Periocular age and gender recognition

A Project as a Course requirement for

Bachelor of Science (Hons.) in Mathematics

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(Deemed to be University)

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April 2023

I humbly dedicate this work to my Guru

Sri Sathya Sai Baba

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CERTIFICATE

This is to certify that this Project titled **Periocular age and gender recognition** submitted by Sai Saketh Cherukuri, 201218, Department of Mathematics and Computer Science, Brindavan Campus is a bonafide record of the original work done under my supervision as a Course requirement for the Degree of Bachelor of Science (Hons.) in Mathematics.

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Date: April 29, 2023

DECLARATION

The Project titled **Periocular age and gender recognition** was carried out by me under the supervision of Dr. Darshan Gera, Department of Mathematics and Computer Science, Brindavan Campus as a Course requirement for the Degree of Bachelor of Science (Hons.) in Computer Science and has not formed the basis for the award of any degree, diploma or any other such title by this or any other University.

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Embarking on this journey in the field of Deep Learning and Machine Learning has been one filled with lessons and learnings from every leg of the journey. I started off confused but the process has taught me a great deal of knowledge that cannot be offered from a book, but only through hands-on experience.

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Abstract

Gender classification and age prediction have been topics of constant research and development in computer vision and have achieved relative success. They have various use cases and often provide solutions for many problems. Images of various levels of occlusions and distortions are found in the wild, making it challenging for even humans to accurately predict someone's age and gender. The onset of the Covid-19 pandemic has forced the entire world to wear face masks wherever they go, and hence facial recognition software must rely only on the periocular region that is left available for their models. Classical models often use the entire face for their results and thus rely heavily on face data points that may not be available now more than ever. Motivated by this, and the superior performance of deep learning across the board in computer vision problems, we decided to implement a model called "PeriGender" proposed by Husaain et al. using PyTorch and convolutional neural networks for gender classification. The proposed system utilizes a dense concept in a residual model. Through skip connections, it reuses features on different scales to strengthen discriminative features. We also decided to compare the performance of the proposed model with existing pre-trained models such as ResNet-18, ResNet-50, and ResNet-34 trained and evaluated on the UBIPr dataset. The ResNet-18, ResNet-34, and ResNet-50 models achieved 91.89%, 91.48%, and 92.48%, respectively, while the PeriGender model, trained and evaluated on the same dataset, received an accuracy of 93.35%. We modified the last fully connected layer of the PeriGender model to give 10 outputs instead of 2 to deal with our age prediction problem and trained the models on the FG-Net dataset. This model is called ‘PeriAge’. The ResNet-18, ResNet-34, and ResNet-50 models achieved 58.03%, 59.51%, and 60.34%, respectively, while the PeriAge model, trained and evaluated on the same dataset, received an accuracy of 50.00%. Combining the PeriGender and PeriAge models into one, called the PeriOcular model, produced an accuracy of 32.29% after training and testing on the UTK-face dataset. The results from GC showed that, in general, the model was able to predict a female face more accurately than a male one, indicating that females have more distinguishing features in the periocular region for gender classification problems

Keywords: Gender recognition; periocular region; deep learning; convolutional neural network; Age prediction

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Chapter 1
Introduction

1.1 Motivation

Facial recognition software continues to be one of the most important developments in the computer vision community, with a wide range of applications. Soft biometric traits, such as ethnicity, gender, and a rough age estimate, can be recognized by humans at first sight. While age changes over time, ethnicity and gender remain permanent and don't change over time. Applications of facial recognition range from security, identification, marketing, advertisement [1], surveillance, psychiatric studies, to law enforcement [2].

Classical models have been developed and improved over the years [3], but they largely rely on features of the entire face. When faced with a face covered with a mask or other occlusions, the performance of these models decreases [4]. Due to the onset of the Covid-19 pandemic, many people have been forced to wear masks, and classical methods employed by surveillance systems can face a decrease in performance due to the partially or wholly occluded face as shown in (Fig. 1). For instance, many criminals wear a mask that fully covers their face, exposing only the periocular region for identification.

Figure 1: Various real life situation that demand face occlusions (source: web, [16,17])

The general public also cover their face when going to a dusty street or sometimes it may be due to religious beliefs and country based laws.

Thus in such situations we cannot gain access to other regions of the face and have only the periocular region to identify from. This increases the difficulty even for a human to correctly classify a person's gender and an accurate age range. GC using the iris is an invasive approach, and it is not socially acceptable or suitable for unconstrained scenarios [5]. The periocular region outperforms the iris in the GC task [6]. Due to facial and iris recognition limitations, an alternative method is the periocular region, the facial area surrounding the eyes (Fig. 2), which can be used as a cue for soft biometrics traits. Brown and Perrett [7] reported that eyebrows and eyes together, eyebrows alone, and eyes alone are the top three facial areas that carry the most discriminative gender information.

Figure 2: Example of the periocular region; right eye image from the UBIPr data

Convolutional Neural Networks show promising results in the field of computer vision, and it is only natural to bring CNN's into gender classification and age prediction problems. Previous studies by Xu et al [8] have shown that the periocular region is feature-rich and contains much of the distinct features required for gender classification problems. They trained their custom-made 'DeepGender' network with whole face images, and they found that periocular images achieved better accuracy than images featuring whole faces with occlusions, illumination variations, and low resolution. After looking at these results and seeing the performance of CNN's, we implemented the model called PeriGender as described by Hussain et al [9]. They developed a model that employs the use of residual blocks and skip connections using ResNet-18 as the backbone for their model. They then trained the model on the UFPR dataset and validated it across various other datasets, including GROUPS, UBIPr, Ethnic-Ocular, IMP, and UFPR.

1.2 Aim and Objectives

The aim of this project is to :

1. implement the PeriGender model for gender classification as proposed by Hussain et al [9].
2. Modify it for age prediction problems as well.

1.3 Organization

This Project is divided as follows:

- **Chapter 2 :** In this chapter we will take a look at the various papers and areas of research that have led up to this project in this field.
- **Chapter 3:** In this chapter we will highlight the methodology and implementation of our model.
- **Chapter 4:** In this chapter we will discuss the results obtained across different metrics.
- **Chapter 5:** In this Chapter we will outline future works and experiments that can be done to further bolster our models' performance across the board and conclude the paper.

Chapter 2
Literature Review

2.1 Field related work

For a long time computer vision has been tackling age prediction and gender classification problems, but the task of identifying human metrics using Periocular features is relatively young.

2.1.1 Gender Classification (GC)

GC (gender classification) continues to be one of the most important problems in face detection and computer vision problems solely because of its vast area of interdisciplinary applications. Since Covid-19, the push to obtain solutions to the problem of Masked facial recognition has increased drastically as seen in [10-14]. As shown by Chandrashekar et al. [15], the performance of GC on the periocular region performs well even when the iris is not visible because the corners of the eyes contain distinguishing features as well. Another interesting observation in the experiments by Chandrashekar et al. is the need for enhancing techniques to be used in case of female periocular samples. The degradation in performance of the female subset may have happened due to possible make-up, eyebrow coloring, use of glasses, and the presence of earrings. Most of the preexisting techniques imply a two-fold algorithm: first, they extract the facial features using landmarks and then pass them to a classifier model for predictions [16, 17]. The main drawback of the previous models was that they were designed on custom rules and did not take into account the nature of an image, thus requiring large amounts of time to evaluate effectively. Some techniques were trained on small CNN models and did not perform well on wild images. Given the exponential growth in facial recognition (FC) problems, particularly in CNN's and non GC related pattern recognition problems [18-20], they must be further explored and developed on periocular related problems.

2.1.2 Age Prediction (AP)

AP is another field of particular interest in areas using FR related software. As displayed by Raschka et al. [22], applying a COnsistent RAnk Logits (CORAL) framework on a simple AP model produced outstanding results. Furthermore, in the paper by Bisogni et al. [21], it was found that the soft biometric traits of a face are very helpful in AP problems. As outlined by Bisogni et al. [21], the use of periocular features for AP problems is twofold: firstly, it preserves the security related to facial features by giving access to a small region of the face. Although it is a small region, it is feature-rich, as shown by Bobeldyk et al. [6], and coupled with the high acceptance rate by subjects to undergo testing, this provides significant benefits and good results of up to 84.45% by Bisogni et al. [21].

2.2 Conclusion

Various methods proposed by fellow researchers have provided us with additional reasons why periocular recognition is essential. Through reading their works, we have identified methods of improvement and gained a better understanding of this area. For instance, the outstanding performance of the in-house PeriGender model developed by Hussain et al has demonstrated the potential of a periocular-related project. This motivated us to modify the PeriGender model and apply it to age prediction problems.

Chapter 3
Age and gender recognition models

3.1 Methodology

As proposed by Hussain et al. [9], we first started with gathering the data sets required for completion. The UBIPr dataset was the obvious choice and was chosen as the main dataset for our project.

3.1.1 Data Pre-processing

The UBIPr dataset contains total 10,252 RGB periocular images from 344 subjects in.bmp format with 501×401 pixels of image resolution. Images in this dataset were captured from 4 m to 8 m distance to include distance variability, but in a controlled environment. This also contains metadata files for each image which include coordinates of canthus points, center of the iris, endpoints and midpoints of eyebrow as well as information about gender, level of pigmentation and angle of gaze and various other landmark points.The dataset comes with an image and an annotated text file containing the labels for each image. The dataset contained more male images than female images so data augmentation was done to balance the dataset. Random image solarization, random crop, random horizontal flip and random invert were performed on the images for augmentation sake as seen in (Fig. 3a)

Figure 3a. Normal Right eye female image, Augmented right eye female image

3.1.2 CNN Model for Periocular Recognition-PeriGender

As explained in [9], The architecture of PeriGender consists of four residual groups Res_Gi(F,C),i = 1,2,3,4. Each Res_Gi is composed of two residual blocks Res_Bj(F,C),j = 1,2, as shown in (Fig. 4b). Each Res_Bj(F,C) consists of a convolutional layer (conv), batch normalization (BN), and a ReLU layer, as shown in (Fig. 4a). We fused multiscale features after the first convolutional layer and each residual block, except for the last, by adding a skip connection Skip(F). Each Skip(F) consists of a 1×1 convolutional layer with three filters followed by an $F \times F$ max pooling layer (maxpool) with stride F, as shown in (Fig. 4c). The multiscale features were fused, adding a depth concatenation layer and resulting in $3 \times 7 \times 524$. The concatenation layer was added to extract a better feature representation for periocular GC. Then, the fused features were passed to the global average pooling and a fully connected layer with two neurons because there were two classes: male and female. (Fig. 4) and (Table 1) visualize this model.

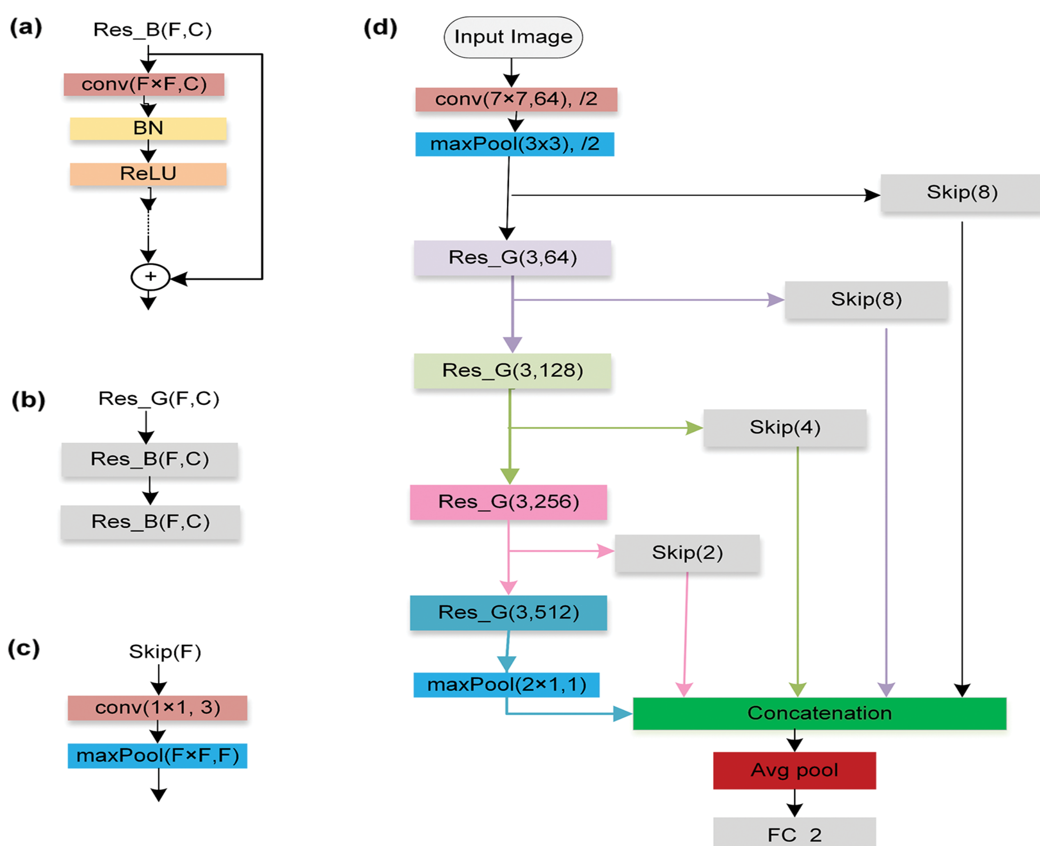

Figure 4: The architecture of PeriGender (a) The architecture of a residual block (b) The architecture of the residual group (c) The architecture of a skip module (d) The overall structure of the network architecture with four skip modules and four residual groups [9]

Layer name	Output size	Architecture
Image Input	$112 \times 224 \times 3$	
Convolution	$56 \times 112 \times 64$	7×7, 64, stride 2
Pool	$28 \times 56 \times 64$	3×3 max, stride 2
Skip Module (1)	$28 \times 56 \times 3$	1×1 conv, 3
	$3 \times 7 \times 3$	8×8 max, stride 8
Residual group (1)	$28 \times 56 \times 64$	$\begin{bmatrix} 3 \times 3, & 64 \\ 3 \times 3, & 64 \end{bmatrix} \times 2$
Skip Module (2)	$28 \times 56 \times 3$	1×1 conv, 3
	$3 \times 7 \times 3$	8×8 max, stride 8
Residual group (2)	$14 \times 28 \times 128$	$\begin{bmatrix} 3 \times 3, & 128 \\ 3 \times 3, & 128 \end{bmatrix} \times 2$
Skip Module (3)	$14 \times 28 \times 3$	1×1 conv, 3
	$3 \times 7 \times 3$	4×4 max, stride 4
Residual group (3)	$7 \times 14 \times 256$	$\begin{bmatrix} 3 \times 3, & 256 \\ 3 \times 3, & 256 \end{bmatrix} \times 2$
Skip Module (4)	$7 \times 14 \times 3$	1×1 conv, 3
	$3 \times 7 \times 3$	2×2 max, stride 2
Residual group (4)	$4 \times 7 \times 512$	$\begin{bmatrix} 3 \times 3, & 512 \\ 3 \times 3, & 512 \end{bmatrix} \times 2$
Pool	$3 \times 7 \times 512$	2×1 max, stride 1
Concatenation	$3 \times 7 \times 524$	Depth concatenation
Classification layer	$1 \times 1 \times 524$	Global Average Pool
	$1 \times 1 \times 2$	Fully connected, SoftMax

Table 1: Proposed model architecture [9]

3.1.3 CNN Model for Periocular Recognition-PeriAge

Inspired by the architecture of PeriGender, we created a sister model for age prediction called 'PeriAge'. This has the same basic skeleton of PeriGender but the key difference is that the last FC layer has been modified to give output of 10 to deal with the age prediction problem.

Chapter 4
Results

4.1 PeriGender (GC)

After building the PeriGender model as described above, the next step was to check the performance of the custom model compared to pretrained ResNet models already available.

4.1.1 Performance of pretrained ResNet models vs PeriGender

The preprocessed dataset was evaluated using three different pre-trained models, namely ResNet-18, ResNet-34, and ResNet-50. The models were trained for 25 epochs with a learning rate of 0.01, momentum of 0.9, SGDM optimizer, ReLU activation function, and CrossEntropyLoss loss function. The training was performed on a Kaggle-provided CPU and a Tesla P100 GPU. Although BCEwithLogitsLoss is preferred for binary classification problems, the results obtained by Hussain et al. showed us that CrossEntropyLoss can work well. The results were as expected, with ResNet-50 outperforming its sister models. The accuracies achieved by ResNet-18, ResNet-34, and ResNet-50 were 91.89%, 91.48%, and 92.48%, respectively, while the PeriGender model trained and evaluated on the same dataset received an accuracy of 93.35%. The confusion matrix of PeriGender can be seen in Fig. 4a, and the accuracy tracked through each epoch can be seen in Fig. 4b.

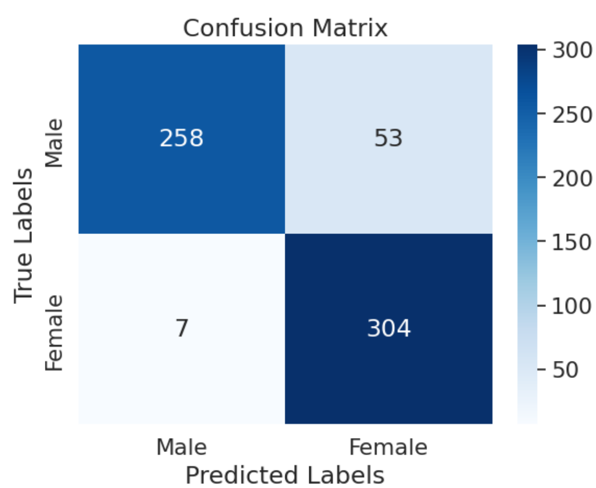

Figure 4a : Confusion matrix of PeriGender

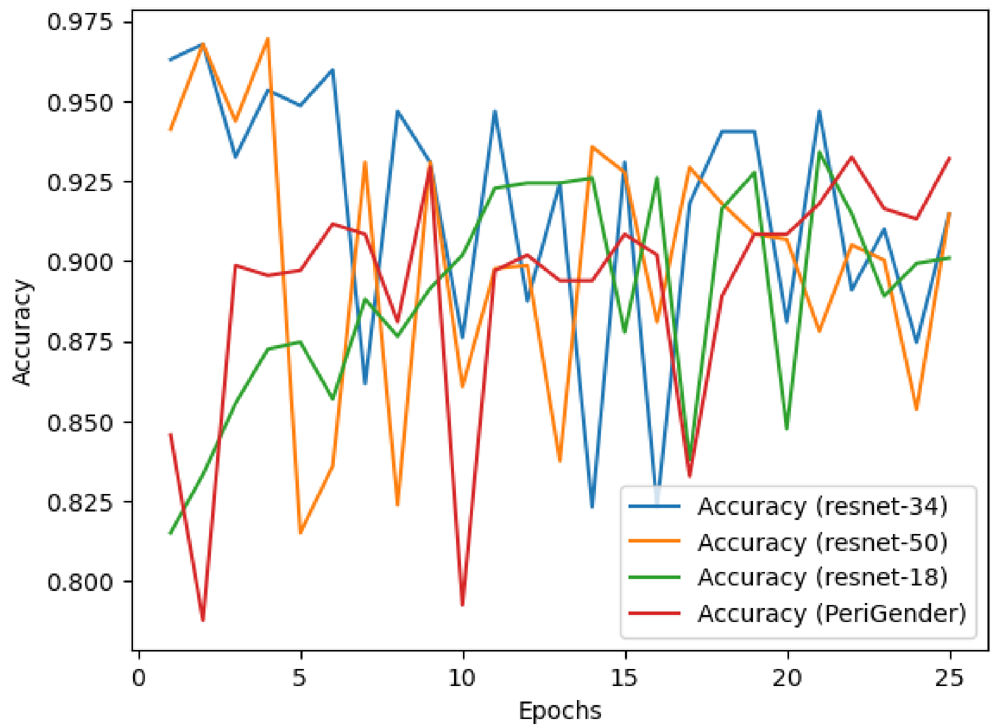

Figure 4b : Accuracy of the different models (UBIPr dataset)

As seen above, ResNet-34 and ResNet-50 initially performed well due to their large number of layers, but their accuracy decreased over time as they learned various features from the dataset. ResNet-18 was chosen as the backbone for the model because it consistently learned the data compared to the other models. However, there were large spikes and drops in accuracy when validating on the validation dataset (also UBIPr). This can be attributed to the data augmentation done on the dataset during preprocessing to obtain a balanced dataset. Another reason for this could be that the mini-batches may not be multiples of 64, meaning that the last batch may have less than 64 samples, leading to inconsistent data for the model to learn from. To address this issue, we can drop the last batch that is not a multiple of 64.

4.2 PeriAge (AP)

After getting good results with the PeriGender model, the next step was to modify the last fully connected layer of the model to give ten from two to give us an age from 0-90 in intervals of ten.

4.2.1 Performance of pretrained ResNet models vs PeriAge

As previously mentioned, the PeriGender model architecture and model were largely the same, but for the PeriAge model, we replaced the last fully connected layer to have ten outputs instead of two to predict ages of an individual from 0-100 divided into equal intervals of ten. However, just before the modified FC, we changed the ArgMax to Softmax because we needed the probabilities of the different age intervals. We used the FG-Net dataset [23] for training and testing, which is a dataset for age estimation and face recognition across ages consisting of a total of 1,002 images of 82 people with an age range from 0 to 69 and an age gap of up to 45 years. However, the results were not as good as the PeriGender model. We trained and tested the same pretrained models as before (ResNet-18, ResNet-34, and ResNet-50), but this time we did not obtain satisfactory results. The accuracies obtained for ResNet-18, ResNet-34, ResNet-50, and our custom PeriAge model were 58.39%, 59.51%, 60.34%, and 50.00%, respectively. The results for this experiment can be seen in Fig. 5a and Fig. 5b.

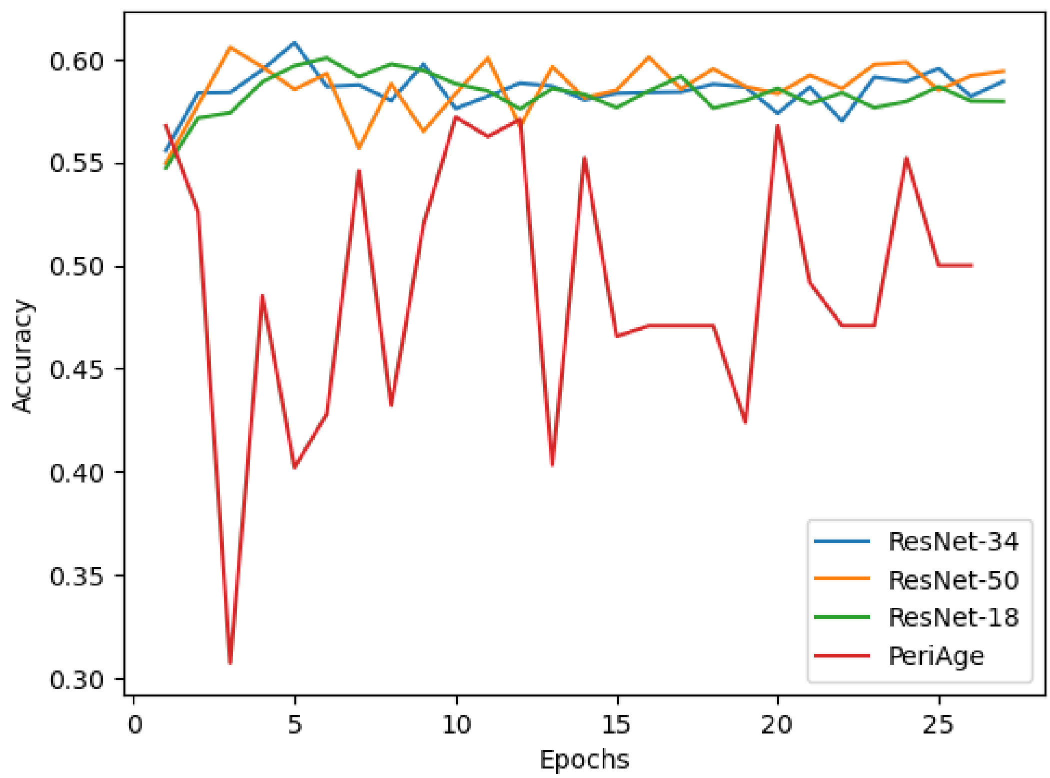

Figure 5a : Accuracy of the different models (FG-Net dataset)

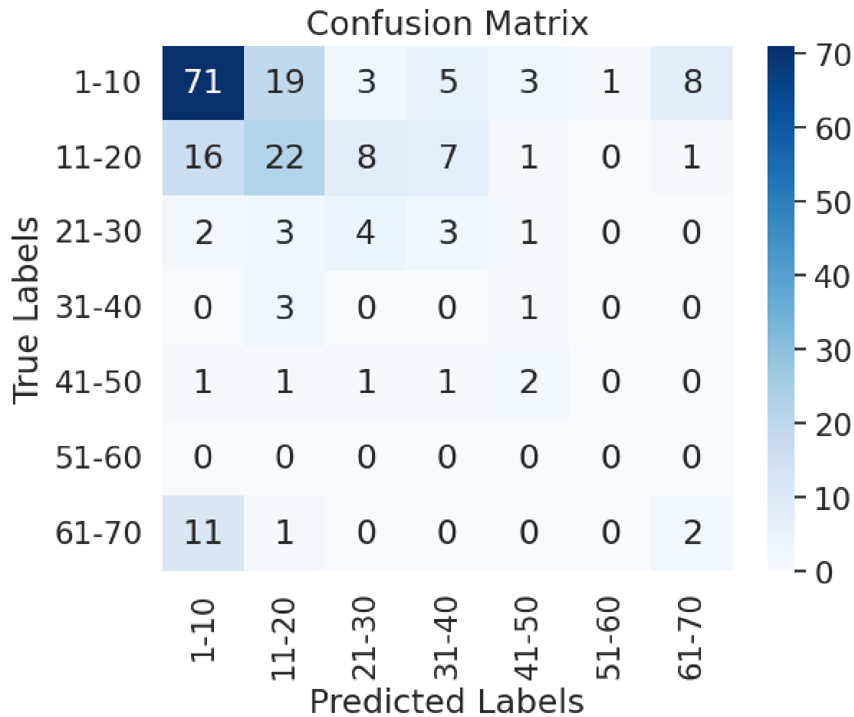

Figure 5b : Confusion Matrix of PeriAge

4.2 PeriOcular (both AP and GC)

Once we got results, for the PeriOcular and PeriAge models, we combined into one single model we called 'PeriOcular' which can predict the age and gender of a given image.

4.3 Performance of the combined model PeriOcular

To create the PeriOcular model, we followed the same architecture as before, but added two fully connected layers and passed a copy of the image outputs into both of them. One fully connected layer had two features for the gender output and the other had ten for the age output. This model was trained and tested on the UTKFace dataset. The UTKFace dataset is a large-scale face dataset with a large age span (range from 0 to 116 years old). The dataset consists of over 20,000 face images with annotations of age, gender, and ethnicity. The images cover large variations in pose, facial expression, illumination, occlusion, resolution, etc. However, the model did not provide promising results, as the images in the UTKFace dataset were meant to be used for classical facial recognition models that employ the use of the entire face. When we used it for our particular model, we resized it to crop only the periocular region, but due to the poor resolution of the images, further cropping resulted in loss of clarity, rendering the images unhelpful. The final results of our experiments can be seen in Table 2.

	Dataset	**Custom Model**	**ResNet-18**	**ResNet-34**	**ResNet-50**
Gender	UBIPr	93.35%	91.89%,	91.48%,	92.48%
Age	FG-Net	50.00%	58.39%,	59.51%,	60.34%,

Table 2. Final Results of our experiments

Chapter 5
Conclusion

5.1 Conclusion

In this project, we wanted to classify periocular images based on gender and age. One of the ways to boost the advancements of the computer vision techniques is to make the model robust. It must be able to detect and correctly identify the images even though there are various and unavoidable occlusions obscuring the image. The fact that we use periocular images for classification already makes this a challenging one but in no way does it hinder the performance and in the case of GC, it even outperforms classical models reliant on the entire face for data. Since the world is still reeling from the effects of the pandemic, this makes this project particularly useful because of the high availability of periocular images and lack of regular images. We implemented a PeriGender model that utilizes skip connections and residual blocks. The performance of this model was then documented and analyzed in comparison to a few pretrained ResNet models, namely, ResNet-18, ResNet-34 and ResNet-50. After this we modified the Perigender model to give us predictions for age intervals. This was also evaluated alongside the aforementioned ResNet models. Finally we Combined both the models into our own model called ‘PeriOcular’ that gives us the age and gender of an individual in the same model using periocular images

In conclusion, these are the findings of our project:

1. Based on our experiments, the PeriGender model performed well and accurately identified the gender of individuals. It outperformed the pretrained models, but there is still room for improvement, such as using a better and more balanced dataset instead of relying on data augmentation. From the confusion matrix, it is clear that the model was able to detect females more accurately, despite the data augmentations. This suggests that females generally have more distinctive features.

2. The PeriAge model, modified from the PeriGender model, did not perform satisfactorily and has a lot of room for improvement. The poor performance, however, can be attributed to the lack of a periocular dataset with age labels. This required us to crop the periocular region from the images, resulting in low-resolution images and loss of data.
3. The combined PeriOcular model performed very poorly as well. Again this can be attributed to the lack of a Periocular dataset with age labels and gender labels resulting in us cropping the images.

5.2 Future work

This project has a large scope for future additions. Some fields on interest that we can still work on are:

1. Improving the performance of AP in PeriAge and PeriOcular by first acquiring the UFPR dataset which includes high resolution periocular images with age and gender labels.
2. Improve the model's robustness to occlusions and variations commonly found in real-world settings, where images may not be captured in a controlled environment. This would enable the model to correctly identify periocular images even in challenging scenarios.
3. Create a real time video version of our model that can give us the age and gender in the video itself.
4. Make the model lightweight.

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