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Gender Prediction from Retinal Fundus Using Deep Learning

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***Abstract**: Deep learning may transform health care, but model development has largely been dependent on availability of advanced technical expertise. The aim of this study is to develop a deep learning model to predict the gender from retinal fundus images. The proposed model was based on the Xception pre-trained model. The proposed model was trained on 20,000 retinal fundus images from Kaggle depository. The dataset was preprocessed them split into three datasets (training, validation, Testing). After training and cross-validating the proposed model, it was evaluated using the testing dataset. The result of testing, the area under receiver operating characteristic curve (AUROC) of the model was 0.99, precision, recall, f1-score and accuracy were 99%, precision, recall, f1-score and accuracy were 96.83%, 96.83%, 96.82% and 96.83% respectively.. Clinicians are presently unaware of dissimilar retinal feature variants between females and males, stressing the importance of model explain ability for the prediction of gender from retinal fundus images. The proposed deep learning may enable clinician-driven automated discovery of novel visions and disease biomarkers.*

Keywords: Gender, Prediction, Retinal Fundus, Deep Learning

Introduction

Machine Learning (ML) is an application of Artificial Intelligence (AI) that provides systems with the ability to automatically learn and improve from experience without being explicitly programmed [1-10]. Machine learning focuses on developing computer models that can access and use data in learning by itself [11-20]. Learning begins with observations or data, such as examples, first-hand experience, or instructions, to search for data patterns and make better decisions in the future based on the examples we provide [21-30]. The primary goal is to make computers learn and act like humans do, and to improve their learning over time in an independent way, by providing them with data and information in the form of real-world observations and interactions [31-40].

Deep learning is a type of machine learning and artificial intelligence (AI) [41-50] that mimics the way humans acquire certain types of knowledge. Deep learning is an important component of data science, which includes statistics and predictive modeling [51-60]. It is extremely useful for data scientists charged with collecting, analyzing and interpreting large amounts of data; deep learning makes this process faster and easier [61-70].

The fundus of the eye is the interior surface of the eye opposite the lens and includes the retina, optic disc, macula, fovea, and posterior pole. The fundus can be examined by ophthalmoscopy [81] and/or fundus photography.
The color of the fundus varies both between and within species. In one study [82] of primates the retina is blue, green, yellow, orange, and red; only the human fundus (from a lightly pigmented blond person) is red. The major differences noted among the "higher" primate species were size and regularity of the border of macular area, size and shape of the optic disc, apparent 'texturing' of retina, and pigmentation of retina.

Fundus photographs of the right eye (left image) and left eye (right image), as seen from the front (so that the person is looking at the viewer the person's nose would be between the two images).
Each fundus has no sign of disease or pathology. The gaze is into the camera, so in each picture the macula is in the center of the image, and the optic disc is located towards the nose. Both optic discs have some pigmentation at the perimeter of the lateral side, which is considered non-pathological [83].

The left image (right eye) shows lighter areas close to larger vessels, which has been regarded as a normal finding in younger people.

Figure1: Fundus photographs of the right eye (left image) and left eye (right image),

Recently, Convolutional Neural Networks (CNN) have achieved physician-level accuracy in numerous image-based health jobs, e.g. in radiology [81], dermatology [82], pathology [83] and ophthalmology [84, 87]. Furthermore, in some cases CNN have been shown to have good performance in jobs that are not easy for physicians: for example, they can accurately predict the gender from retinal images [85]. As this task is typically not clinically relevant, ophthalmologists are not explicitly trained for it. Yet, the comparably poor performance of ophthalmologists at this task suggests that gender differences in fundus images are not obvious or salient. Even though saliency maps used by [85] and follow-up studies [88,89] have tentatively pointed at the optic disc, the macula, and retinal blood vessels as candidate regions for gender-related anatomical differences in fundus images, conclusive evidence is still lacking. Therefore the high gender prediction performance of CNNs has created lots of interest in the medical imaging community as one hope for CNNs is to unravel biomarkers that are not easily found by humans. Here, we performed a proof of principle study to make progress on the question of how CNNs are able to detect gender differences in retinal fundus with much higher accuracy.

We trained a deep learning model based on customized Xception pre-trained model on a large collection of retinal fundus images obtained from the Kaggle depository [90].

2 Related Work

Previous work on gender prediction from fundus images have used either standard CNN architectures or simple logistic regression on top of expert-defined features. For example, [85] trained Inception-v3 networks on the UK Biobank dataset to predict cardiovascular risk factors from fundus images and found that CNNs were also capable of predicting the patient's gender (AUC = 0.97). A similar network was used by [86]. In both studies, the authors computed posthoc saliency maps to study the features driving the network's decisions. In a sample of 100 attention maps, [85] found that the optic disc, vessels, and other nonspecific parts of the images were frequently highlighted. However, this seems to be the case for almost all the dependent variables and it is very hard to derive testable hypotheses for gender specific differences. Likewise, [87] manually inspected a sample of occlusion maps and concluded that CNNs may use geometrical properties of the blood vessels at the optic disc for predicting gender. More recently, [84] demonstrated that CNNs can predict gender not only from retinal fundus images but also from OCT scans, where the foveal pit region seemed most informative based on gradient-based saliency maps. Taking a different approach, [88] used expert-defined image features in a simple logistic regression model. Although the performance of their model was worse (AUC = 0.78), they found various color-intensity-based metrics and the angle between certain retinal arteries to be significant predictors, but most effect sizes were small.

3 Methods

3.1 Data and preprocessing

The Kaggle [90] offers a large-scale and multi-modal repository of health-related data. From this, we obtained 20,000 fundus images from both eyes. Male and female subjects constituted 46% and 54% of the data, respectively. As a substantial fraction of the images were not gradable due to image quality issues. We partitioned the dataset into training, validation and testing datasets with 60%, 20% and 20% of subjects, respectively, making sure that all images from each subject were allocated to the same set. Figure 3 outlines some of the samples in the dataset.

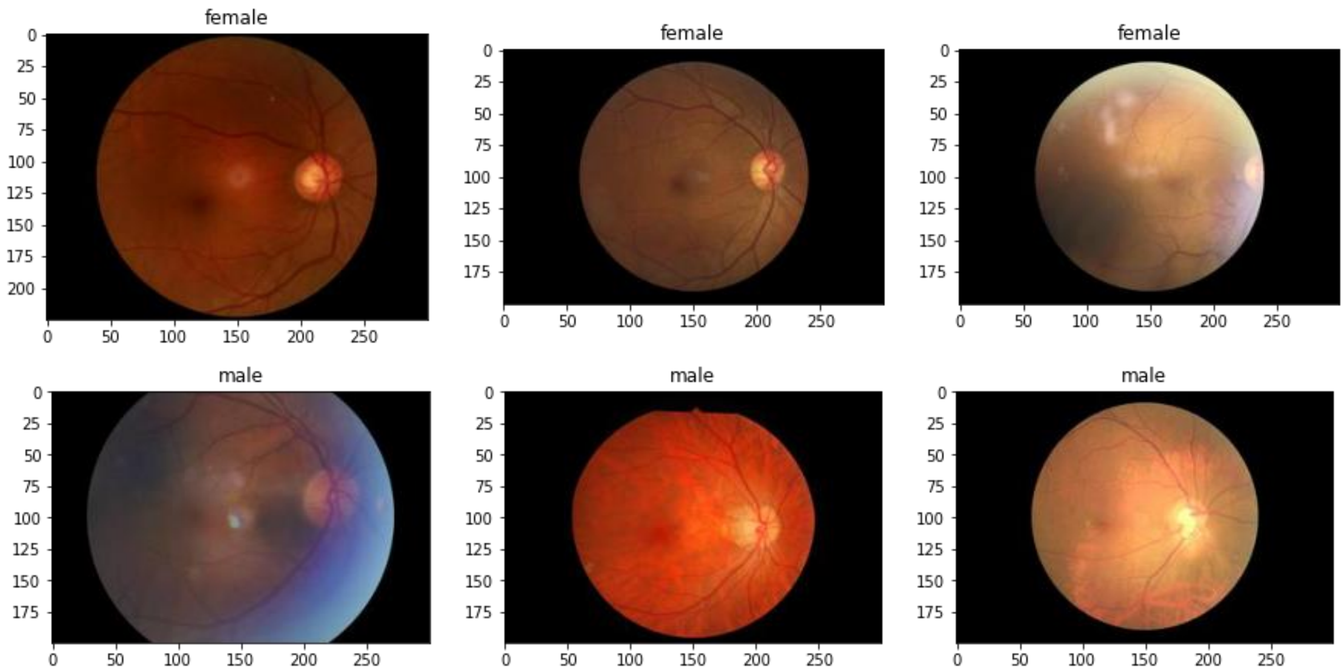

Figure 3: Samples from the dataset

3.2 Network architecture and training

We used Xception network as implemented in Keras [18]. It was proposed by Francois Chollet. Xception is an extension of the inception Architecture which replaces the standard Inception modules with depth wise Separable Convolutions. Xception is a convolutional neural network that is 71 layers deep. The pre-trained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images.

The data first goes through the entry flow, then through the middle flow which is repeated eight times, and finally through the exit flow. Note that all Convolution and Separable Convolution layers are followed by batch normalization, Xception architecture has over performed VGG-16, ResNet and Inception V3 in most classical classification challenges (As seen in Figure 2) [39].

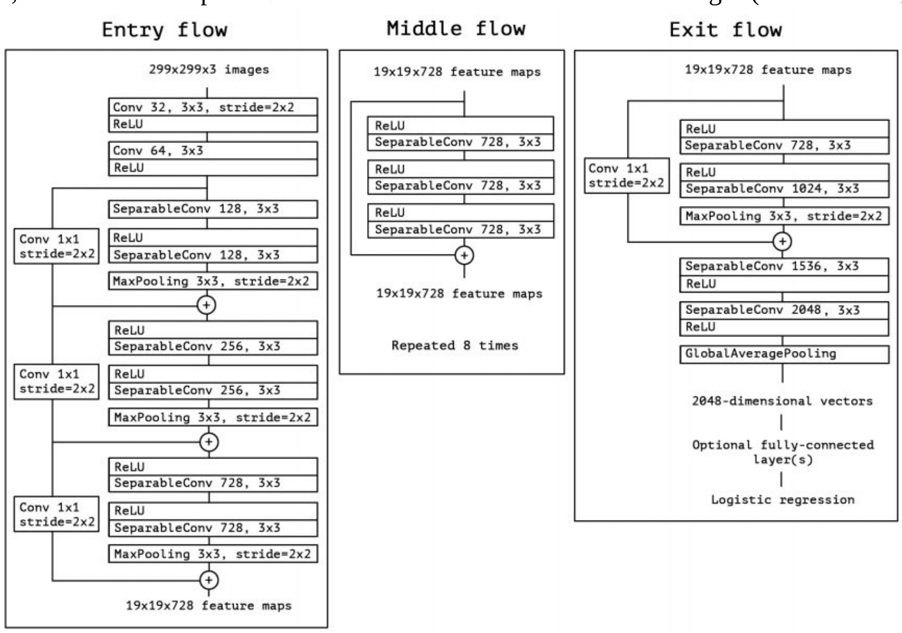

Figure 4. The architecture of Xception (Entry Flow>Middle Flow>Exit FLow).

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All networks had been pre-trained on ImageNet [36] by their respective developers. For our binary classification problem, we replaced the 1000-classes softmax output layer with a single logistic output neuron. We initially trained only the output layer using the fundus images for 40 epochs. This was followed by fine-tuning all layers for 100 epochs. We used Adam optimization algorithm which is an extension to stochastic gradient descent that has recently seen broader adoption for deep learning applications in computer vision and natural language processing, that's been designed specifically for training deep neural networks, the algorithms leverages the power of adaptive learning rates methods to find individual learning rates for each parameter. It also has advantages of Adagrad, which works really well in settings with sparse gradients, but struggles in non-convex optimization of neural networks, and RMSprop, which tackles to resolve some of the problems of Adagrad and works really well in on-line settings [40].

Adam can be looked at as a combination of RMSprop and Stochastic Gradient Descent with momentum. It uses the squared gradients to scale the learning rate like RMSprop and it takes advantage of momentum by using moving average of the gradient instead of gradient itself like SGD with momentum [49].
Adam is an adaptive learning rate method, which means, it computes individual learning rates for different parameters. Its name is derived from adaptive moment estimation, and the reason it's called that is because Adam uses estimations of first and second moments of gradient to adapt the learning rate for each weight of the neural network, that can used instead of the classical stochastic gradient descent procedure to update network weights iterative based in training data [72].

Result and discussion

We trained and validated our proposed model for 140 epochs. Figure5 and Figure 6 show the Accuracy and loss of training and validating history of our proposed model for the last 20 epochs. Training Accuracy (99.84), Training Loss (0.0047), Validating Accuracy (96.82%), Validating Loss (0.1316).

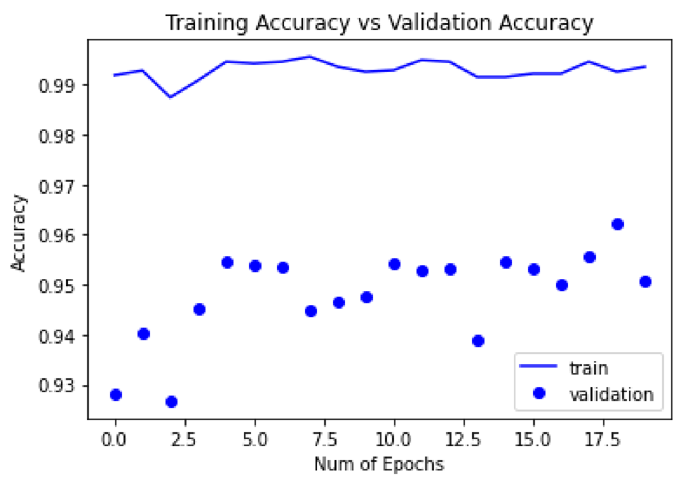

Figure 5: Accuracy of training and validating the proposed model

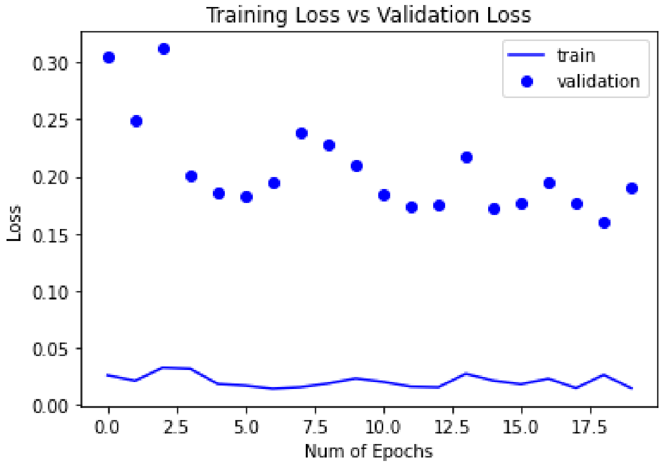

Figure 6: Loss of training and validating the proposed model

The roc curve for each class (Male and Female) in our proposed model achieved 99% as shown in Figure 7.

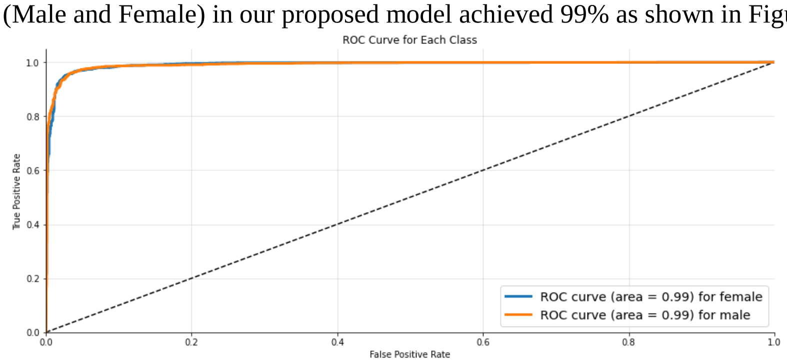

Figure 7: ROC curve for male and female.

The classification report of our proposed model is as flows: Accuracy (96.83), Recall (96.83%), Precession (96.83%), and F1-Score (96.82%) as seen in table 1.

Table1: report classification of the proposed model

	Precision	Recall	F1-score	Support
Female	0.9675	0.9690	0.9683	2000
Male	0.9690	0.9675	0.9682	2000
Accuracy			0.9683	4000
Macro avg	0.9683	0.9683	0.9682	4000
Weighted avg	0.9683	0.9683	0.9682	4000

The performance of our proposed, model much better than other previous studies; however, the dataset we used is different from the one used in the previous studies.

Conclusions

In summary, our study is, to the best of our knowledge, the first to predict gender based on retinal fundus images from kaggle depository. The model's performance was better than the others in previous studies. Our developed model proved that deep learning can predict gender based on retinal fundus images effectively. The performance of the developed model with area under receiver operating characteristic curve (AUROC) was 0.99, precision, recall, f1-score and accuracy were 96.83%, 96.83%, 96.82% and 96.83% respectively. Clinicians are presently unaware of dissimilar retinal feature variants between females and males, stressing the importance of model explain ability for the prediction of gender from retinal fundus images. The proposed deep learning model may enable clinician-driven automated discovery of novel visions and disease biomarkers.

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