Diabetic Retinopathy Using Deep Learning

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Abstract— **According to a recent survey by WHO, every fourth person is diabetic. It can be due to lifestyle, pollution, heredity or many other reasons. A diabetic person with the time has some threats in life. One of these threats is Retinopathy which is a well-known microvascular consequence of diabetes mellitus that poses a risk to vision is diabetic retinopathy. Worldwide, 93 million people have diabetic retinopathy at this time. Studies on the prevalence of diabetic retinopathy and risk factors are lacking. People who have diabetes may have more chances to develop diabetic retinopathy, an eye disorder that can lead to blindness. The retina's blood vessels are impacted (the light-sensitive layer of tissue in the back of your eye). It's crucial to undergo a thorough dilated eye exam at least once a year if you have diabetes. In this paper, we have used the deep learning method by taking a single snapshot of the human fundus for detecting the stage of diabetic retinopathy. We have also suggested the multistage transfer learning method, which uses comparable datasets with various labelling. With a sensitivity and specificity of 0.99, the proposed method can be used as early diagnosis of diabetic retinopathy on APTOS 2019 dataset for Detecting Blindness (13000 images). We employed a deep learning model Shapley Additive exPlanations (SHAP) for game theoretic strategies to research the diagnosis of diabetic retinopathy. In order to associate optimal credit allocation with local explanations, it makes use of the conventional Shapley values from game theory and their related extensions. To understand the predictions of our model and how to further improve its performance, in this study we will train a base ResNet50 model, evaluate it, and use the SHAP model's explain ability technique.**

Keywords: Diabetes mellitus (DM2), SHAP (Shapley Additive exPlanations), Diabetic retinopathy (DR), Sentiment Analysis.

I. INTRODUCTION

Diabetic retinopathy screening is essential for preventing blindness and vision impairment, according to WHO. However, many Asian countries do not routinely do diabetic retinopathy screening, which means that chances to save people from losing their eyesight and becoming blind are being overlooked. The World Health Organization (WHO) considers diabetes to be the only non-communicable disease that is an epidemic. Currently, there are 480 million diabetic patients worldwide; this number is anticipated to rise to almost half a billion by 2045, with current projections indicating that there would be 700 million diabetic people worldwide. Considering further epidemiological data, since 1945, the number of diabetic patients has doubled every 20 years. There are 62 million diabetic people overall in Asia, in which 85 to 95 percent of diabetes cases are caused by type 2 diabetes mellitus (DM2), and cases of the disease have significantly increased in emerging nations. According to statistics, Diabetic Retinopathy is one of the severe illnesses, as it has symptoms which might cause blindness, including as cataracts and glaucoma. Every stage has its own unique symptoms, where doctors sometimes fail to consider some of them and diagnose a patient incorrectly as a result. Consequently, this inspires the notion of developing an automated Diabetic Retinopathy detection system. Proper Care and attention of regular checkup, as well as regular eye screening, at least 56 percent of new instances of this condition, might be decreased (Rohan T, 1989)[1]. However, the early stages of this illness do not exhibit any warning symptoms, and well-trained doctors occasionally were unable to manually analyze and assess the diagnostic photographs of the patient's fundus which resulted in the cases of diabetic retinopathy detection methods. The initial algorithm was based on various classical computer vision algorithms and thresholding.

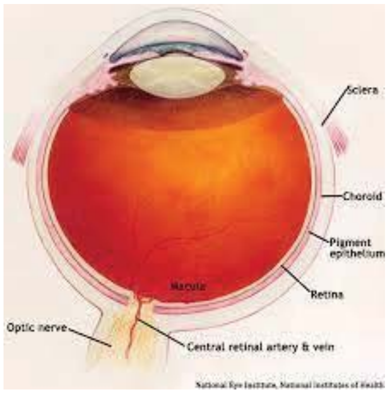

Fig. 1. Normal view of Eye.

However, during the past several years, object identification and classification tests have demonstrated that deep learning techniques outperform traditional algorithms (Harry Pratt, 2016) [2]. This paper includes five more parts which are as follows: Section II: Literature Reviews, Section III: Dataset, Section IV: Methodology, Section V: Results, and Section VI: Conclusion. The normal view of an eye is shown in Figure 1

II. LITERATURE REVIEWS

The issue of early diabetic retinopathy is a challenging issues. Priya and Aruna [4] proposed a Support vector machine to detect diabetic retinopathy. Experimental results show SVM performs better compared to Probabilistic Neural Network. Ganjar Alfian et. al [5] presented deep neural network to detect diabetic retinopathy. The proposed model shows 82.033% detection accuracy.

TABLE I. PROGRESS OF RESEARCH ON DIABETIC RETINOPATHY

Ref.	Dataset	Method	Features	Accuracy
Harry Prat [3]	5000 validation photos	CNN classification	CNN architecture and data augmentation	75
Priya and Aruna [4]	250 Photos	Probabilistic Neural Network	Features to the SVM for Binary Classificaction	89.60%
Ganjar Alfian et. al [5]	133 diabetic patients	deep neural network (DNN)	DNN	82.033%
Carson Lam and Lindsey[7]	evaluated a sizable number of accessible techniques and datasets	CNN	deep learning algorithms	74.5
Hagos and Kant [8]	ImageNet dataset	InceptionNet V3 for five-class classification	CNN architectures for transfer learning	78
Rubina Sarki [9]	Datasets from APTOS and Kaggle	VGG using ImageNet	ResNet50, Xception Nets, DenseNets	81.3

Harry Pratt et. al [3] proposed a CNN approach to predict diabetic retinopathy from digital images. The experiments were performed on 80,000 images and achieved an accuracy of up to 75 %. Carson Lam and Lindsey [7] demonstrated the applications of the Convolutions Neural Network on colour fundus images for detecting diabetic retinopathy staging. The system shows detection accuracy up to 74.5%. Misgina Tsighe Hagos, and Shri Kant [8] proposed InceptionNet V3 for five-class classification for detecting diabetic retinopathy. The techniques show accuracy up to 78%. Rubina Sarki et. al [9] demonstrated a CNN model for mild diabetic retinopathy detection. The system shows an accuracy up to 86%. the brief literature reviews are shown in Table 1.

III. DATASET

The research's picture data came from a number of sources. From the 2015 Kaggle Diabetic Retinopathy Detection Challenge, we utilized an available dataset. To train our CNNs beforehand. This is the biggest freely accessible dataset. It includes of 35126 images of the left and right fundus of Americans who have been diagnosed with diabetes retinopathy: Figure 2 and 3 shows stages of eye fundus and enlarge view of fundus.

- No retinopathy due to diabetes
- diabetic retinopathy that is mild
- diabetic retinopathy of moderate severity
- Diabetes with severe retinopathy
- Diabetic retinopathy that is proliferative

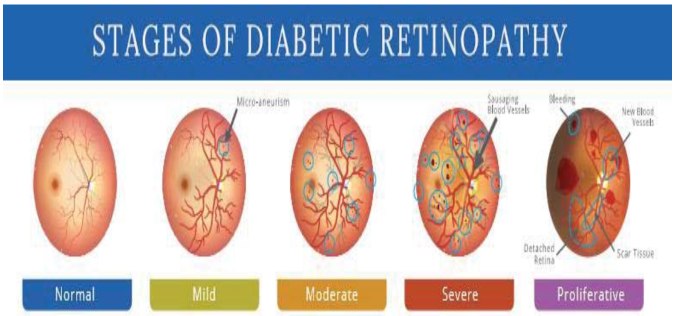

Fig. 2. Stages of the eye fundus.

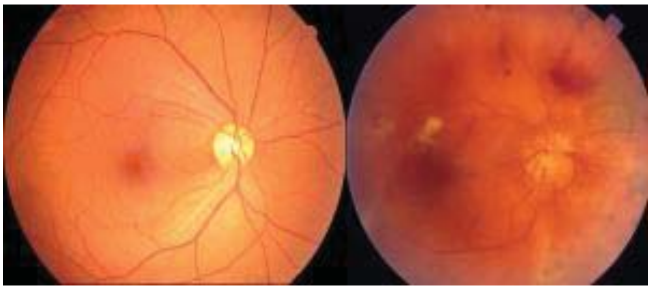

Fig. 3. Enlarge view of eye fundus.

We also made use of other, smaller datasets, such as: Indian Images of diabetic retinopathy. This is from 413 images of the fundus was utilized in this study, and Messidor Methods to Assess Indexing and Segmentation Techniques in Retinal Ophthalmology) dataset from, where 1200 fundus pictures were utilized. As with the original According to a panel of ophthalmologists' standard grading 2018 (Google Brain). Given that Kaggle APTOS [9] was used for the assessment Dataset for 2019 Blindness Detection, and we merely had access to the instruction. some of it. The complete collection contains 18590 fundus images, and photos, which are broken up into 3662 lessons, 13000 testing photographs and 1928 validation shots by the organizers of the Kaggle contest. Each dataset shares the same class distributions; APTOS 2019 distribution is seen in Figure 2. Given that the distribution across multiple datasets is comparable, We viewed it as one of the basic characteristics of this kind of data.

A. Metrics

In this study, we utilized quadratic weighted our primary metric is the kappa score. Kappa rating determines the degree of agreement between two ratings. The correlation between the predicted and human rater-assigned ratings is calculated using quadratic weighted kappa scores. Figure 4 shows

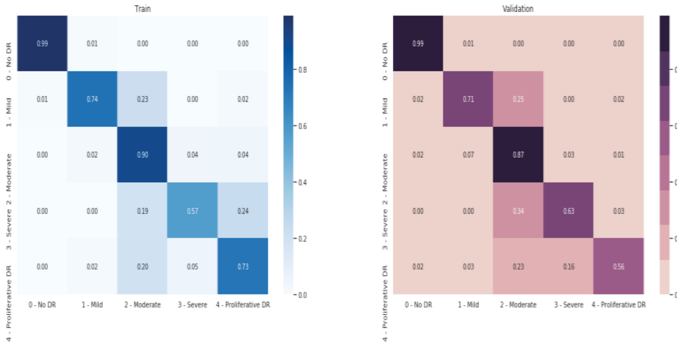

Fig. 4. Confusion Matrix

The range of this measure is -1 (total disagree) ranging from 0 (not disagree) to 1 (complete rate). K is described as follows:

$$k = 1 - \frac{\sum_{i=1}^{k}\sum_{j=1}^{k} w_{ij} o_{ij}}{\sum_{i=1}^{k}\sum_{j=1}^{k} w_{ij} e_{ij}} \qquad \text{(i)}$$

where o_{ij} and e_{ij} are components of the observed and predicted matrices, respectively, and k is the number of categories. The formula for calculating w_{ij} is:

$$w_{ij} = \frac{(i-j)^2}{(k-1)^2} \qquad \text{(ii)}$$

IV. Methodology

The difficulty in detecting diabetic retinopathy can be seen from a variety of perspectives, including classification, regression, and ordinal regression (Ananth and Kleinbaum, 1997). The disease progresses in stages, making this conceivable.

B. Preprocessing

Utilizing altered versions of the original photos, the model was trained and validated. Cropping and scaling of the images made up the preprocessing. There are erroneous associations among the stages of the disease and a number of image meta-feature, as a result of how APTOS2019 was gathered. In Figure 4, a correlation matrix is displayed. We utilized a significant number of augmentations to prevent CNN from overfitting to the feature and decrease correlations between image and their meta-feature. Data Augmentation has been applied at least one of the online augmentations to the images before feeding to the CNN model. Figure 5 shows the working structure of CNN.

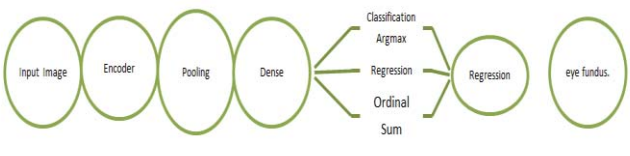

Fig. 5. Working in three head CNN structure

C. Network architecture

Each fundus image will be appropriately categorized. We construct neural network utilizing traditional deep CNN architecture, with a smaller decoder and feature extractor for a particular task. However, given the little training data, it is challenging to train the encoder from scratch. As a result, we initialize the encoder using CNNs that have been trained on Imagenet (Iglovikov and Shvets, 2018). To identify diabetic retinopathy, we suggest using a multi-task learning technique. Three decoders are used. Classifications head, regressions head, and ordinals regression head are three that are trained to do their tasks based on features retrieved with CNN backbone. The output of the classification head is a one-hot encoded vector in which the presence of each stage is indicated by the number 1. The output of the regression head is a real number in the [0;4:5] range that is rounded to an integer to indicate the illness stage. We employ the strategy given in to calculate the

ordinal regression head. A data point immediately enters all categories from 0 to k1 if it falls into category k, to put it simply. Thus, the goal of this head is to forecast every category up to the target. Figure 5 displays the structure of a neural network. We discovered that labelling strategies differed amongst datasets, thus we chose to pre-train our CNNs using the largest dataset Transfer learning is feasible since the natural characteristics of diabetic retinopathy are constant across individuals and independent of datasets. Additionally, many datasets are gathered using various tools. By including this information, the model becomes more generalizable and elevates the significance of natural features by becoming less sensitive to noises. The CNN model [11] was trained with the Imagenet dataset. Following pretraining, we initialize succeeding stages using encoder weights. In our trials, we found that replacing head weights with random initialization before the main training consistently improved metrics, therefore we threw away trained heads.

D. Main training

IDRID, MESSIDOR [10], and 2019 data are all used for the main training. We ran 5-fold validation and tested t using weights generated during the pretraining phase. Figure 6 displays the T-SNE of embeddings with predicted classes and ground truth data labels. It is clear from the image that photos without any DR indications can be distinguished from other images with DR indications by a significant margin. Additionally, DR phases follow one another in embedding space, which is similar to the semantics of actual diagnoses.

E. Post training

After training, we just used linear regression to fit the data model to various head outputs. We felt it was crucial to prevent updates while because if it doesn't go back, it converges to the two-weighted suboptimal local minima heads nearly at zero. These coefficients stop gradients from updating the weights of the respective heads and further prevent network convergence. Every head's initial weights were set at 1=3 and then taught for five iterations to reduce the mean squared error mistake function.

Figure 6 shows features that are embedded with T-SNE with ground truth.

F. Regularization

We regularize our models during training to increase their resilience. We employ traditional techniques, such as dropout and weight decay. Additionally, by employing label smoothing, we penalize the network for making too optimistic predictions. We also suggest a label smoothing method for the linear regression head and for classification and ordinal regression heads. If it is known that the underlying objectives are discrete, it may be employed.

Figure 7 shows the output of the regression head and linear regression. To discrete targets, random uniform noise is added:

$T_s = T + \Delta$

$$\Delta \sim U(a,b)$$

If U is the uniform distribution, T is the original label, and T_s is the smoothed target label. Here, the discrete target labels a = b = Ti Ti+1 3 and Ti Ti+1 are close by using this smoothing method, we might lessen the significance of incorrect tagging.

G. *Ensembling*

Here three encoder architectures were combined with models at different resolutions that performed best on the holdout dataset, including SE-ReNeXt50 (380x380 and 512x512), ENet-B4 (380x380), and ENet-B5 (456x456). An ensemble of 20 models (4 architecture with 5 folds) with test-time augmentation is our best-performing result. 200 predictions were produced overall by this approach for each fundus picture. These forecasts to remove outliers from potentially over fitted models, data were averaged with a 0.25-trimmed mean. To reduce variance, outliers are filtered out using a trimmed mean.

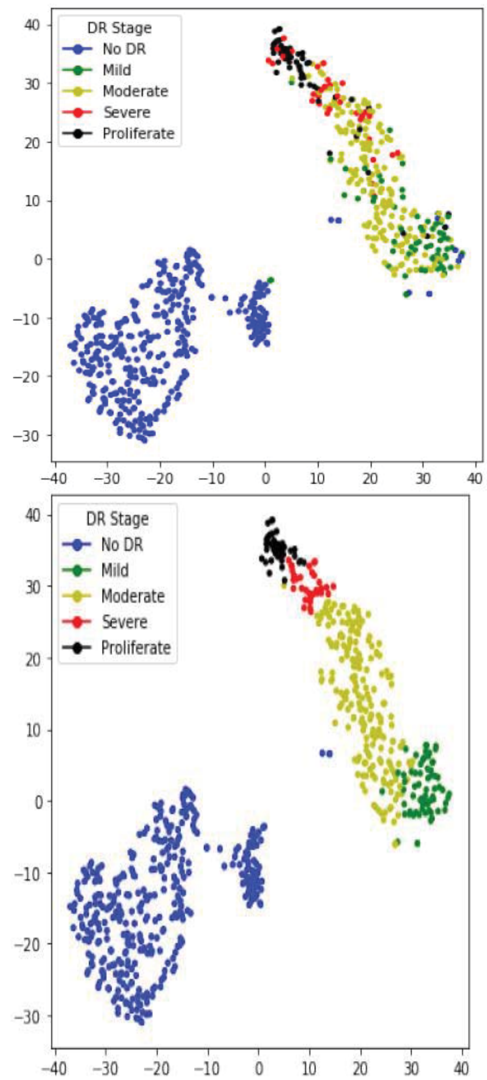

Fig. 6. Features that are embedding with T-SNE.

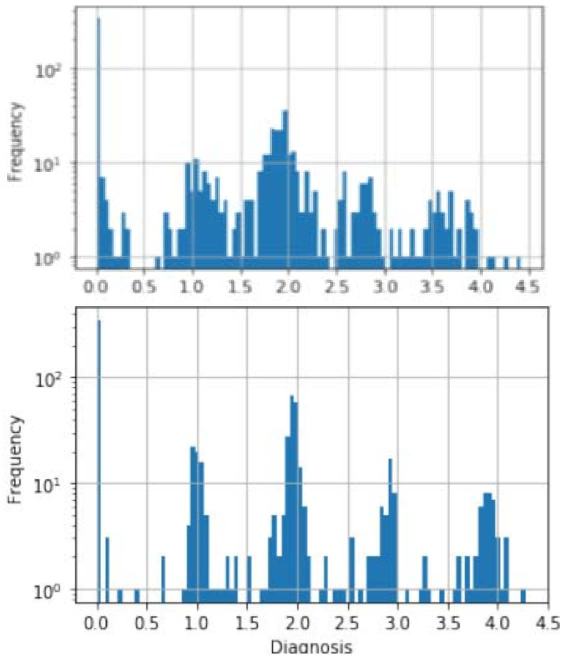

Fig. 7. Output of regression regression

V. Results

As a consequence of the experiment, we present a table with metrics that the Evaluation stated paragraph. The table shows the various local validation used which also includes involves TTA. Test phase into two sections: local testing and testing on Kaggle. As we observed in our area, the assembly approach is the most effective, and we assessed it. on test and validation datasets from Kaggle. With TTA inclusion results were better with the 13000 picture dataset because it is more able to generalize based on imaginary pictures. Moreover, we assessed binary classification To evaluate the quality of the top model as a (DR/No DR) screening technique (see Table, last row) The group using TTA demonstrated its stability in the ultimate rankings, maintaining consistency (58 and 54 of 2943) on the testing and validation datasets, separately.

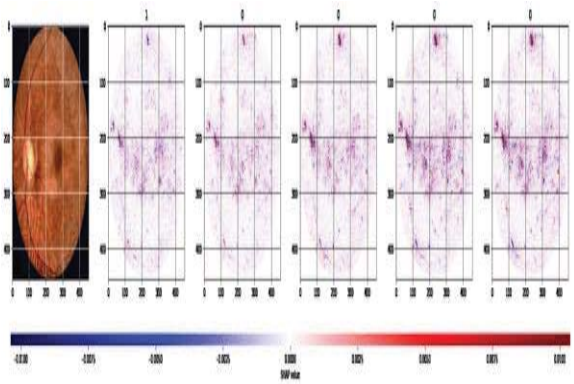

Fig. 8. Analysis of SHAP images.

VI. Conclusion

In the study, we developed a multistage transfer learning method for detecting the various stages of diabetic retinopathy using a single image of the human fundus. Our final solution was created via transfer learning and an ensemble of different CNN architectures. The experimental results demonstrate that the proposed strategy, even with an unstable measure, nevertheless produces high and steady outcomes. By deploying an ensemble of networks that have been pretrained on a sizable dataset and fine-tuned on the target dataset, this method's key benefit is that it boosts generalization and decreases variance. Future research can expand on this approach by computing SHAP ensemble rather than some other network and by performing more precise hyper parameter optimization. Additionally, we can conduct experiments utilizing pre-trained encoders on various tasks related to eye diseases. It has been noted that this requires a separate in-depth study.

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