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Deep Learning Framework for Forecasting Diabetic Retinopathy: An Innovative Approach

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ABSTRACT- In the realm of diabetic retinopathy, extensive research has been conducted by numerous scholars, who have explored and implemented a variety of machine learning techniques, contributing significantly to both healthcare and data science domains. With the increasing availability of deep learning procedures, packages, and libraries, these advancements have become pivotal in enhancing model performance. Consequently, this study embraces a novel methodology and platform in contrast to existing approaches to diabetic retinopathy, taking into account the outcomes and discoveries. For the deep learning model, the researcher leveraged the GPU provided by Google Colab. The dataset was sourced from a Kaggle competition hosted on the Kaggle website. Subsequently, the image data was stored in the researcher's personal server memory, and the URLs for each image were documented in an Excel sheet.

KEYWORDS- Deep Learning, Retinopathy, Diabetic Retinopathy.

I. INTRODUCTION

In the realm of diabetic retinopathy, numerous researchers have diligently undertaken extensive studies. They have proposed and implemented a variety of machine learning strategies, contributing efforts to both the healthcare and data science domains. With the increasing availability of deep learning techniques, software packages, and libraries, these advancements can serve as a crucial factor influencing the model's performance. Consequently, the investigator has embraced a novel methodology and platform in contrast to prevailing approaches to diabetic retinopathy, taking into account the produced results and discoveries. In this deep learning model, the researcher utilized a GPU provided by Google Colab [4]. The dataset was acquired from the Kaggle competition hosted on the Kaggle website. Subsequently, the image data was stored in the researcher's personal server memory, and the URLs for each image were documented in an Excel sheet [1, 2, 3].

II. PROPOSED WORK

A. *Utilizing the Fast AI Framework for Image Categorization*

The Fast AI framework enables developers to construct models using minimal lines of code. Its primary objective is to democratize access to artificial intelligence for all programmers by leveraging the superior features of PyTorch. The Fast AI library is developed through contemporary methods or techniques, utilizing PyTorch, which offers advanced prototyping capabilities. In this study, the investigator employed the 'Diabetic Retinopathy Detection' dataset from Kaggle, training the machine to differentiate between a normal retina and a retina with diabetic retinopathy.

B. *Google Colaboratory*

Google Colaboratory is a tool constructed upon the Jupyter Notebook. The Jupyter, an open-source technique supported by browsers, incorporates tools for visualization, multiple programming languages, and libraries [7, 8, 15-18]. This open-source Jupyter can execute tasks on local machines or in the cloud. Google Colaboratory was initiated with the goal of promoting data science learning and exploration [12-16, 2, 30]. The Colab notebooks feature in Google Docs enables collaborative work for both the public and users within the same notebook. This collaborative tool provides pre-configured environments for both Python 3 and 2, specifically tailored for AI and ML research. It includes runtimes along with essential libraries from Keras, Tensor Flow, and Matplotlib.

C. *CNN using Fast AI*

The proposed deep learning classification framework comprises convolution with pooling layers and fully connected layers, providing binary categorization into diabetic retinopathy [DR] and normal retina, denoted as no diabetic retinopathy [NODR]. The investigator employed a CNN support with a completely linked head node containing hidden layers serving as a classifier or differentiator (Fig. 1). In the final step, the model is applied to predict diabetic retinopathy and normal retina. For this compact model, the researcher utilized a dataset containing retinal images of human subjects with dimensions exceeding 2000×3000 pixels [5, 6, 7, 9, 11, 12]. The retinal images used in this study were sourced from the Kaggle dataset [19-21], freely accessible on the website, with 678 images earmarked for training and 170 for testing. Due to the varied resolution properties of retinal images, the dataset's size fluctuates across different images. In this research, 848 retinal images were selected, maintaining an 8:2 ratio for training and testing [26, 27, 28]. The CNN model is tasked with learning to distinguish between two categories: normal retina and diabetic retina. The use of the fastai library streamlines the training process, enhancing performance due to its rapid and accurate image processing capabilities [10, 19, 22-25].

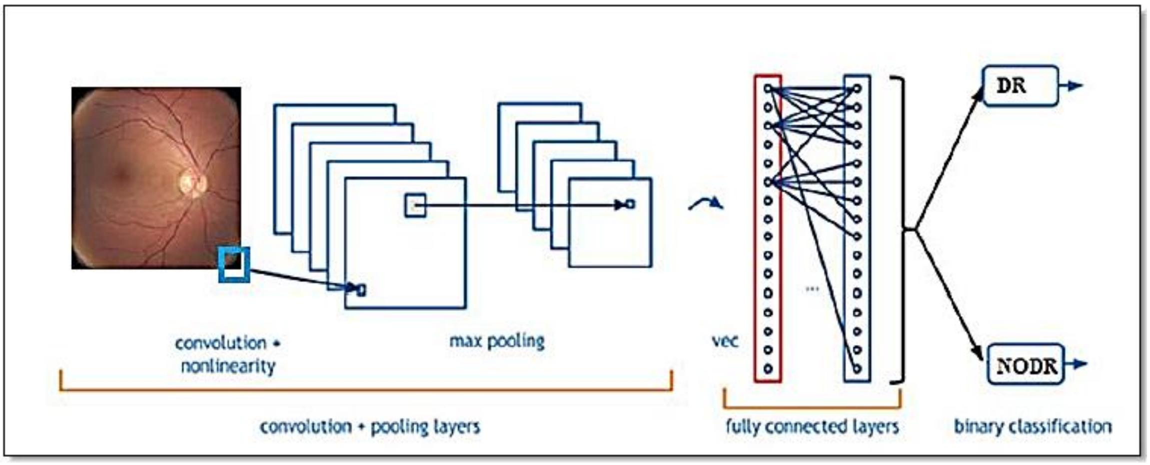


Figure 1: CNN for diabretina and normalretina

To construct the image classification model, the investigator employed Fast AI in conjunction with the cloud GPU service provided by Google Colaboratory. The steps executed for the image classification are outlined below:

Step 1:

Acquiring image data The Fast AI library possesses the capability to access various datasets and can download images from a specified location on the web or a Uniform Resource Locator (URL). To retrieve the URL of the image file, the dataset is stored on a personal server [20, 21, 26].

Step 2:

Loading and Previewing Data to facilitate the training of the designed framework, the library Fast AI employs an object called data bunches. This object is created using the function Image Data Bunch. From folder( ) for loading datasets that are relevant to problem-solving approaches (Figure 2 and 3).

```
[ ]  data.classes

['diabretina', 'normalretina']
```

Figure 2: Data Classes

Step 3:

Model Development and Training In this phase, the library aids in crafting and constructing a framework with minimal lines of code, a feature beneficial for learners as provided by Fast AI. The function "create_cnn ( )" is utilized to establish a Convolutional Neural Network (CNN), specifically the resnet34 architecture with weights assigned to the dataset

epoch	train_loss	valid_loss	error_rate	accuracy	time
0	0.240868	0.621682	0.210526	0.789474	00:01
1	0.196123	0.644820	0.157895	0.842105	00:01
2	0.203185	0.662209	0.157895	0.842105	00:01
3	0.185842	0.667164	0.157895	0.842105	00:01
4	0.199340	0.659575	0.157895	0.842105	00:01

Figure 3: Fit one cycle

Step 4: Data Cleansing

To fulfill the goal of data cleansing within the Jupyter framework, the Fast AI library provides the necessary functionality. The Image Cleaner ( ) function facilitates the removal and relabeling of images. In employing Image Cleaner, the researcher utilized the function Dataset Formatter ( ). from top losses to identify misclassified or inaccurately labeled images as top losses..

Step 5: Interpretation

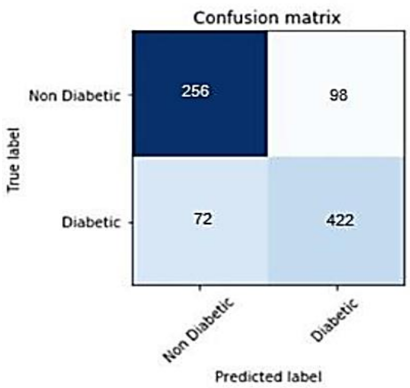
To comprehend the output generated at the conclusion of framework creation, the class "Classification Interpretation" is employed, utilizing its function. By invoking the function "from learner( )" and supplying the learner framework, accurate predictions are obtained.

III. ACCURACY OF MODEL

For this binary classification issue, scholars delineate specificity as the count of images accurately identified as the diabetic retina (diabretina) and normal retina (normalretina).

• Accuracy, as defined by researchers, corresponds to the number of test images with a correct classification.

• The ultimately trained network attained an 80% accuracy rate in figure 4. The FastAI CNN demonstrates proficiency in classifying a substantial quantity of test images. To enhance accuracy, one may consider expanding the dataset size. This trained convolutional neural network exhibits swift prediction and provides prompt responses to users [27].



Accuracy =[Correct Prediction]/total*100
=[256+422]/848*100
=678/848*100
=79.95
=80

Figure 4: Accuracy of CNN

IV. RESULTS ANALYSIS

In addressing this binary classification challenge, the researcher defines specificity as the count of images accurately identified as diabetic retina (diabretina) and normal retina (normalretina). Accuracy, in the researcher's terms, pertains to the precise classification of retina images. The final developed network achieved an accuracy level of 80%. Leveraging Fastai libraries allows for the classification of an arbitrary number of images. The trained convolutional neural network swiftly predicts and provides an immediate response to users. The researcher has presented some test cases for predicting the class of images for which the model was created. Google provides cloud services with virtual machines equipped with graphical processing units capable of over nine hundred and sixty teraflops, ensuring efficient execution for each event. Deep learning (DL), molecular modeling, and simulation are animated with V100, P4, P100, Tesla K80, NVIDIA, and T4GPUs. Regardless of the scale of your noteworthy task, anyone can obtain a flawless GPU as provided by [29].

V. CONCLUSION

Deep learning methodologies are increasingly proving to be efficacious in the healthcare domain, particularly in tasks involving image processing, disease diagnosis, and risk assessment. This scholarly article aims to present a model for detecting diabetic retinopathy using FastAI. The utilization of the FastAI library facilitates enhanced outputs with minimal programming efforts. The Convolution Neural Network (CNN) model deployed in this study is adept at image processing, trained efficiently with the GPU system provided by Google Colab. The precompiled neural network ensures timely and accurate results. The proposed model proficiently classifies images distinguishing diabetic retinopathy from normal retina images. In future iterations, an improved model employing a larger dataset can be devised to detect various stages of diabetic retinopathy. This CNN model serves as valuable assistance for ophthalmologists in healthcare diagnosis.

CONFLICTS OF INTEREST

The authors declared that they have no conflicts of interest.

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