A Deep Learning Based Approach for the Classification of Diabetic Retinopathy in Human Retina

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Abstract—**Diabetic Retinopathy, a common diabetes complication causes damages to the blood vessels of light sensitive tissues in the human retina. Due to the limitations in the manual screening process, there exists a compelling requirement of an automated approach for the Diabetic Retinopathy screening which can be applied regularly and in abundance in any kind of a healthcare environment. This paper suggests a Deep Learning based automated approach to classify retinal fundus images into five major severity levels while focusing on achieving the optimal accuracy-efficiency balance in performance. In the classification task, a lightweight Convolutional Neural Network (CNN) model with only 6 convolutional layers was suggested to classify retinal fundus images to five major severity levels. CNN refinements such as Hyperparameter Tuning, Regularization and Data Augmentation were applied to increase the model accuracy. The suggested model achieved an Accuracy of 72.28%, a Sensitivity of 71.12% and a Specificity of 93.1% for a testing dataset of 267 retinal fundus images from Kaggle and Messidor-2 datasets. By comparing with four pre-trained CNN models VGG16, ResNet50, InceptionV3 and Xception, it was observed that the accuracy of the suggested model is slightly lesser than that of VGG16 and ResNet50 models. However, the number of FLOPs in the suggested model is 23 times lesser than VGG16 and 6 times lesser than ResNet50, indicating that the suggested model is more efficient than the mentioned pre-trained models. The accuracy of the suggested model can be further improved without increasing the number of FLOPs by increasing the number of training data samples.**

Keywords—Diabetic Retinopathy, Deep Learning, Lightweight CNN

I. INTRODUCTION

Diabetic Retinopathy (DR), is a common diabetes complication which causes damages to the blood vessels of the light sensitive tissues in the human retina [1]. Although it would show no symptoms or only mild vision problems in the beginning, if not identified and treated properly, a patient could end up in permanent blindness. According to the statistics provided by the International Diabetes Federation, in 2019 approximately 463 million adults (20-79 years) were living with diabetes. They have estimated that by 2045, the number of diabetes patients will rise to 700 million [2]. All these individuals are at risk of developing DR conditions [3]. Over the years, DR has become one of the leading causes of blindness in the working age population, making huge impacts not only in the health sector but in the economy as well.

The main classification of DR is into two groups as Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). NPDR is the earlier stage where the walls of blood vessels in the eyes becomes weak and small dots of blood called Microaneurysms protrude from the vessel walls. PDR is the advanced stage where the damaged blood vessels close off while growing new fragile ones. This results in many complications and sometimes ends up with complete vision loss. Fig. 1 shows the differences between NPDR, PDR and normal retinal images respectively.

NPDR can be further categorized into three stages as Mild NPDR, Moderate NPDR and Severe NPDR. According to the International Clinical Diabetic Retinopathy Severity Scale proposed by C. P. Wilkinson et al. (2003) there are five major severity levels of DR as, No DR (Healthy), Mild NPDR, Moderate NPDR, Severe NPDR, and PDR [4]. These severity levels are identified with the presence of three major lesion types, Microaneurysms, Hemorrhages and Exudates [5].

Throughout the world, the screening of Diabetic Retinopathy is mostly done manually by the trained ophthalmologists. Although 70% of diabetes cases occur in low and lower-middle income countries, still the clinical practice guidelines for DR management and screenings are not well established [6]. Manual Screening of DR needs the involvement of experts as well as expensive instruments which are hard to be achieved in lower-income healthcare environments. Also, there is a shortage of eye care specialists needed to screen the large amount of diabetes patients regularly [7]. Moreover, manual DR screening is a time-consuming task which is widely affected by the inconsistencies in manual readings [8]. Due to these limitations, the early detection, regular screenings and treatments required to prevent the further complications of the disease are harder to be achieved. Therefore, it is crucial to have an automated approach for the DR screening which can be applied regularly and in abundance in any kind of a health care environment.

Identifying the correct DR severity level is a main objective of DR screening. This is essential to identify DR patients in early stages in order to prevent the possible irreversible blindness [9]. The motivation behind this work is to facilitate this objective by automating the tasks of classifying DR, while optimizing the accuracy and the efficiency via Deep Learning approaches.

The remainder of this paper is as follows. Section II presents a literature review on the classification of Diabetic Retinopathy. Section III includes a detailed description of the design and methodology of the suggested approach for the classification of DR. Section IV discusses the evaluation of the suggested approach. Section V presents the conclusion of the study.

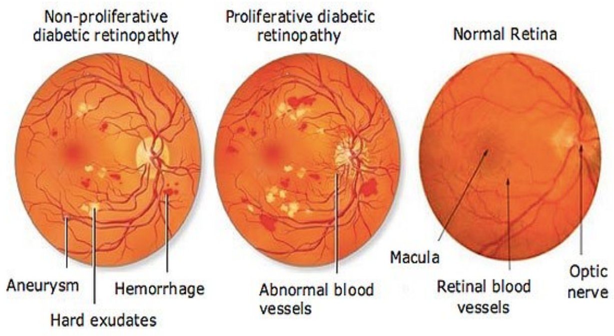

Fig. 1. Differences between NPDR, PDR and normal retina [10]

II. RELATED WORK

With the advancement of the computing sector, many approaches have been used to automate the tasks of classifying Diabetic Retinopathy. In recent years, Deep Learning approaches have been widely used for this task [9]. The advantage of using Deep Learning based approaches over other Computer Vision approaches is that it does not need hand-crafted feature extraction [11]. Recently, Convolutional Neural Networks (CNN) has become the most widely used Deep Learning based approach in medical image analysis [12].

CNN is a class of Deep Neural Networks, consisting of input layers, output layers as well as multiple hidden layers of convolution, subsampling and fully connected layers. The convolutional layers are composed with a set of learnable parameters called filters. When training a CNN, each filter is convolved across the input image performing a dot product with filter entries and image entries. Filters are associated with features and when a certain feature is presented in the input, the convolution between the filter and the input provides higher values. With these values, the network gains the ability to detect the features associated with filters [13].

A. Deep Learning based Diabetic Retinopathy Screening Approaches

M. T. Esfahani et al. (2018) have used 35,000 retinal images of Kaggle dataset to be fine-tuned using a pre-trained ResNet34 CNN architecture to classify retinal fundus images to two classes as No DR and DR [14]. They have pre-processed the input images by blurring the background using Gaussian blur, normalized the images to eliminate image defects and resized into 512 × 512 pixels before feeding images into the pre-trained CNN. From 2000 test images, they have achieved 85% and 86% as their overall precision and recall values respectively. The limitation of this study is that the authors have not considered the five major severity level classification, which is most commonly used in the medical domain.

X. Wang et al. (2018) have evaluated three pre-trained CNN models in classifying retinal images to the five major DR severity levels [15]. A dataset of 166 Kaggle images was resized as a pre-processing step and fed into pre-trained VGG16, AlexNet and InceptionNetV3 models separately. The average accuracy received after training was 50.03%, 37.43% and 63.23% respectively. Using a limited number of images for training and applying limited pre-processing techniques have reduced the capability of the CNN to learn more robust features from input retinal images.

J. J. Orlando et al. (2018) have used a light CNN, augmented with domain knowledge to automate the detection of Microaneurysms and Hemorrhages which are collectively known as red lesions [17]. The features extracted from the CNN were fed into a Random Forest Classifier to remove false lesion candidates. The maximum lesion probability assigned by the Random Forest Classifier was used as a feature for DR screening. E-Ophtha, DIARETDB1 and Messidor datasets have been used for the evaluation where the maximum sensitivity of 48.83% was achieved with DIARETDB1 dataset. Detection of Exudates and the stage-based classification were not covered in this study.

B. Efficiency Perspective related to Deep Learning based Classifications.

Since the remarkable results of AlexNet in 2012 [18], Deep Learning based solutions have contributed to significant improvement in accuracy for many Computer Vision applications. Besides accuracy, efficiency is an equally important factor which is essential in real-time tasks such as DR classification. Majority of the most accurate Deep Learning based solutions in DR screening have a larger number of layers and thousands of parameters which requires millions of floating-point operations (FLOPs) in computations [19]. This makes these models extremely complex and inefficient. Efficiency perspective has become a recent trend in the Computer Vision domain, since present-day applications are expected to have an optimal efficiency accuracy balance which aids these applications to operate easily under limited computational budget and even on embedded devices [20].

The concept of lightweight CNN architecture has become more popular recently as a method of enhancing the efficiency perspective related to Deep Learning based studies [21, 22]. Rather than applying Transfer Learning or Fine-Tuning techniques on pre- trained models or custom models with a large number of layers, here the main objective is to achieve the best efficiency-accuracy balance by applying refinements and special pre-processing techniques on CNN models with a lesser number of layers and parameters. Data Augmentation, Hyper-parameter Tuning, Dropouts layers, Batch Normalization layers and L1, L2 Regularizations can be named as some of the widely being applied refinements in these kinds of CNNs.

K. Xu et al. (2017) have used a custom CNN model with 8 convolutional layers trained with 800 retinal images from Kaggle dataset, for a binary classification [23]. Images resized to 224×224×3 pixels were fed as input to the CNN and Data Augmentation techniques were applied on input images with rotation, flipping, shearing, scaling and translation as the types of transformations. For a testing dataset with 200 images, they achieved an overall accuracy of 94.5% and 91.5% with Data Augmentation and without Data Augmentation respectively. The limitation of this study is that it has classified the retinal images only into two classes.

S. Gayathri et al. (2020) have trained a custom CNN with 6 convolutional layers with a smaller number of parameters to make the model suitable for real-time processing [24]. After feature extraction, the output feature map of CNN has been fed to different machine learning classifiers and evaluated the performance. SVM, AdaBoost, Naive Bayes, J48 and Random Forest were the machine learning classifiers used for comparison. Out of these, J48 provided the best accuracy when evaluated with MESSIDOR, Kaggle and IDRiD datasets. For binary classification, J48 classifier accuracy was 99.89% and for multi class classification, accuracy was 99.59%. The limitation of this study is that rather than using a single CNN for feature extraction and classification both, they have used different machine learning classifiers after extracting features through a lightweight-CNN which results in a higher computational cost.

W. L. Alyoubi et al. (2020) have analysed the most recent automated systems of DR classification and detection that used Deep Learning techniques [9]. They have identified that 73% of the studies they have covered, classified the input images only into two classes as DR and No-DR (Healthy). Even in the studies which classified retinal images into all five severity levels, there were accuracy and efficiency limitations. Also, majority of the existing studies have covered only the accuracy perspective of the research by focusing on achieving the optimal accuracy through suggested models. Therefore, there exists a research gap that is needed to be covered, in order to identify systems that have the ability to recognize the five major DR severity levels with a high accuracy and efficiency.

III. Design & Methodology

Existing studies on this domain have used both pre-trained CNN models and custom CNN models for the severity level classification of Diabetic Retinopathy [15, 16, 23, 24]. Majority of the existing pre-trained models have a larger number of convolutional layers and parameters which results in a higher computational cost in the feature extraction process [19]. Once the number of convolutional layers increases, the number of floating-point operations (FLOPs) performed when predicting model outputs increases by making the models inefficient and complex. Since the objective of this study is to achieve the optimal efficiency-accuracy balance, a custom lightweight custom CNN model was suggested for the feature extraction as well as for the severity level classification.

As the initial step of the Classification Phase, 1000 retinal fundus images from the publicly available Kaggle dataset [25] were subjected to basic pre-processing steps such as resizing to 224×224, cropping the background and the normalization. Since the data sample distribution among the five DR severity levels of the Kaggle dataset was not uniform, Data Augmentation techniques [26] were applied to increase the number of training images belonging to the classes with a lesser number of data samples. The transformation techniques used for Data Augmentation were, rotation, horizontal and vertical flips, zooming, shearing and the changing of brightness. Fig. 2 displays a sample retinal fundus image before and after the Data Augmentation

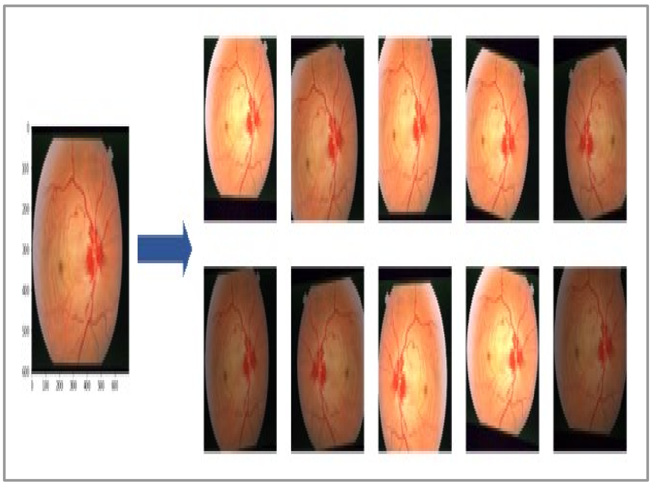

Fig. 2. A sample retinal image before and after Data Augmentation

After pre-processing the input images, the first step was to identify the optimal number of convolutional layers for the proposed custom CNN model. The pre-processed images were trained by changing the number of convolutional layers in the model within the range of 4 to 9. By evaluating the accuracy and the loss of the model for each instance, the optimal number of convolutional layers was identified as six.

Several stages of CNN refinements were applied on the suggested custom CNN model with six convolutional layers as displayed in Fig. 3. As the first refinement, Hyperparameter Tuning approach was applied on the suggested custom CNN model to observe the changes of the model accuracy with different parameter combinations [27]. TABLE I displays the experimental values for hyperparameters. Best accuracy for the custom CNN model was obtained when the number of units of the second dense layer was 256, dropout rate was 0.1 and the optimizer was the Stochastic Gradient Descent (SGD) algorithm.

After identifying the optimal hyperparameters, Regularization techniques were applied on the model as the second refinement. Regularization is a machine learning technique that is used to reduce the overfitting problems of the suggested models [28].

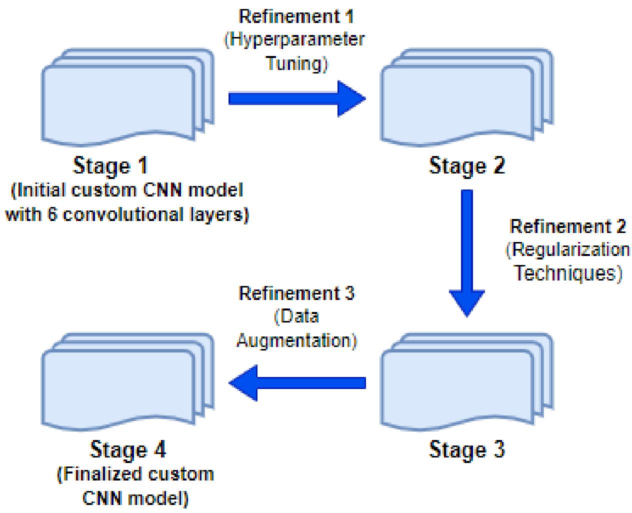

Fig. 3. Stages of applying CNN refinements

TABLE I. EXPERIMENTAL VALUES FOR HYPERPARAMETERS

Hyperparameter	Experimented Values
Number of units in the second dense layer	1024, 512, 256, 128, 64, 32
Dropout rate in the dropout layer	Range between 0.1 and 0.25
Optimizer	Adam, SGD

After applying L1 Regularization, L2 Regularization and the Dropout Regularization techniques, the Dropout method was selected as the best suited regularization technique for the suggested CNN model by comparing the model performance at each instance. In the Dropout method, a randomly selected portion of the neurons of a particular layer was ignored in each training, to avoid the model being overly dependent on just a few weights [29].

As the final refinement, Data Augmentation was applied on the initial dataset to increase the number of training and validation images. Another objective of applying this technique was to generate different transformations of images which can be seen in real-world scenarios, such as the brightness changes, shearing, flipping and slight rotations. After applying Data Augmentation, the size of the training dataset was increased to 2500 images from the original size of 1000 images, and the size of the validation dataset was increased to 500 images from the original size of 200 images. The finalized custom CNN model was trained for 1000 epochs with a learning rate of 0.001 and a batch size of 50 on Google Colaboratory with 2 CPU cores, 2.30GHz CPU Frequency and a 12 GB RAM. Fig. 4 displays the architecture of the finalized custom CNN model.

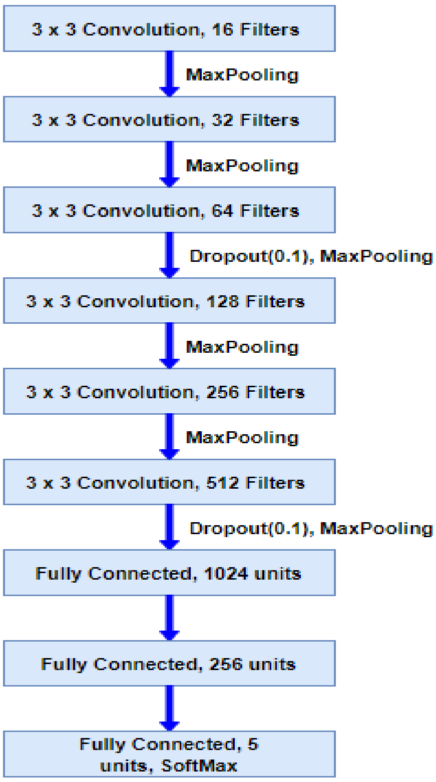

Fig. 4. Architecture of the suggested custom CNN model

In order to compare the performance of the suggested lightweight custom CNN architecture, four pre-trained CNN models VGG16 [30], InceptionV3 [31], Xception [32], and ResNet50 [33] which have achieved the best accuracy in 2014 ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) [34] were trained on the same training dataset using both Transfer Learning and Fine-Tuning techniques. In Transfer Learning, convolutional layers of these models were only used for the feature extraction and their weights were not updated through the training process. In Fine Tuning, models were trained from the scratch to learn more robust features specific to the dataset. Each model was trained with the original dataset with 1000 training images and 200 validation images for 100 epochs without applying any of the CNN refinements used for the lightweight custom CNN model.

IV. RESULTS & EVALUATION

A. *Evaluation of the suggested lightweight custom CNN model*

The suggested lightweight custom CNN model with six convolutional layers was evaluated by using a testing dataset of 267 retinal fundus images obtained from both Kaggle and Messidor-2 datasets [35]. The retinal fundus images used for the training process were not used for the testing purposes. Testing dataset was equally distributed between the 5 severity levels of DR, containing at least 50 images from a single class. Among these 267 images, augmented images with slight rotations, brightness changes and translations were also included. The finalized lightweight custom CNN model obtained an accuracy of 72.28%, an average sensitivity of 71.12%, and an average specificity of 91.3% in the classification task. The performance of the model evaluated at each stage of experimented CNN refinements is displayed in TABLE II. The Confusion Matrix of the finalized custom CNN model after identifying the optimal refinement techniques is displayed in Fig. 5. The number of correctly predicted retinal images under each class is displayed along the diagonal of the confusion matrix. TABLE III presents the statistical measures of performance of the finalized custom CNN model obtained from the testing dataset of 267 retinal fundus images.

B. *Performance Comparison of the custom CNN with pre-trained CNN models.*

TABLE IV displays the accuracy obtained from each of the four pre-trained models with transfer learning and fine tuning respectively, for a testing dataset with 267 retinal fundus images. According to the obtained results, fine-tuned ResNet50 and VGG16 models have surpassed the accuracy obtained from the custom CNN model for DR severity level classification. However, compared to these pre-trained models the suggested custom CNN model consists of a lightweight architecture with only 6 convolutional layers. A key objective of this study was to achieve the best classification accuracy through a lightweight custom CNN model, which has a higher efficiency and a lower complexity.

TABLE II. EVALUATION RESULTS AT EACH STAGE OF APPLYING RETINEMENTS TO THE CUSTOM CNN MODEL

Refinement Stage	Accuracy	Precision	Recall	F1 Score
Stage 1	0.568	0.496	0.562	0.527
Stage 2	0.636	0.652	0.638	0.645
Stage 3	0.679	0.634	0.674	0.653
Stage 4	0.722	0.718	0.717	0.708

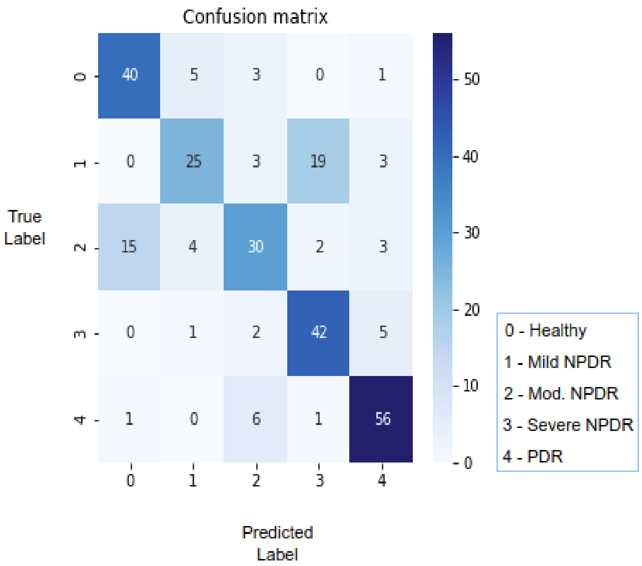

Fig. 5. Confusion Matrix of the finalized custom CNN model

TABLE III. STATISTICAL MEASURES OF PERFORMANCE FOR THE FINALIZED CUSTOM CNN MODEL

	Sensitivity	Specificity	F1 Score
No DR	0.816	0.927	0.762
Mild NPDR	0.500	0.954	0.588
Moderate NPDR	0.555	0.934	0.612
Severe NPDR	0.840	0.99	0.737
PDR	0.875	0.941	0.849
Average	0.717	0.931	0.708
Model Accuracy			72.28 %

TABLE IV. ACCURACY OF PRE-TRAINED MODELS WITH TRANSFER LEARNING AND FINE TUNING

Pre-trained Model	Accuracy in Transfer Learning	Accuracy in Fine Tuning
VGG16	75.78 %	80.34 %
ResNet50	77.34 %	78.12 %
InceptionV3	43.75 %	49.22 %
Xception	36.72 %	43.97 %

The number of floating-point operations (FLOPs) is a widely used indirect metric used in the domain of Deep Learning in measuring the complexity and the efficiency of targeted models. Decreasing the number of FLOPs results in monotonically decreasing inference times in models [36]. Since it was hard to find a direct metric to evaluate the efficiency of the pre-trained models and the suggested custom CNN model, the number of FLOPs for the models were calculated as an indirect metric, using the formula suggested by P. Molchanov et al. (2016) [36]. TABLE V displays the accuracy and FLOPs comparison for the suggested custom CNN model and the pre-trained models with fine-tuning.

TABLE V. ACCURACY AND THE FLOP COMPARISON FOR THE CUSTOM MODEL AND THE PRE-TRAINED MODELS

Model	Number of Convolutional Layers	Accuracy	Number of FLOPs
Custom CNN model with refinements	6	72.28 %	6.42×10^8
VGG16 with fine tuning	13	80.34 %	15.3×10^9
ResNet50 with fine tuning	48	78.12 %	3.8×10^9
InceptionV3 with fine tuning	48	49.12 %	5.72×10^9
Xception with fine tuning	36	43.97 %	74.69×10^9

From the above results, it can be observed that although the fine-tuned VGG16 and ResNet50 models have slightly higher accuracies in classifying DR into five severity levels, the number of FLOPs in the custom CNN model is approximately 23 times lesser than VGG16 and 6 times lesser than the ResNet50 model.

V. CONCLUSION

The objective of this study was to automate the classification task of Diabetic Retinopathy while obtaining an optimal accuracy-efficiency balance in performance. In order to address this research problem, a fully automated deep learning based approach was suggested. In order to achieve the optimal accuracy-efficiency balance in the classification task, a lightweight custom CNN model with only 6 convolutional layers was suggested. There are very few works existing in the literature which focuses on using a lightweight custom CNN model in classifying DR. To the best of our knowledge this work is the first to use only six convolutional layers and increase the accuracy of the model by applying CNN refinements, to classify retinal fundus images into all 5 major severity levels of DR. The suggested model was trained by using 2500 augmented images generated from 1000 retinal images from the Kaggle dataset. The classification accuracy of 72.28% can be further improved without increasing the number of FLOPs, by training the model with a larger dataset of retinal images. After enhancing the accuracy, this lightweight model can be easily applied even in environments with low computational facilities such as rural hospitals. Since Data Augmentation techniques were applied on the training dataset, the suggested model has the ability to predict successful outcomes even when there are slight rotations, illumination variations and translations in input retinal images. The lesser number of FLOPs and parameters in the model makes it easy to be used under limited computational budget and even on embedded devices.

The performance of the suggested lightweight classification model can be further improved by increasing the number of training images and by experimenting with different pre-processing and refinement techniques. A complete DR screening system which has the ability to identify the severity level of an input image after detecting the types of lesions can be implemented by integrating the suggested classification model with a successful lesion detection model. In order to build such a system, the performance of the classification model has to be maximized. The three major lesion types associated with Diabetic Retinopathy are indicators for some other retinal diseases such as Diabetic Macular Edema. Feature extraction capability of the suggested lightweight CNN model can be extended for the classification and the diagnosis of such diseases. Incorporating the knowledge from the domain specialists in increasing the model performance is also a possible enhancement that can be applied on this study.

REFERENCES

[1] *Diabetic Retinopathy*, Mayo Foundation for Medical Education and Research, Accessed on: May 30, 2021. [Online]. Available: mayoclinic.org/diseases-conditions/diabeticretinopathy/symptomscauses/syc-20371611

[2] *IDF Diabetes Atlas*, International Diabetes Federation, Accessed on: May 30, 2021. [Online]. Available: diabetesatlas.org/en/

[3] S. Wild, G. Roglic, A. Green, R. Sicree and H. King, "Global Prevalance of Diabetes – Estimates for the year 2000 and projections for 2030," in *Diabetes Care*, vol. 27, no. 5, 2004, pp. 1047–1053.

[4] C. P. Wilkinson, F. L. Ferris III, R. E. Klein, P. P. Lee, C. D. Agardh, M. Davis, A. Kampil, R. Pararajasegaram, J. T. Verdaguer, "Proposed international clinical diabetic retinopathy and diabetic macular edema disease severity scales," in *Ophthalmology*, vol. 110, no. 9, 2003, pp. 1677–1682.

[5] L. Wu, P. Fernandez-Loaiza, J. Sauma, E. Hernandez-Bogantes and M. Masis, "Classification of diabetic retinopathy and diabetic macular edema," in *World Journal of Diabetes*, vol. 4, no. 6, 2013, pp. 290–294.

[6] R. Chakrabarti, C. A. Harper and J. E. Keeffe, "Diabetic retinopathy management guidelines," in *Expert Review of Ophthalmology*, vol. 7, no. 5, 2012, pp. 417–439.

[7] V. Gulshan, R. P. Rajan, K. Widner, D. Wu, P. Wubbles, T. Rhodes, K. Whitehouse, M. Coram, G. Corrado, K. Ramasamy, R. Raman, L. Peng and D. R. Webster, "Performance of a Deep-Learning Algorithm vs Manual Grading for Detecting Diabetic Retinopathy in India," in *JAMA Ophthalmol*, vol. 137, no. 9, 2019, pp. 987–993.

[8] C. Lam, D. Yi, M. Guo and T. Lindsey, "Automated Detection of Diabetic Retinopathy using Deep Learning," in *AMIA Joint Summits on Translational Science*, 2018.

[9] W. L. Alyoubi, W. M. Shalash and M. F. Abulkhair, "Diabetic Retinopathy detection though deep learning techniques: A review," in *Informatics in Medicine Unlocked*, vol.20, 2020.

[10] *Diabetic Retinopathy*, New England Retina Associates, Accesed on: May 30, 2021. [Online]. Available: retinamd.com/diseases-and-treatments/retinal-conditions-and-diseases/diabetic-retinopathy/

[11] N. O. Mahony, S. Campbell, A. Carvalho, S. Harpanahalli, G. V. Hernandez, L. Krpalkova, D. Riordan and J. Walsh, , "Deep Learning Vs. Traditional Computer Vision," in *Science and Information Conference*, 2019.

[12] M. Bakator and D. Rodasav, "Deep Learning and Medical Diagnosis: A review of Literature," in *Multimodal Technol. Interact.*, vol. 2, no. 3, 2018, p. 47.

[13] R. Vasudev, *Understanding and Calculating the number of parameters in Comvolutional Neural Networks (CNNs),* towards data science, Accessed on: May 30, 2021. [Online]. Available: towardsdatascience.com/understanding-and-calculating-the-number-of-parameters-in-convolution-neural-networks-cnns

[14] M. T. Esfahani, M. Ghaderi and R. kafiyeh, "Classification of diabetic and normal fundus images using new deep learning method," in *Leonardo Electronic Journal of Practices and Technologies*, no. 32, 2018, pp. 233-248.

[15] X. Wang, Y. L. Lu, Y. Wang and W. B. Chen, "Diabetic Retinopathy Stage Classification Using Convolutional Neural Networks," in *2018 IEEE International Conference on Information Reuse and Integration (IRI)*, Salt Lake City, 2018.

[16] C. Kone, *Introducing Convolutional Neural Networks in Deep Learning* , towards data science, Accessed on: May 30, 2021. [Online]. Available: towardsdatascience.com/introducing-convolutional-neural-networks-in deep-learning

[17] J. J.Orlando, E. Prokofyeva, M. del Fresno and M. B. Blaschko, "An ensemble deep learning based approach for red lesion detection in fundus images," in *Computer Methods and Programs in Biomedicine*, vol. 153, 2018, pp. 115-127.

[18] A. Krizhevsky, I. Sutskever and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in *Advances in neural information processing systems*, 2012, pp. 1097-1105.

[19] J. Luo, *Light-weight CNN model Design for Faster and Better Object Detector – Research Thesis*, Accessed on: May 30, 2021. [Online]. Available: jing-luo.github.io/files/MegviiThesis.pdf

[20] N. Ma, X. Zhang, H. Zheng and J. Sun, "ShuffleNet V2: Practical Guidelines for Efficient CNN Architecture Design," in *European Conference on Computer Vision*, 2018, pp. 116-131.

[21] S. K. Nikouei, Y. chen, S. Song, R. Xu, B. Choi and T. Faughnan, "Real-Time Human Detection as an Edge Service Enabled by a Lightweight CNN," in *2018 IEEE International Conference on Edge Computing (EDGE)*, 2018, pp. 125-129.

[22] S. K. Nikouei, Y. chen, S. Song, R. Xu, B. Choi and T. Faughnan, "Smart Surveillance as an Edge Network Service: From Haar-Cascade, SVM to a Lightweight CNN," in *2018 IEEE 4th International Conference on Collaboration and Internet Computing (CIC)*, 2018, pp. 256-265.

[23] K. Xu, D. Feng and H. Mi, "Deep Convolutional Neural Network-Based Early Automated Detection of Diabetic Retinopathy Using Fundus Image," in *Molecules*, vol. 22, no. 12, 2017, p. 2054.

[24] S. Gayathri, V. P. Gopi and P. Palanisamy, "A lightweight CNN for Disbetic Retinopathy classification from fundus images," in *Biomedical Signal Processing and Control*, vol. 62, 2020.

[25] *Diabetic Retinopathy Detection*, Kaggle Inc. Accessed on: May 30, 2021. [Online]. Available: kaggle.com/c/diabetic-retinopathy-detection/data

[26] L. Perez and J. Wang, "The Effectiveness of Data Augmentation in Image Clssification using Deep Learning," 2017.

[27] M. Feurer and F. Hutter, "Hyperparameter Optimization," in *AutoML: Methods, Systems, Challenges,* 2018, pp. 3-37.

[28] S. Jain, *An overview of Regularization Techniques in Deep Learning*, Analytics Vidhya, Apr. 19, 2018. Accessed on: May 30, 2021. [Online]. Available: analyticsvidhya.com/blog/2018/04/fundementals-deep-learning-regularization-techniques/

[29] P. Baldi and P. Sodowski, "Understanding dropout," in *Proceedings of Neural Information Processing Systems (NIPS)*, 2013.

[30] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," 2015.

[31] C. Szegedy, W. Liu, Y. Jia, P. Sermant, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke and A. Rabinovich, "Going Deeper with Convolutions," in *The IEEE Conference on Computer Vision and Pattern Recognition,* 2015.

[32] F. Chollet, "Xception: Deep Learning with Depth wise Separable Convolutions," 2016.

[33] K. He, X. Zhang, S. Ren, J. Sun, "Deep Residual Learning for Image Recognition," 2015.

[34] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg and L. Fei-Fei, "ImageNet Large Scale Visual Recognition Challenge," *IJCV*, 2015.

[35] *Messidor-2 Dataset*, ADCIS, Accesed on: May 30, 2021. [Online]. Available: adcis.net/en/thirdparty/messidor2/

[36] P. Molchanov, S. Tyree, T. Karras, T. Aila and J. Kautz, "Pruning Convolutional Neural Networks for Resource Efficient Inference," 2016.