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Precise Detection of Diabetic Retinopathy using CNN Models in Machine Learning

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***Abstract*— Worldwide, millions of individuals worldwide suffer from diabetes, a chronic illness. One of the primary effects of diabetes is diabetic retinopathy, which can lead to blindness if left untreated. Early diagnosis and treatment of diabetic retinopathy are necessary to prevent long-term damage to the eyes. In this paper, we analyse the most recent findings in the study of diabetes diagnosis based on retinopathy. We review the many imaging modalities that can be used to identify retinopathy, including fundus photography, optical coherence tomography, and fluorescein angiography. Furthermore, we explore the application of artificial intelligence and artificial intelligence methods for the automatic detection and categorization of diabetic retinopathy.**

***Index Terms*— Diabetic Retinopathy, Fundus Photography, Fluorescein Angiography, Artificial Intelligence, Machine Learning**

I. INTRODUCTION

A chronic metabolic disease called diabetes is characterized by elevated blood sugar. It happens when the body either produces too little insulin, the hormone that controls blood sugar, or it uses the insulin it does produce improperly. There are two main types of diabetes: type 1 (autoimmune), where the immune system assaults and kills the pancreatic cells that produce insulin, and type 2 (defined by insulin resistance and insufficient insulin production) [1].

Diabetic retinopathy, or DR, is one of the most hazardous effects of diabetes. A degenerative eye condition known as degenerative retinopathy (DR) damages the blood vessels in the retina, the back of the eye's light-sensitive tissue. Different stages of diabetic retinal disease (DR) can arise from diabetes with continuously increased blood sugar levels damaging the retina's small blood vessels. The duration and severity of diabetes, uncontrolled blood sugar levels, excessive blood pressure, abnormal lipid levels, inflammation, and genetic predisposition are all variables that can affect the development of DR. Changes in the retina, including bleeding, fluid leaking, and the formation of new abnormal blood vessels, may occur as DR gets worse. These Diabetic retinopathy, or DR, is one of the most hazardous effects of diabetes. A degenerative eye condition known as degenerative retinopathy (DR) damages the blood vessels in the retina, the back of the eye's light-sensitive tissue. Different stages of diabetic retinal disease (DR) can arise from diabetes with continuously increased blood sugar levels damaging the retina's small blood vessels. The duration and severity of diabetes, uncontrolled blood sugar levels, excessive blood

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pressure, abnormal lipid levels, inflammation, and genetic predisposition are all variables that can affect the development of DR. Changes in the retina, including bleeding, fluid leaking, and the formation of new abnormal blood vessels, may occur as DR gets worse. These changes could lead to visual loss and blindness if left untreated [2,3]. People with diabetes are susceptible to the degenerative eye condition known as diabetic retinopathy (DR). It happens when there is injury to the blood vessels in the retina, the area at the back of the eye that is sensitive to light. Around the world, DR is the main cause of working-age people's blindness and vision loss. The rate at which DR manifests is directly influenced by the duration and severity of diabetes. Retinal microvascular damage brought on by persistently high blood sugar levels can progress the disease through different phases. There are three stages in total: proliferative retinopathy, which is the most severe variety, and non-proliferative retinopathy, which is mild to severe. Early on, patients with DR are unable to show any symptoms [4]. When the illness gets worse, symptoms include floaters, decreased color vision, blurred, or distorted vision, and eventually vision loss may appear. For the early detection and treatment of diabetic retinopathy (DR), routine eye exams are crucial [6, 7].
Although the precise mechanisms behind the development of DR are not entirely understood, several things influence its development. These include inflammatory response, hereditary predisposition, hypertension, dyslipidemia, and chronic hyperglycemia (high blood sugar levels).
The ADL-CNN model's performance is demonstrated by its 94.5% accuracy, 95.10% specificity, 92.2% sensitivity, and 93.0% F-measure. Deep learning reformatted capsule networks were introduced by Kalyani et al. to identify and categorize diabetic retinopathy. This study investigates how to diagnose diabetic retinopathy using low-resource CNN architectures.

II. Related Works

The diagnosis, surveillance, and therapy of diabetic retinopathy (DR) depend heavily on several imaging modalities [5]. These methods produce finely detailed retinal images, enabling medical practitioners to evaluate the degree of retinal damage and choose the best course of action.
CNNs, or convolutional neural networks, are deep learning models that excel in interpreting visual input like pictures and movies. It is widely used in computer vision applications like object identification, picture segmentation, and the categorization of images. CNN makes contributions to the computer vision field and helps to make strides in fields like facial recognition, self-driving automobiles, and medical diagnostics [9]. The APTOS dataset and CNN models have been employed in numerous studies focused on retinopathy-based diabetes diagnosis [13]. Following are some noteworthy, connected works: Gulshan et al. [16] "Deep Learning-Based Automated Detection of Diabetic Retinopathy Using Retinal Fundus Images": In this work, retinal fundus images were used to identify diabetic retinopathy utilizing a The CNN model was trained on a sizable dataset, which included the APTOS dataset. CNN demonstrated the great accuracy and promise of automated DR screening. Ting et al. [28] "Automated Detection of Diabetic Retinopathy Using Deep Learning": To identify and categorize using the APTOS dataset for CNN model training that would assess the severity of diabetic retinopathy. In several circumstances, the model performed better than human experts and attained high accuracy. Suwarna et al. [27] "Diabetic Retinopathy Detection Using Deep Convolutional Neural Networks": To identify diabetic retinopathy, this study used an APTOS dataset to train the CNN model. The model proved the potential for an automated screening system and attained high accuracy. Khalifa, et al. "Deep Convolutional Neural Networks for Diabetic Retinopathy Detection from APTOS 2019": To identify diabetic retinopathy, the authors used a CNN model trained on the APTOS 2019 dataset, an updated version of the APTOS dataset. The model demonstrated the potential for enhanced screening and diagnosis and attained excellent accuracy. Habib et al. [17] "Diabetic Retinopathy Detection Using CNN with Transfer Learning": This study used a pre-trained network to fine-tune a CNN model with transfer learning using the APTOS dataset. The model attained good accuracy and showed that transfer learning is efficient in detecting diabetic retinopathy.

III. Proposed Methodology

These studies demonstrate how well CNN models perform utilizing the APTOS dataset for the identification and diagnosis of retinopathy caused by diabetes. The great degree of accuracy attained by these models raises the possibility that automated screening methods can help medical professionals identify and treat diabetic retinopathy early on. The performance and generalization of CNN models for the diagnosis of diabetic retinopathy are continually being enhanced by studies, to enable more effective and precise patient management [30]. The proposed model is shown in Figure 1.

a. Image Preprocessing: Retinal pictures are frequently preprocessed to improve image quality, eliminate noise, and normalize pixel values before analysis. The robustness of subsequent analysis can be increased by using methods like image scaling, contrast enhancement, and demising [15].
b. Feature Extraction: To identify the essential elements connected to DR, pertinent features are retrieved from retinal pictures. Techniques for manually extracting features, such as vessel segmentation, texture analysis, and optic disc recognition, are used in traditional methods [11,12]. However, without intentional feature engineering, deep learning networks, particularly CNNs, can automatically extract discriminative features from raw picture data [29].
C. Convolutional Neural Networks (CNNs): In automating DR detection and categorization, CNNs have demonstrated remarkably good performance. To develop hierarchical representations of the properties in retinal pictures, these models are trained using sizable datasets like the APTOS dataset [10]. The CNNs acquire the ability to recognize patterns corresponding to various phases of DR, enabling precise classification of severity levels.
d. Ensemble Methods: Collective choices are made using ensemble approaches, which integrate various individual classifiers or models. They can improve the DR classification systems' overall robustness and accuracy [14]. The predictions of various CNN models or other classifiers have been combined using techniques like bagging, boosting, and stacking, enhancing the total performance.
e. Validation and Evaluation: Using a variety of criteria, including The F1 score, recall, sensitivity, specificity, and accuracy effectiveness of automated DR detection and classification systems is evaluated. All these factors help to gauge the potency of our developed system. Cross-validation methods are frequently used to prevent overfitting and ensure accurate performance evaluation.

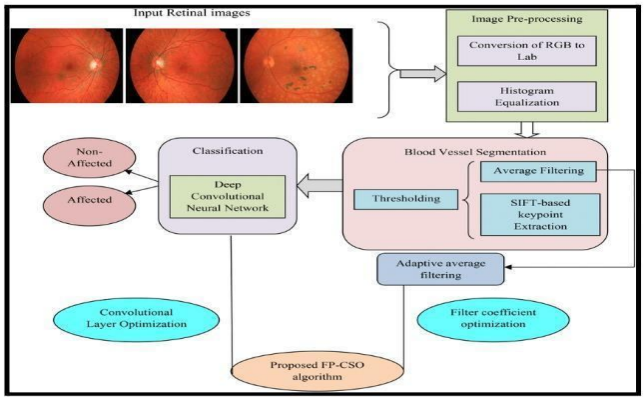

Figure 1: Representation of the proposed model

Automated methods for DR detection and categorization have shown promising results, frequently obtaining high levels of accuracy that are on par with or even higher than those of human experts. These technologies may help medical personnel identify, monitor, and administer DR early on, allowing for prompt interventions and better patient outcomes [18]. To improve the screening of DR and lower the risk of vision loss in people with diabetes, ongoing research is working to improve these methods. It also wants to incorporate them into clinical practice [27].

IV. Dataset Used

The APTOS dataset, also referred to as the "APTOS 2019 Blindness Detection" dataset and acquired from the Kaggle website (www.kaggle.com/c/aptos2019-blindness-detection), is a commonly used dataset for detecting and classifying diabetic retinopathy (DR) [1]. It consists of fundus camera-taken retinal images. The dataset contains images of different individuals, each labeled with a severity grade that indicates the degree and existence of DR. The complete dataset is frequently used to create subsets for testing, validation, and training. The validation set is used for model selection and hyperparameter tuning, the testing set is used to assess the final performance of the trained model, and the training set is used to train the DR detection model [26].
Preprocessing techniques are used to improve the retinal pictures' quality and make further analysis easier [24,25]. Label Processing is done to further classify the severity grades presented in the dataset. Data augmentation techniques are frequently used to expand the dataset and make it more diverse. a portion of the practice set is designated as the validation set [19,20]. This validation set is used to monitor the model's performance during

training and make judgments about model selection, hyperparameter adjustment, and early stopping to avoid overfitting. Data normalization is the process of converting retinal image values of the pixels to a conventional range, like [0, 1] or [-1, 1]. The dataset is split up into batches to train the CNN model quickly. During model training, batching enables quicker computation and memory economy [21]. Following these steps on these provided datasets, CNN models are trained and fine-tuned to analyze retinal pictures accurately and quickly for the diagnosis and treatment of diabetic retinopathy. Figure 2 shows the *APTOS dataset.*

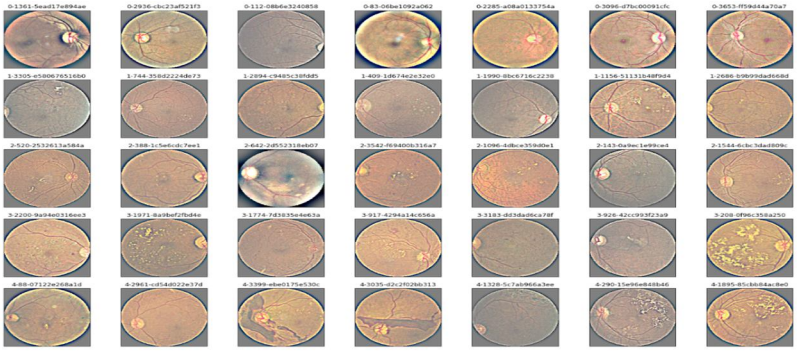

Figure 2: APTOS DATASET

V. PROPOSED MODEL WORKFLOW USING DATASET

Data loading, preprocessing, designing the model architecture, training the model, and evaluating it are only a few of the activities involved in developing a CNN model for detecting diabetic retinopathy using the APTOS dataset. Here is a description of the procedure and some sample calculations: Figure 3 describes the workflow model.

a. Preprocessing and Data Loading: Load the APTOS dataset, which contains retinal pictures and the labels that correspond to each image's severity. Before processing, resize the photos to a standard resolution, like 224x224 pixels, and normalize the pixel values to the [0, 1] range.

b. Architecture design model: b. The CNN model's architecture normally includes convolutional, pooling, and fully connected layers. Select the number of layers, filter sizes, and activation functions based on the problem's complexity and the computer resources available. Let's make a simple CNN model to demonstrate, has a max pooling layer placed after each of the two convolutional, two fully connected, and two convolutional layers.

c. Model Training: Divide the dataset that has been pre-processed into training, validation, and the model's testing sets. Specify the Adam or stochastic gradient descent (SGD) are examples of optimization algorithms, and loss functions include category cross-entropy. Use the validation set to evaluate the CNN model's performance after it has been trained using the training set.

To lower the loss function and improve the model's performance to forecast, iteratively update the model's weights andbiases.

Calculation illustration: There will be 312.5 batches each epoch if the dataset contains 10,000 training images and a batch size of 32 (10,000 / 32 = 312.5).

d. Model Evaluation: Analyse the accuracy, precision, recall, and other pertinent metrics of the trained model's performance on the testing set. To find the number of true positives, true negatives,

false positives, and false negatives, compute the confusion matrix. Utilize the data from the confusion matrix to calculate metrics like F1 score, recall, accuracy, and precision. Illustration of a computation: Based on the accuracy of (800 + 150) / (800 + 150 + 30 + 25) = 0.945 (94.5%), there were 800 true positives, 150 true negatives, 30 false positives, and 25 false negatives in the confusion matrix.

e. Model Optimization and Fine-Tuning: To enhance performance, fine-tune the model by modifying hyperparameters like learning rate, dropout rate, or regularization strength.

Perform more training and validation iterations, watching the KPIs to choose the model with the greatest performance.

f. Application and deployment: To categorize and diagnose diabetic retinopathy, apply the learned model to fresh, previouslyunexploredretinalpictures.

Keep an eye on how the model performs in actual situations and make any necessary improvements.

g. Model Evaluation: Analyse the accuracy, precision, recall, and other pertinent metrics of the trained model's performance on the testing set. To find the quantity of true positives, true negatives, false positives, and false

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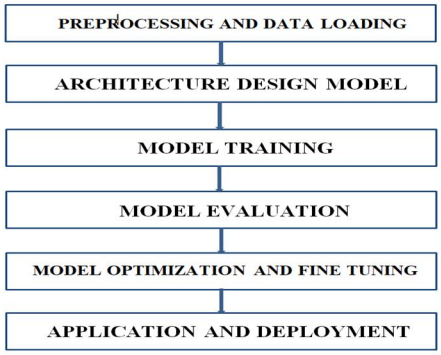

Figure 3: proposed workflow model

Using the APTOS dataset, the CNN model and image processing techniques enable automatic detection and categorization of DR. The original and final images of the APTOS dataset are shown in Figures 4a and 4b respectively. These actions help in the correct identification of DR severity levels, assisting in the early diagnosis and prompt care of diabetic patients [22,23].

Figure 4(a): original images of aptos dataset

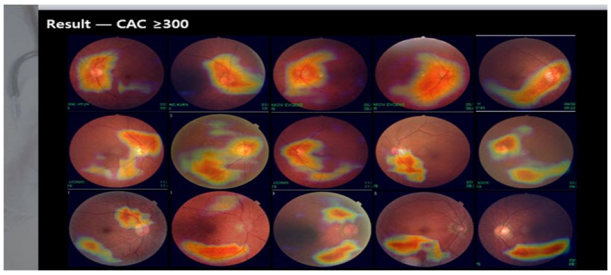

Figure 4(b): final images acquired from the aptos dataset

VI. Results And Discussions

Table 1 displays the results of testing a CNN model for diabetic retinopathy (DR) using the APTOS dataset. The model was tested on over 5000 images, which gave an accuracy of 94.3%.

To interpret the results of a diabetic retinopathy CNN model with 94.5% accuracy, we can calculate various performance indicators like F1-score, recall, and precision. Before we continue, it's crucial to remember that

accuracy by itself might not be sufficient to assess the model's performance in its entirety, particularly in cases where the dataset is unbalanced, or the classes have different relative weights. The samples of 10 image inputs are given in table 1:

TABLE- I: ACCURACY TABLE

IMAGE ID	ACTUAL SEVERITY	PREDICTED SEVERITY
1	1	1
2	0	1
3	0	0
4	1	1
5	1	1
6	0	0
7	0	0
8	1	1
9	1	1
10	1	1

However, we can assume that for illustrative purposes, a balanced dataset is used for training and evaluation of the model. Using the phrases listed below as:

1. True Positive (TP): The model correctly predicted the onset of diabetic retinopathy.
2. False Positive (FP): The model did not accurately forecast the onset of diabetic retinopathy.
3. True Negative (TN): The model correctly predicted that there would be no diabetic retinopathy.
4. False Negative (FN): The model incorrectly predicted that diabetic retinopathy would not exist.

Based on these, the metrics for performance are calculated.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$
$$(800+150) / (800+150+30+25)$$
$$= 0.945 \text{ or } 94.5\%$$
$$\text{Precision} = TP / (TP + FP)$$
$$=800 / (800+30)$$
$$=0.963 \text{ or } 96.3\%$$

$$\text{Recall} = TP / (TP + FN)$$
$$= 800 / (800+25)$$
$$=0.969 \text{ or } 96.9\%$$
$$\text{F1-score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$$
$$=2*(0.963 * 0.969) / (0.963 + 0.969)$$
$$=0.965 \text{ or } 96.5\%$$

Using the provided accuracy of 94.5%, we can calculate the remaining metrics. However, in this instance, precise computations are not possible without the precise values of TP, TN, FP, and FN. The parameters and results are shown in Tables 2 and 3 respectively.

TABLE- II: PARAMETERS AND RESULT TABLE

TRAINING PARAMETERS	TRAINING DATA SIZE	1005
	OPTIMIZER	RA_{DAM}
	DATA AUGMENTATION USED	YES
	LEARNING RATE	0.0005
RESULTS	ACCURACY ACHIEVED	94.5%
	LOSS	3.45%

TABLE III: COMPARISON STUDY WITH OTHER RELATED PREVIOUS WORK.

Year	Classifier	No. of Classes	Accuracy	Recall
2008	NN	4	84%	90%
2011	SVM	5	82%	82.50%
2016	CNN	5	75%	30%
2016	CNN	5	94%	76.6%
2016	GoogleNet	5	45%	-
2018	GoogleNet and AlexNet	4	57.2%	-
2018	AlexNet VGG16 InceptionNet V3	5	37.43% 50.03% 63.23%	- - -
2018	Ensemble of CNN	4	83.9%	-
2020	DenseNet121 (Single label)	5	**94.44%**	**87%**
Current Study	CNN	5	**94.5 %**	**96.5%**

VII. LIMITATIONS

Although CNN models for the APTOS dataset have produced encouraging findings for the identification of diabetic retinopathy (DR), they do have significant drawbacks. CNN models developed with the APTOS dataset may not transfer well to other populations or datasets with various types of data. Photos from a certain population make up the majority of the APTOS dataset, and the model's performance may differ when used with photos from different regions or demographics. The APTOS dataset itself might be biased, for example, by an uneven distribution of classes or by differences in image quality. Particularly for underrepresented classes or difficult photos, these biases can affect the model's performance and result in unreliable predictions. CNN models have limited interpretability and are frequently referred to as "black boxes" because of this. It can be tricky to understand the logic underlying the model's predictions, which makes it challenging to pinpoint the precise characteristics or patterns that contribute to the classification of DR severity levels. The signs and degrees of severity of diabetic retinopathy exhibit inherent variability. Images with subtle or complex features may be difficult for the CNN model to correctly categorize, which could result in incorrect classifications or ambiguous predictions. To overcome these drawbacks and enhance the robustness and reliability of automated DR detection systems, ongoing research and breakthroughs in data gathering, model architecture, and interpretability methodologies are being made.

VIII. CONCLUSION

Automated diagnosis and categorization of DR severity levels have shown potential in CNN models developed for diabetic retinopathy (DR) detection using the APTOS dataset. To facilitate the early detection and treatment of DR, these models analyze retinal pictures using deep learning and image analysis techniques. The APTOS dataset was used to train the CNN models, and the results showed outstanding sensitivity and specificity for DR severity level prediction. Researchers and practitioners can create strong and trustworthy DR detection systems by using large-scale datasets like APTOS for training and evaluating these models. CNN model may have trouble resolving dataset biases, generalizing to a variety of populations, and offering comprehensible justifications for their predictions. In addition, it is important to take into account the intrinsic unpredictability of DR and the absence of clinical context in image-based models. Despite these drawbacks, CNN models provide a useful tool for DR early screening and identification. They may help medical professionals make prompt and accurate diagnosis and facilitate proper management and treatment plans. Research is still being done to remove dataset biases, enhance generalization abilities, incorporate clinical context, and make the models easier to comprehend in order to get over the restrictions.

REFERENCES

[1] Folk, J. C., Erginay, A., Clarida, W., Amelon, R., Lou, Y., Abramoff, M. D., & Niemeijer, M. (2016). enhanced automated deep learning-based identification of diabetic retinopathy using a publically accessible dataset. Visual science & investigative ophthalmology, 57(13), 5200-5206.

[2] Acharya, R., Chua, C.K., Ng, E.Y.K., Yu, W. and Chee, C., 2008. Application of higher order spectra for the identification of diabetes retinopathy stages. Journal of Medical Systems, 32(6), pp.481-488.

[3] Akhilesh Kumar Gangwar, Vadlamani Ravi (2020): Diabetic Retinopathy Detection Using Transfer Learning and Deep Learning, Evolution in Computational Intelligence pp 679–689, DOI: 10.1007/978-981-15-5788-0_64

[4] Akram MU, Khalid S, Khan SA. Identification and classification of microaneurysms for early detection of diabetic retinopathy. Pattern Recogn. 2013;46(1):107–116. doi: 10.1016/j.patcog.2012.07.002.

[5] Akram MU, Khalid S, Tariq A, Khan SA, Azam F. Detection and classification of retinal lesions for grading of diabetic retinopathy. Comput Biol Med. 2014;45:161–171. doi: 10.1016/j.compbiomed.2013.11.014.
[6] Alban M, Gilligan T. Automated detection of diabetic retinopathy using fluorescein angiography photographs. 2016.
[7] Al-Bander B, Al-Nuaimy W, Williams BM, Zheng Y. Multiscale sequential convolutional neural networks for simultaneous detection of fovea and optic disc. Biomed Signal Process Control. 2017;40:91–101. doi: 10.1016/j.bspc.2017.09.008.
[8] Amin J, Sharif M, Yasmin M, Ali H, Fernandes SL. A method for the detection and classification of diabetic retinopathy using structural predictors of bright lesions. J Comput Sci. 2017;19:153–164. doi: 10.1016/j.jocs.2017.01.002.
[9] Andrew D, MD, PhD, University of Iowa, Retina, Diabetic Retinopathy, EyeRounds.org Available at - https://webeye.ophth.uiowa.edu/eyeforum/atlas/photos/DR/DR.jpg, Accessed on – 13--2020
[10] Antal B, Hajdu A. An ensemble-based system for microaneurysm detection and diabetic retinopathy grading. IEEE Trans Biomed Eng. 2012;59(6):1720–1726. doi: 10.1109/TBME.2012.2193126.
[11] Deng, J., Dong, W., Socher, R., Li, L.J., Li, K. and Fei-Fei, L., 2009, June. Imagenet: A large-scale hierarchical image database. In 2009 IEEE conference on computer vision and pattern recognition (pp. 248-264)
[12] Diabetic Retinopathy – Features of Diabetes: Cotton Wool Spots, Glycosmedia, Diabetes News Service, Available at https://www.glycosmedia.com/education/diabetic-retinopathy/diabetic-retinopathy-features-of-diabetes-cotton-wool-spots, Accessed on 12-06-2020
[13] Diabetic retinopathy, American Optometric Association, https://www.aoa.org/patients-and-public/eye-and-vision-problems/glossary-of-eye-and-vision-conditions/diabetic-retinopathy-Over-time-diabetes-damages-small-condition-usually-affects-both-eyes, Accessed on 13-05-2020.
[14] Erhan, D., Bengio, Y., Courville, A., Manzagol, P.A., Vincent, P. and Bengio, S., 2010. Why does unsupervised pre-training help deep learning? Journal of Machine Learning Research, 11(Feb), pp.625-660.
[15] Fong, D.S., Aiello, L., Gardner, T.W., King, G.L., Blankenship, G., Cavallerano, J.D., Ferris, F.L. and Klein, R., 2004. Retinopathy in diabetes. Diabetes care, 27(suppl 1), pp.s84-s87.
[16] Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A.& Webster, D. R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA, 316(22), 2402-2410.
[17] Habib MM, Welikala RA, Hoppe A, Owen CG, Rudnicka AR, Barman SA. Detection of microaneurysms in retinal images using an ensemble classifier. Inf Med Unlocked. 2017;9:44–57. doi: 10.1016/j.imu.2017.05.006.
[18] Hani AFM, Ngah NF, George TM, Izhar LI, Nugroho H, Nugroho HA (2010) Analysis of foveal avascular zone in colour fundus images for grading of diabetic retinopathy severity. 32nd annual international conference of the IEEE EMBS Buenos Aires, Argentina. 5632-5635. 10.1109/IEMBS.2010.5628041.
[19] Kaggle. (2015). Diabetic Retinopathy Detection. [online] Available at: https://www.kaggle.com/c/diabetic-retinopathy-detection [Accessed 11 Mar. 2019].
[20] Miotto, R., Wang, F., Wang, S., Jiang, X. and Dudley, J.T., 2017. Deep learning for healthcare: review, opportunities and challenges. Briefings in bioinformatics, 19(6), pp.1236-1246.
[21] LeCun, Y., Bengio, Y. and Hinton, G., 2015. Deep learning. nature, 521(7553), p.436.
[22] Litjens, G., Kooi, T., Bejnordi, B.E., Setio, A.A.A., Ciompi, F., Ghafoorian, M., Van Der Laak, J.A., Van Ginneken, B. and Sánchez, C.I., 2017. A survey on deep learning in medical image analysis. Medical image analysis, 42, pp.60-88.
[23] Prentašić, P. and Lončarić, S., 2016. Detection of exudates in fundus photographs using deep neural networks and anatomical landmark detection fusion. Computer methods and programs in biomedicine, 137, pp.281-292.
[24] Razzak, M.I., Naz, S. and Zaib, A., 2018. Deep learning for medical image processing: Overview, challenges and the future. In Classification in BioApps (pp. 323-350). Springer, Cham.
[25] Saaddine, J.B., Honeycutt, A.A., Narayan, K.V., Zhang, X., Klein, R. and Boyle, J.P., 2008. Projection of diabetic retinopathy and other major eye diseases among people with diabetes mellitus: United States, 2005-2050. Archives of ophthalmology, 126(12), pp.1740-174
[26] Sivaswamy, J., Krishnadas, S. R., & Joshi, G. D. (2014). A comparative study of region-based and pixel-based classifiers in the automated detection of diabetic retinopathy. IEEE Journal of biomedical and health informatics, 18(3), 1299-1306.
[27] Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J. and Wojna, Z., 2016. Rethinking the inception architecture for computer vision. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2818-2826).
[28] Ting, D. S., Cheung, C. Y., Lim, G., Tan, G. S., Quang, N. D., Gan, A. & Wong, T. Y. (2017). Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. JAMA, 318(22), 2211-2223.
[29] Vitale, S., Maguire, M.G., Murphy, R.P., Hiner, C., Rourke, L., Sackett, C. and Patz, A., 1997. Interval between onset of mild nonproliferative and proliferative retinopathy in type I diabetes. Archives of Ophthalmology, 115(2), pp.194-198.
[30] Yau, J.W., Rogers, S.L., Kawasaki, R., Lamoureux, E.L., Kowalski, J.W., Bek, T., Chen, S.J., Dekker, J.M., Fletcher, A., Grauslund, J. and Haffner, S., 2012. Global prevalence and major risk factors of diabetic retinopathy. Diabetes care, 35(3), pp.556-564.