APTOS Blindness Detection

Report of Kaggle competition for Project Computer Vision

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***Abstract*—Millions of people suffer from diabetic retinopathy, the leading cause of blindness among working aged adults. Aravind Eye Hospital in India hopes to detect and prevent this disease among people living in rural areas where medical screening is difficult to conduct. Successful entries in this competition will improve the hospital's ability to identify potential patients. Further, the solutions will be spread to other Ophthalmologists through the 4th Asia Pacific Tele-Ophthalmology Society (APTOS) Symposium**

***Index Terms*—Blindness, Deeplearning , Models , etc.**

I. Introduction

The goal of the Kaggle-hosted APTOS 2019 Blindness Detection competition was to treat diabetic retinopathy, an acute global health concern. If left untreated, diabetic retinopathy—a serious eye ailment that affects people with diabetes—can result in blindness. In order to manage this disorder and prevent vision loss, early detection and proper diagnosis are essential.

Participants in this competition were to create machine learning models that could categorize retinal images into five groups, from proliferative diabetic retinopathy to no diabetic retinopathy. The dataset that was made available for the task had labels that indicated the severity of the disease in addition to high-resolution retinal photographs.

Healthcare professionals' diagnostic abilities were to be improved through the competition by utilizing AI and machine learning. The organizers aimed to promote creativity and expedite the development of automated diagnostic tools by offering a comprehensive dataset and cultivating a competitive atmosphere.

This competition is significant not just because it has the potential to enhance patient outcomes but also because it adds to the larger area of medical image analysis. The influence of the solutions produced by this competition may be expanded if developments in this field result in the creation of instruments that assist in the identification of other ailments.

This study explores the specifics of the competition, including the information, implemented approaches, evaluation metrics, and results. The findings' consequences for the field of medical imaging in general and the future of diabetic retinopathy detection.

II. Literature Review

In "Convolutional neural networks for mild diabetic retinopathy detection: an experimental study" Rubina Sarki, Sandra Michalska, K. A. H. W. Y. Z. worked on the objective of to identify cases of mild diabetic retinopathy (DR), which are difficult to diagnose because convolutional neural networks (CNNs) frequently overlook minor signals. Experiments were carried out using 13 CNN architectures pre-trained on ImageNet utilizing transfer learning, using annotated fundus photos from public sources. To enhance performance, methods like volume growth, data augmentation, and fine-tuning were used. The best accuracy of 86% was obtained by the fine-tuned ResNet50 model on the No DR/Mild DR classification assignment. The work suggests a system for mild DR detection and highlights the significance of early DR identification. Through the utilization of deep learning and performance enhancement methodologies, the system exhibits resilience and flexibility in real-world scenarios, optimizing eye-screening processes and functioning as a diagnostic tool.

In the paper "Deep Learning Approach to Diabetic Retinopathy Detection" Tymchenko, B., Marchenko, P., & Spodarets, D. describes an automated deep learning technique that uses single fundus imaging to detect the stage of diabetic retinopathy. Using a multistage transfer learning strategy, the method ranks 54 out of 2943 competing methods on the APTOS 2019 Blindness Detection Dataset, with a sensitivity and specificity of 0.99. The approach exhibits stability and resilience by fine-tuning on the target dataset and integrating an ensemble of three CNN architectures. Prospective enhancements encompass comprehensive ensemble SHAP computations, enhanced hyperparameter optimization, and investigation of pretrained encoders for associated assignments. The paper emphasizes how deep learning can improve the diagnosis of diabetic retinopathy and calls for more research on meta-learning strategies.

And Hagos, M. T., & Kant, S. wrote "Transfer Learning based Detection of Diabetic Retinopathy from Small Dataset" With the goal to overcome the problem of limited annotated training data in medical picture classification, this work investigates the effectiveness of transfer learning utilizing a pre-trained Inception-V3 model for Diabetic Retinopathy (DR) detection. Through subsampling a smaller dataset from the Kaggle DR challenge, the authors outperform existing methods in binary classification. Their method, which combines a cosine loss function and an ascending learning rate with stochastic gradient descent, demonstrates how deep learning can effectively learn from tiny datasets in the medical field. The results point to the wider applicability of such methods to solve the lack of labeled data in other medical picture classification tasks. For a thorough assessment, more testing with different pre-trained convolutional networks is advised.

III. Data Exploration

The dataset provided for the APTOS 2019 Blindness Detection competition on Kaggle consists of images and associated labels intended for building a machine learning model to classify the severity of diabetic retinopathy in patients. The primary goal is to utilize these images to detect and categorize the stage of diabetic retinopathy, which is a leading cause of blindness globally.

A. Dataset Description

1. Images:

The dataset includes high-resolution images of eyes captured using fundus photography, which is a specialized form of medical imaging that provides a view of the retina. These images are color representations of the interior surface of the eye, including the retina, optic disc, macula, and posterior pole (including the arteries, veins, and fundus).

2. Labels:

Each image in the dataset is labeled with a corresponding severity grade of diabetic retinopathy. The labels are integer values representing different stages of the disease: 0: No diabetic retinopathy 1: Mild diabetic retinopathy 2: Moderate diabetic retinopathy 3: Severe diabetic retinopathy 4: Proliferative diabetic retinopathy

3. Files:

"train.csv": This file contains the training data with two columns: id_code (the unique identifier for each image) and diagnosis (the severity grade of diabetic retinopathy). "test.csv": This file contains the testing data with one column: id_code, which can be used to match with the images for making predictions. "train_images": A folder containing the training images with filenames matching the id_code in "train.csv". "test_images": A folder containing the testing images with filenames matching the id_code in "test.csv".

B. Data Composition

1. Training Data Shape: (3662, 4) Columns: id_code: Unique identifier for each image. diagnosis: Severity grade of diabetic retinopathy (0 to 4). file_path: Path to the image file. file_name: Name of the image file.

2. Testing Data Shape: (1928, 3) Columns: id_code: Unique identifier for each image. file_path: Path to the image file. file_name: Name of the image file.

C. Class Distribution in Training Data

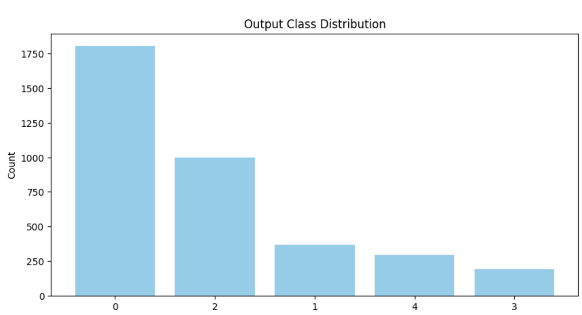

Fig. 1. Class distribution of training data.

The training dataset consists of 3662 images, each labeled with a specific DR severity grade. The distribution of the classes is as follows:

No DR (Class 0): 1805 images Mild DR (Class 1): 370 images Moderate DR (Class 2): 999 images Severe DR (Class 3): 193 images Proliferative DR (Class 4): 295 images This distribution highlights a significant class imbalance, with the majority of images falling into the 'No DR' category.

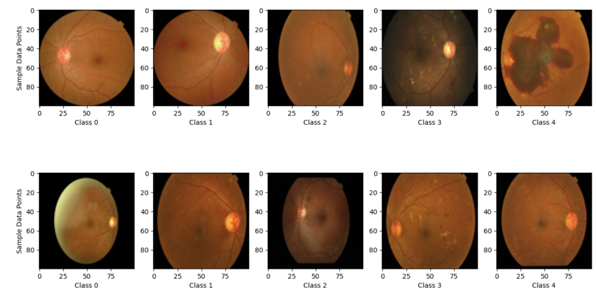

Fig. 2. Retina Images of different class in the training dataset.

IV. Pre-Porcessing

The images above demonstrate that they were not all taken simultaneously, as technicians visited the different locations to take pictures. As a result, the photos are in non-uniforemd form is evident. Pre-processing the photos is crucial to ensure uniformity and improve the effectiveness of machine learning models, as the APTOS 2019 Blindness Detection dataset has variable image capture. The two primary phases in this pre-processing are resizing photographs without altering their aspect ratio and cutting off unwanted borders. To further guarantee that the preprocessing is effective and scalable for big datasets, multiprocessing has been used.

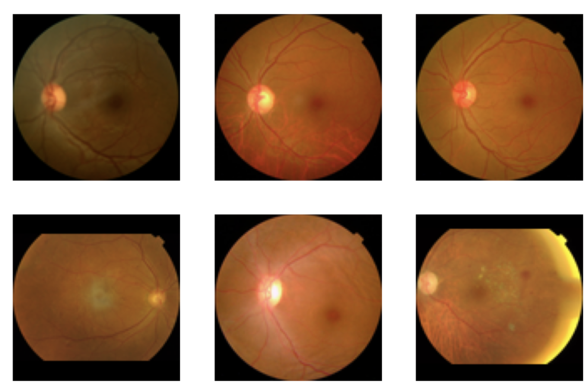

Fig. 3. Retina Images after pre-processing.

1. Cropping Insignificant Borders: Since the photos in the dataset were gathered from rural regions, they frequently include black borders as a result of uneven capture techniques.

2. Resizing to Consistent Size While Preserving Aspect Ratio: In order to avoid distortion, photos are cropped and then resized to a constant size while keeping their aspect ratio. To match the required dimensions, the image is resized and padded using the "resize_maintain_aspect" function.

3. Saving the processed Image: The previously mentioned routines process each image and save it to the designated directory. One image's cropping, scaling, and saving are handled by the function ”save_single”.

4. Batch Processing with Multiprocessing: Multiprocessing is used to process a large dataset in an effective manner. ”Fast_image_resize” is a function that speeds up preprocessing greatly by dividing the task among several CPU cores.

Pre-processing ensures that every image has the same dimensions and that, in order to prevent distortion, their aspect ratios are maintained. Every image has the retinal area centered within it, removing any extraneous black borders while preserving the important details(Fig. 3). As a result, the dataset is more reliable and consistent, which makes it easier to train algorithms that detect diabetic retinopathy.

V. Model Implmentation Methodologies

VI. Evaluation & Results

VII. Discussion and Summary

Referances