's performance in terms of recognition. Table 4.1 illustrates the performance evaluation of the RGCNN model on the race and gender dataset.

Table 4.1. The four races and gender performance evaluation based on RGCCN model.

Race and Genders	Precision	Recall	F1-score	Accuracy
African	0.989	0.994	0.992	0.996
Asian	0.983	0.982	0.982	0.974
Caucasian	0.998	0.976	0.987	0.980
Indian	0.967	0.989	0.978	0.967
Female Male	0.930 0.950	0.960 0.930	0.950 0.940	0.944

As the table illustrates, the African race shows the highest accuracy ratio, with 99.6% compared to other races. The Caucasian race, on the other hand, comes in second with 98%. Finally, Asian and Indian are the last two races with a lower accuracy rate, at 97.4% and 96.7. For classifying genders, the accuracy is 94.4.

Table 4.2 illustrates the performance evaluation of the VGG19 model.

Table 4.2. The four races performance evaluation based on VGG19 model.

Race and Genders	Precision	Recall	F1-score	Accuracy
African	0.982	0.980	0.987	0.994
Asian	0.963	0.981	0.972	0.958
Caucasian	0.968	0.966	0.977	0.968
Indian	0.967	0.969	0.968	0.951
Male	0.930	0.960	0.950	0.870
Female	0.950	0.930	0.940	

In comparison to other races, the African race exhibits the highest accuracy ratio (99.4%), as the table demonstrates. In contrast, the Caucasian race ranks second with 96.8%. The final two races with lower accuracy rates, at 95% each, are Asian and Indian. For classifying genders, the accuracy is 87.0. Table 4.2 presents the evaluation of performance by the VGG19 model.

Table 4.3. The four races performance evaluation based on

InceptionV3	Precision	Recall	F1-score	Accuracy
African	0.994	0.98.3	0.985	0.994
Asian	0.956	0.98.8	0.970	0.958
Caucasian	0.990	0.940	0.960	0.950
Indian	0.990	0.960	0.970	0.960
Female	0.950	0.910	0.930	0.934
Male	0.920	0.960	0.940	

In comparison to other races, the African race exhibits the highest accuracy ratio (99.4%), as the table demonstrates. In contrast, the Indian race ranks second with 96%. The final two racial groups with lesser accuracy rates are Asian and Caucasian, with 95%, respectively. For classifying genders, the accuracy is 93.4. Lastly, Table 4.4 presents the ResNet50 model's performance evaluation.

Table 4.4. The four races performance evaluation based on ResNet50 model.

ResNet50	Precision	Recall	F1-score	Accuracy
African	0.990	0.990	0.990	0.997
Asian	0.974	0.981	0.976	0.967
Caucasian	0.998	0.964	0.981	0.964
Indian	0.996	0.973	0.984	0.976
Female	0.910	0.960	0.940	0.934
Male	0.960	0.910	0.930	

In comparison to other races, the African race exhibits the highest accuracy ratio, at 99.7%, as the table demonstrates. In contrast, the Indian race ranks second with 97.6%. The final two races with lower accuracy rates, both at 96%, are Asian and Caucasian. For classifying genders, the accuracy is 93.4, as shown in Table 4.4. shows the performance evaluation of the four models on the race dataset.

Table 4.5. The race performance evaluation based on four models.

Models	Precision	Recall	F1-score	Accuracy
RGCNN	0.989	0.988	0.989	0.978
VGG19	0.983	0.982	0.983	0.968
InceptionV3	0.983	0.983	0.985	0.972
ResNet50	0.989	0.987	0.989	0.977

The table illustrates the highest accuracy ratio (97.8%) for the RGCNN model compared to other models. The ResNet50 model ranks second with a value of 97.7%, the InceptionV3 model ranks third with a value of 97.2%, and the VGG19 model ranks fourth with a value of 96.8%.Table 4.6 shows the model's number of layers and parameters. Model RGCNN has a smaller total number, as table 4.6 shows. In contrast, the VGG19 Model takes the second position. Finally, the ResNet50 model is the last one with a total number of parameters, followed by the InceptionV3 model in third place.

Table 4.6. The model's number of layers and parameters.

Gender Model	Total Number of parameters	Training Time
RGCNN	1,500,530	907s
VGG19	21,073,346	4044s
InceptionV3	24,162,466	901s
ResNet50	30,118,786	1401s

5. Conclusion

The most important productions relating to this study are:

A new dataset was created for facial race and gender, containing 2400 samples of four races (African, Asian, Caucasian, and Indian), of which 1200 are female and the rest are male. We trained, validated, and tested the three convolutional neural network models, InceptionV3, ResNet50, and VGG19, on the new facial race dataset. The performance accuracy rate of the models InceptionV3, ResNet50, and VGG19 is 97.2, 97.7%, 96.8%, and, respectively. We trained, validated, and tested the three convolutional neural network models on the new gender dataset. The performance accuracy rate of the models InceptionV3, ResNet50, and VGG19 is 93.4%, 93.4%, and 87.0%, respectively. The newly created model (RGCNN) was trained, validated, and tested on the new facial race and gender datasets. The new model's performance accuracy rate on the new facial race dataset is 97.8%, and on the new gender dataset, it is 94.4%, which is better than InceptionV3, ResNet50, and VGG19 with less executing time. The system's predictive capabilities, encompassing race and gender classifications across a sample size of 40 individuals, achieve an impressive 98% accuracy rate. Additionally, this study used a multiclass classification approach for classifying four races. The excremental shows that the One-Versus-All approach outperforms multiclass classification for classifying four races. The result for multiclass classification is 96.64% accuracy. For One-Versus-All is 97.8 % accuracy.

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