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Ocular Disease Intelligent Recognition using Hybrid CNN Approach

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Abstract: *Ocular disease early detection is an economic and productive path to forestall visual defect caused by diabetes, glaucoma, cataract, age-related devolution (AMD), and plenty of other diseases. Currently according to planet Health Organization (WHO), a minimum of 2 billion people round the world have vision impairments, of whom a minimum of 1 billion have a vision impairment that might are prevented. Speedy and automatic detection of diseases is critical and urgent in reducing the ophthalmologist's workload and prevents vision damage of patients. Computer vision and deep learning can automatically detect ocular diseases by providing high-quality medical eye fundus images.*

Key Word:*hybrid CNN, deep learning, ocular disease, resnet50*

I. INTRODUCTION

Automated grading of medical pictures could be used to address these issues by reducing the physicians' job complexity, increasing the potency and repeatability of screening programs, and refining patient prognosis through premature detection and treatment. Recent advances on deep learning algorithms, particularly convolutional neural networks (CNN), have created it potential to be told the foremost prognosticative options of malady directly from medical pictures once given an oversized dataset of tagged examples. In this project, we proposed a novel Hybrid CNN model using ResNet50 architecture to extract features for our CNN model to classify the disease of a person from their iris scan images. Then, we performed an evaluation of the algorithm's diagnostic performance on outpatients in a prospective manner.

II. APPROACH

A. Data Loading and Pre-processing

The dataset explaining about the image files will be loaded into the python environment as DataFrame and the images will be matched with their respective labels and redundant or mismatched data will be eliminated. Once the images get loaded, they are pre-processed using OpenCV library and prepared for the model training and evaluation.

B. Visualizing Data

The loaded image will be visualized using matplotlib library to view the input images graphically.

C. Input Requirement

The images will be resized of width and height as 11x11 and reshaped to (11, 11, 1) since the images will be of grayscale. The images will be passed as vectors of arrays as features to the model and the target will be passed as an array of One Hot Encoded columns.

D. Train test split

The model will be split into 70-30 where the training data will be of 70% and the test data will be of 30% of the whole data.

E. Model creation

The model is a hybrid combination of ResNet50, ResNet50V2 and a CNN architecture. The ResNet50 and ResNet50V2 layers will be used to acquire the features from the images and the output from them will be feed to the CNN architecture for classification process.

F. Model training and results

The model will be trained using the train data and while the model is being trained through the 100 epochs, the test data is passed as validation data for the analysis of each and every epoch. From the epochs result, we can get the loss and accuracy of the train and testing dataset and the model is further evaluated using classification report to get the precision, recall, f1-score and support of the model we acquired.

III. ABOUT DATA

Ocular Disease Intelligent Recognition (ODIR) is a structured ophthalmic database of 5,000 patients with age, colour fundus photographs from left and right eyes and doctors' diagnostic keywords from doctors.This dataset is meant to represent a ‘‘real-life’’ set of patient information collected by Shang gong Medical Technology Co., Ltd. from different hospitals/medical centers in China. Fundus images were captured using different cameras in different hospitals and medical centers. Therefore, the dimensions of images vary.

Annotations were labeled by trained human readers with quality control management. They classify patient into eight labels including:

- Normal (N),
- Diabetes (D),
- Glaucoma (G),
- Cataract (C),
- Age related Macular Degeneration (A),
- Hypertension (H),
- Pathological Myopia (M),
- Other diseases/abnormalities (O)

IV. PREPROCESSING OF DATA

Resizing a picture refers to changing the size of the picture, which in turn changing height or width or changing both of them. The ratio of the original image may also be well preserved within the resized image. To resize an image, OpenCV provides the cv2.resize() function. Image interpolation works in two directions, and tries to attain a best approximation of a pixel's intensity supported the values at close pixels.

INTER_AREA interpolation is used which uses pixel area relation for resampling. This is best suited for reducing the size of an image (shrinking). The dataset is next loaded and converted into an array format for training purposes using the NumPy library.

V. MODEL TRAINING

A. Modeling

Resnet50:

ResNet50 is a convolutional neural network which has 48 Convolution layers along with 1 Max Pooling layer and 1 Average Pool layer. It has 3.8 x 10^9 Floating points operations. ResNet improves the efficiency of deep neural networks with more neural layers while minimizing the percentage of errors. In other words, the skip connections add the outputs from previous layers to the outputs of stacked layers, making it possible to train much deeper networks than previously possible.

Resnet50V2:

ResNet50V2 is a modified version of ResNet50 that performs better than ResNet50 and ResNet101 on the ImageNet dataset. In ResNet50V2, a modification was made in the propagation formulation of the connections between blocks.

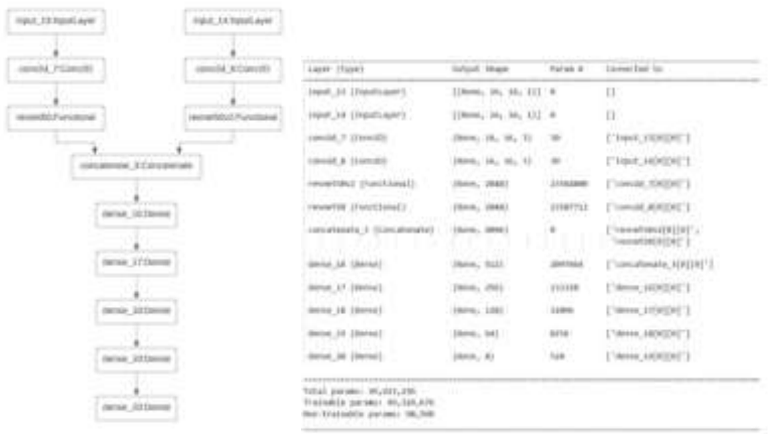

Fig 5.1 Model Architecture of Hybrid CNN

The proposed system contains a hybrid CNN model which includes 2 input layers,2 convolutional layers ,5 fully connected layers and 2 resnet 50 models for feature extraction.Two unique eye data are sent to an input layer.The data is later merged through concatenation layer after convolution and feature extraction process.The data shape after merge is (None,4096) and after reaching dense_19 it is (None,64) and then finally it is (None,8) once it reaches dense_20 layer.

A. Activation functions

ReLU:

The ReLU (Rectified function is a non-linear activation function that helps to prevent the exponential growth in the computation required to operate the neural network.

Sigmoid:

Sigmoid function is used to normalize neural networks output to fit between zero and one. It is used to represent the certainty probability in the network output.

Adam Optimizer:

Adaptive Moment Estimation (Adam) is an algorithm for optimization technique for gradient descent. It requires less memory and is efficient. Intuitively, it is a combination of the ‘gradient descent with momentum’ algorithm and the ‘RMSP’ algorithm.

VI. RESULTS

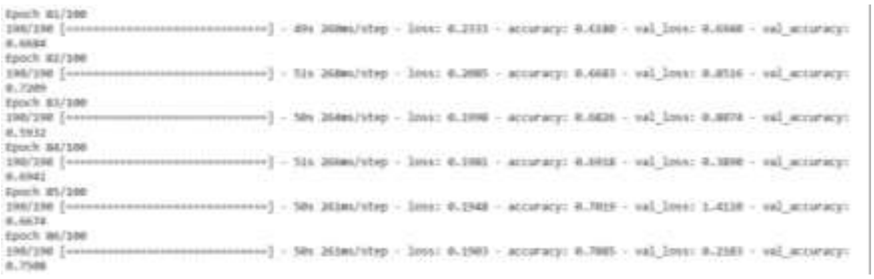

Fig 6.1 Training epoch result of proposed model

The Neural Network’s training results will display two different metrics as follows,

Loss metrics:

In general, it is the distance between the actual values and predicted values. The loss metric is evaluated based on the loss function provided in the compile function and the inputs and outputs acquired in each training epoch. “loss” is the loss value calculated over the training data and “val_loss” is the loss calculated over the validation data.

Accuracy metrics:

The accuracy metric will show how good the model has interpreted over the data. It shows the fraction of predictions that our model ruled out correctly. The closer the accuracy gets to 1, the higher the model’s prediction precision improves. “accuracy” is the model’s accuracy evaluated on the training data and that of “val_accuracy” is over the validation data in each training epoch.

From the epochs’ output, the proposed model has achieved validation accuracy of 76% at 86th epoch with validation loss of 0.2103.

	precision	recall	f1-score	support
N	0.814286	0.423267	0.557003	404.0
D	0.651163	0.537170	0.588699	417.0
G	0.660000	0.478261	0.554622	69.0
C	0.888889	0.648649	0.750000	74.0
A	0.000000	0.000000	0.000000	76.0
H	0.000000	0.000000	0.000000	33.0
M	0.732143	0.788462	0.759259	52.0
O	0.200000	0.003731	0.007326	268.0
micro avg	0.719444	0.371859	0.490298	1393.0
macro avg	0.493310	0.359942	0.402114	1393.0
weighted avg	0.576800	0.371859	0.434839	1393.0
samples avg	0.425453	0.391131	0.402252	1393.0

Fig 6.2 Classification report of proposed model

The classification report for the model is generated using python's library scikit learn function called classification_report. The report displays four different evaluation metrics for the generated model: Precision, Recall, F1 Score and Support. The formulae for precision, recall and F1 Score are as follows:

$$Precision = \frac{\text{True Positive}}{(\text{True Positive } + \text{ False Positive})}$$

$$Recall = \frac{\text{True Positive}}{(\text{True Positive } + \text{ False Negative})}$$

$$F1\ Score = \frac{\text{2 x Precision x Recall}}{\text{Precision} + \text{Recall}}$$

Support is the total number of actual occurrences of a given class.

From the classification report of the proposed model, the model has achieved higher precision value for Cataract class with 88.89%, higher recall value for Pathological Myopia and higher F1 Score for Pathological Myopia. The drawback of the model has been displayed through the classification report that the model has failed to recognize Age related Macular Degeneration and Hypertension related eye diseases.

VII. CONCLUSION

Recognition of ocular disease at the early stage itself not only reduces the damage inflicted in eyes but also identifies the root cause of the disease and helps the filed experts to cure the root disease itself. The Hybrid CNN produced reasonable output values that correspond to recorded data of real conditions. The proposed test results show that the system can predict the anomalies and normal usage well, and the prediction accuracy can reach more than 76%. However, the model has a flaw on recognizing two different disease such as Age-related Macular Degeneration and Hypertension. This inability of the model will be resolved in the future studies by further developing the model. The accuracy will be improved further by improvising the model architecture and parameters in future.

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