



MACHINE LEARNING FOR GLUCOMA DETECTI

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ABSTRACT_ Glaucoma is a progressive and irreversible eye condition that can cause a person's vision and overall quality of life to deteriorate over time. In this paper, we develop an automated method for the diagnosis of glaucoma using deep learning (DL) architecture combined with a convolutional neural network. Deep learning systems, like as convolutional neural networks (CNNs), have the ability to infer a hierarchical representation of pictures, which allows them to differentiate between glaucoma patterns and non-glaucoma patterns for the purposes of diagnostic choices. There are a total of six learnt layers inside the DL architecture that has been suggested, including four convolutional layers and two fully-connected layers. In order to further improve the efficacy of glaucoma diagnosis, dropout and data augmentation procedures are implemented. On both the ORIGA and SCES datasets, a significant amount of testing is carried out. The results demonstrate that the area under the curve (AUC) of the receiver operating characteristic curve in glaucoma detection is 0.831 and 0.887 in the two databases, respectively. This is significantly better than the techniques that are considered to be state-of-the-art. The approach has the potential to be utilised for the diagnosis of glaucoma.

1.INTRODUCTION

Glaucoma is one of the most prevalent causes of blindness, and it is anticipated that over 80 million individuals will have the condition by the year 2020 [16]. It is a long-term condition of the eye that weakens or destroys the optic nerve over time, which ultimately results in vision impairment. Glaucoma is known as the "silent thief of sight" because symptoms don't appear until the disease has progressed to a very advanced stage. Glaucoma is a disease that cannot be cured, however the progression of the disease can be slowed down with treatment. It is critical to have reliable imaging tools in order to perform early detection of glaucoma.

One of the most common and important diagnostic techniques for glaucoma today is the digital fundus image. Because it is possible to obtain DFIs in a noninvasive manner that is suitable for large scale screening, DFI has emerged as the preferred modality for large-scale glaucoma screening. This is because glaucoma can cause damage to the optic nerve, which can lead to blindness. An image is analysed by an automated system to determine whether or not it contains any glaucoma warning indicators in order to participate in a screening programme for the eye condition. Ophthalmologists will only review the photos of patients whose eyes appear to have abnormalities once the system identifies them as suspicious.



Glaucoma can be diagnosed by looking at the patient's medical history, performing tests to measure intraocular pressure and vision field loss, and then performing an ophthalmoscopic examination to manually evaluate the optic disc (OD). OD is the site where the axons of ganglion cells leave the eye to create the optic nerve. The optic nerve is the pathway via which the visual information gathered by the photoreceptors is sent to the brain. In 2D imaging, the OD can be broken up into two separate zones: a central bright zone known as the optic cup (in shortcup), and a peripheral region known as the neuroretinal rim. Both of these zones can be seen as a rim around the retina

2.LITERATURE SURVEY

[1] The image of the retinal fundus is an important diagnostic tool that is frequently used to diagnose ocular illnesses such as glaucoma, diabetic retinopathy, and age-related macular degeneration. It is also an important modality to document the health of the retina. On the other hand, the large amount of retinal data that is received in modern times is mostly retained locally, and the valuable therapeutic knowledge that is encoded within it is not adequately exploited. In this study, we offer ORIGA(-light), an online repository with the goals of sharing clinical ground truth retinal pictures with the general public and providing open access for researchers to benchmark their computer-aided segmentation methods. ORIGA(-light) is named after the Greek word for "light." For the purpose of making the construction of ORIGA(-light) easier, an in-house image segmentation and grading tool is being developed.

[2] It is proposed that a quantitative and objective benchmarking approach be developed, with a primary emphasis on optic disc and cup segmentation as well as Cup-to-Disc Ratio (CDR). At the moment, ORIGA(-light) is equipped with 650 retinal images that have been annotated by experienced experts from the Singapore Eye Research Institute. An extensive catalogue of picture indicators that are necessary for the diagnosis of glaucoma has been annotated. The system will undergo regular updates in which additional clinical ground-truth photos are added. On demand, access to the online version of ORIGA (light) can be provided.

3.PROPOSED SYSTEM

Because of this, we are inspired to suggest a deep learning framework for the purpose of capturing the discriminative features that better characterise the hidden patterns associated with glaucoma. The chosen DL structure consists of six layers: four convolutional layers and two fully-connected layers. This infers a hierarchical representation of pictures, which is necessary for distinguishing between glaucoma patterns and non-glaucoma patterns for the purposes of diagnostic choices. In addition, we use response-normalization layers and overlapping-pooling layers to cut down on the overfitting problem. In the suggested deep learning architecture, dropout and data augmentation algorithms have also been incorporated in order to further improve the performance of the system. Within this, we proposed a classification of glaucoma based on CNN



3.1 IMPLEMENTATION

Dataset exploration:

The dataset, as well as the data dictionary of the properties involved, are studied in the Python environment.

Data mutilation:

It is necessary to estimate missing values in some factors since inadequate data prohibits most interpretations from being made. This term refers to the estimation of incomplete data in some variables. In the case of a variable, the missing data are substituted with the value of the mean, and in the case of a class label, the missing values are substituted with the value of the mode.

Feature Selection:

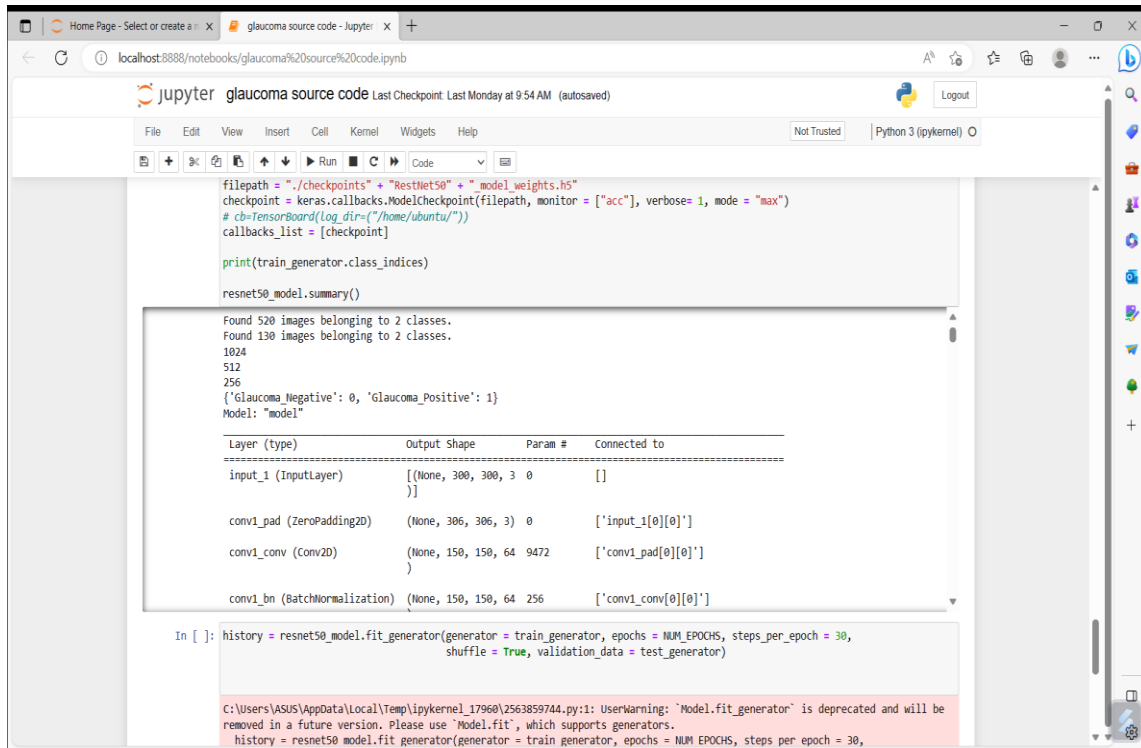
It is crucial for any type of predictive modelling, and it is carried out with the goals of preventing multicollinearity, removing redundant attributes that are closely correlated with one another, and improving the model's performance. We eliminated characteristics that aren't necessary for disease identification by employing a method known as backward selection. First, we consider each of the model's attributes, and then, using the p-value as a guide, we delete some of them. This helps in establishing the significance of the data when running a test in statistics to determine whether or not the null

hypothesis is true. The characteristics that had a p-value that was more than 0.05 were eliminated from the model, and the model was then re-fitted with the variables that were left over. This method was carried out multiple times until each of the model's pre-existing variables reached a level that could be considered meaningful. The most recent value of R square was recorded at the conclusion of each repetition. to determine the proportion of the total variation that can be accounted for by only those independent variables that have a significant bearing on the prediction of the target variable..

Model fitting and Testing:

After feature selection was complete, five different classification algorithms, namely Logistic Regression, Decision Trees, Random Forest, Support Vector Machine (SVM), and Adaptive Boosting, were applied to the data using the selected feature, and the accuracy of their respective predictions was evaluated utilising the Train/Test split methodology. Because the test size for the comparison was set at 0.1, this indicates that ninety percent of the dataset was utilised for the training of the classifier, while the remaining ten percent was utilised for testing.

4.RESULTS AND DISCUSSION



```
filepath = "./checkpoints" + "ResNet50" + "model_weights.h5"
checkpoint = keras.callbacks.ModelCheckpoint(filepath, monitor = ["acc"], verbose= 1, mode = "max")
# cb=TensorBoard(Log_dir="/home/ubuntu/")
callbacks_list = [checkpoint]

print(train_generator.class_indices)

resnet50_model.summary()

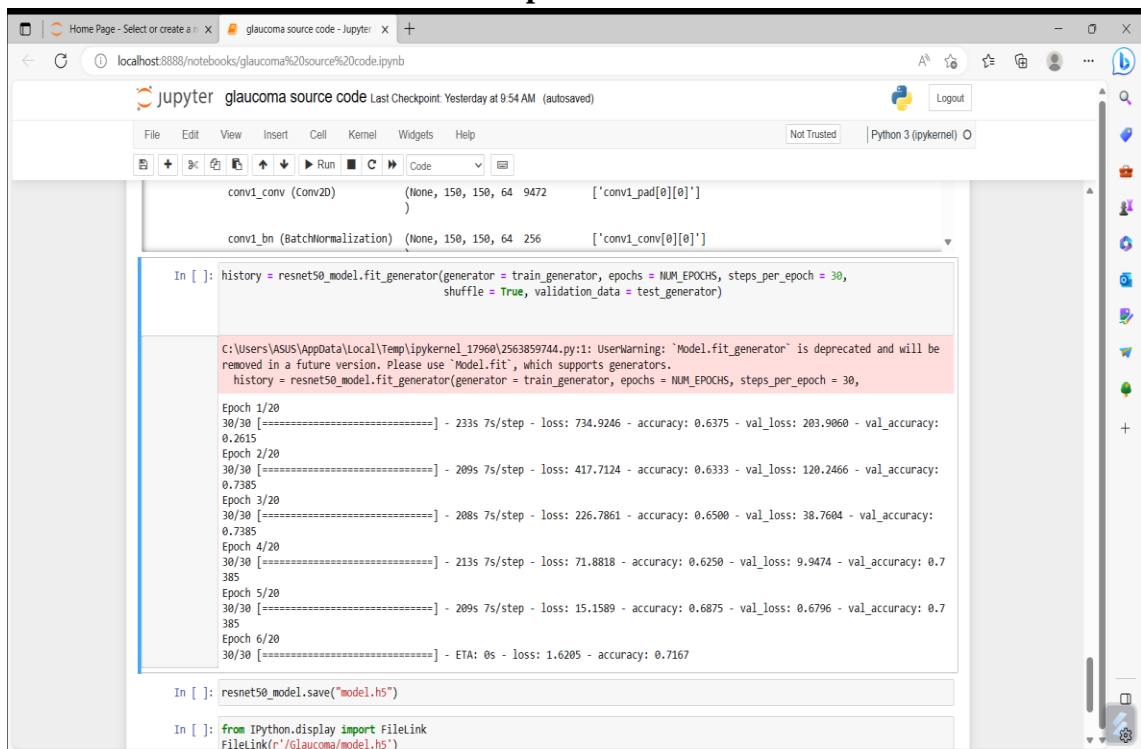
Found 520 images belonging to 2 classes.
Found 130 images belonging to 2 classes.
1024
512
256
{'glaucoma_Negative': 0, 'glaucoma_Positive': 1}
Model: "model"

Layer (type)                 Output Shape              Param #                    Connected to
-----
input_1 (InputLayer)         [(None, 300, 300, 3) 0]   []
conv1_pad (ZeroPadding2D)    (None, 306, 306, 3) 0    ['input_1[0][0]']
conv1_conv (Conv2D)          (None, 150, 150, 64) 9472 ['conv1_pad[0][0]']
conv1_bn (BatchNormalization) (None, 150, 150, 64) 256 ['conv1_conv[0][0]']

In [ ]: history = resnet50_model.fit_generator(generator = train_generator, epochs = NUM_EPOCHS, steps_per_epoch = 30,
shuffle = True, validation_data = test_generator)

C:\Users\ASUS\AppData\Local\Temp\ipykernel_17960\2563859744.py:1: UserWarning: 'Model.fit_generator' is deprecated and will be removed in a future version. Please use 'Model.fit', which supports generators.
history = resnet50_model.fit_generator(generator = train_generator, epochs = NUM_EPOCHS, steps_per_epoch = 30,
```

Fig 1:Importing the tensorflow libraries to find the total number of images in two different classes and every image goes through 6 layers to detect whether the glaucoma is positive or not



```
conv1_conv (Conv2D)          (None, 150, 150, 64) 9472 ['conv1_pad[0][0]']
conv1_bn (BatchNormalization) (None, 150, 150, 64) 256 ['conv1_conv[0][0]']

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history = resnet50_model.fit_generator(generator = train_generator, epochs = NUM_EPOCHS, steps_per_epoch = 30,

Epoch 1/20
30/30 [=====] - 233s 7s/step - loss: 734.9246 - accuracy: 0.6375 - val_loss: 203.9060 - val_accuracy: 0.2615
Epoch 2/20
30/30 [=====] - 209s 7s/step - loss: 417.7124 - accuracy: 0.6333 - val_loss: 120.2466 - val_accuracy: 0.7385
Epoch 3/20
30/30 [=====] - 208s 7s/step - loss: 226.7861 - accuracy: 0.6500 - val_loss: 38.7684 - val_accuracy: 0.7385
Epoch 4/20
30/30 [=====] - 213s 7s/step - loss: 71.8818 - accuracy: 0.6250 - val_loss: 9.9474 - val_accuracy: 0.7385
Epoch 5/20
30/30 [=====] - 209s 7s/step - loss: 15.1589 - accuracy: 0.6875 - val_loss: 0.6796 - val_accuracy: 0.7385
Epoch 6/20
30/30 [=====] - ETA: 0s - loss: 1.6205 - accuracy: 0.7167

In [ ]: resnet50_model.save("model.h5")

In [ ]: from IPython.display import FileLink
FileLink(r'/glaucoma/model.h5')
```

Fig 2: Doing the different epochs to find the final accuracy



5.CONCLUSION

In this paper, we present a deep learning framework for glaucoma detection based on deep CNN. Using CNN, this method is able to capture the discriminative features that better describe the hidden patterns associated with glaucoma. The adopted DL structure consists of six layers in total, four of which are convolutional and two of which are fully connected. To address the issue of overfitting, we used response-normalization layers in addition to overlapping-pooling layers. Dropout and data augmentation are two approaches used in the deep CNN that was proposed to boost performance even further. In future work, we intend to expand our investigation of deep learning architectures that are based on CNN to the identification of multiple ocular disorders.

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