International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 04 | April - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Diabetic Retinopathy Using Deep Learning and CNN

[1]Y. SAI ARUN TEJA, [2]V. MAHENDRA, [3]V. PRAVEEN

[4]M. PRIYANGA, [5]G. SONIYA PRIYATHARSINI

[1]Y. SAI ARUN TEJA,
Dr. M.G.R Educational and Research and institute,
saiarunteja1234@gmail.com

[2]V. MAHENDRA
Dr. M.G.R Educational and Research and institute,
mahendrareddy8374@gmail.com

[3]V. PRAVEEN
Dr. M.G.R Educational and Research and institute,
praveenveerla3@gmail.com

[4]M. PRIYANGA,
Dr. M.G.R Educational and Research and institute,
priyanga.cse@drmgrdu.ac.in

[5]Dr. G.SONIYA PRIYATHARSINI,
Dr. M.G.R Educational and Research and institute
soniya.cse@drmgrdu.ac.in

Abstract

Diabetic retinopathy (DR) is an eye disease triggered by diabetes, which can lead to permanent vision loss or blindness. To prevent diabetic patients from becoming blind, early diagnosis and accurate detection of DR are vital. Deep learning models and convolutional neural networks (CNNs) are widely used in diabetic retinopathy (DR) detection by classifying blood vessel pixels from the surrounding pixels. In this paper, an improved activation function was proposed for diagnosing DR from fundus images that automatically reduces loss and processing time. The model is then fine-tuned, such that the low-level layers learn the local structures of the lesion and normal regions. As the fully connected (FC) layers encode high-level features, which are global in nature and domain-specific, we replace them with a new FC layer based on the principal component analysis PCA and use it in an unsupervised manner to extract discriminate features from the fundus images. This step reduces the model complexity, significantly avoiding the overfitting problem. This step also lets the model adopt the fundus image structures, making it suitable for DR feature detection. Finally, we add a gradient boosting-based classification layer. The evaluation of the proposed system using 10-fold cross-validation on two challenging datasets (i.e., Eye PACS and Messidor) indicates that it outperforms state-of-the-art methods. It will be useful for the initial screening of DR patients and will help graders in deciding quickly as regards patient referral to an ophthalmologist for further diagnosis and treatment.

Keywords: Diabetic retinopathy, fundus images, CNNs, activation function.

1. INTRODUCTION

Diabetes frequently results in diabetic retinopathy (DR), a common consequence that, if not promptly detected and treated in its early stages, can cause vision impairment and blindness. This presents a serious public health concern. The current diagnostic landscape relies heavily on manual examination by trained ophthalmologists, a process that is both time-consuming and inherently subjective. As the prevalence of diabetes continues to rise globally, there is an urgent need for more efficient and objective methods of DR detection.

Symptoms of diabetic retinopathy include:

- Seeing spots or floaters
- Blurred vision
- Having a dark or empty spot in the center of your vision
- Difficulty seeing well at night.

What causes diabetic retinopathy? Diabetic retinopathy results from the damage diabetes causes to the small blood vessels located there. These damaged blood vessels can cause vision loss: Fluid can leak into the macula, the area of the retina responsible for clear central vision. Although small, the macula is part of the retina that allows us to see colors and fine detail. The fluid causes the macula to swell, resulting in blurred vision. Diabetic retinopathy is classified into two types:

A. Non-proliferative diabetic retinopathy (NPDR) is the early stage of the disease in which symptoms will be mild or nonexistent. In NPDR, the blood vessels in the retina are weakened. Tiny bulges in the blood vessels called Microaneurysms may leak fluid into the retina. This leakage may lead to the swelling of the macula.

B. Proliferative diabetic retinopathy (PDR) is the more advanced form of the disease. At this stage, circulation problems deprive the retina of oxygen. If left untreated, PDR can cause severe vision loss and even blindness. Risk factors for diabetic retinopathy include:

- **Diabetes:** People with type 1 or type 2 diabetes are at risk for developing diabetic retinopathy. The longer a person has diabetes, the more likely he or she is to develop diabetic retinopathy, particularly if the diabetes is poorly controlled.
- **Race:** Hispanics, Africans &Americans are at greater risk for developing diabetic retinopathy.
- **Medical conditions:** People with other medical conditions, such as high blood pressure and high cholesterol, are at greater risk.
- **Pregnancy:** Pregnant women face a higher risk of developing diabetes and diabetic retinopathy. If a woman develops gestational diabetes, she has a higher risk of developing diabetes as she ages.

The goal of any treatment is to slow or stop the progression of the disease. In the early stages of nonproliferative diabetic retinopathy, regular monitoring may be the only treatment. Following your doctor's advice for diet and exercise and controlling blood sugar levels can help control the progression of the disease. Injections of medication in the eye are aimed at discouraging the formation of abnormal blood vessels and may help slow down the damaging effects of diabetic retinopathy.

If the disease advances, the abnormal blood vessels can leak blood and fluid into the retina, leading to macular edema. Laser treatment (photocoagulation) can stop this leakage. A laser beam of light creates small burns in areas of the retina with abnormal blood vessels to try to seal the leaks. Widespread blood vessel growth in the retina, which occurs in proliferative diabetic retinopathy, can be treated by creating a pattern of scattered laser burns across the retina. This causes abnormal blood vessels to shrink and disappear. With this procedure, some side vision may be lost to safeguard central vision.

Transfer learning:

Humans have an inherent ability to transfer knowledge across tasks. What we acquire as knowledge while learning about one task, we utilize in the same way to solve related tasks. The more related the tasks, the easier it is for us to transfer or cross-utilize our knowledge. Simple examples would be: know how to ride a motorbike> Learn how to ride a. The first thing to remember here is that transfer learning is not a new concept that is very specific to deep learning. There is a stark difference between the traditional approach of building and training machine learning models and using a methodology following transfer learning principles.

Traditional learning is isolated and occurs purely based on specific tasks, datasets, and training separate isolated models on them. No knowledge is retained that can be transferred from one model to another model. In transfer learning. You can leverage knowledge (features, weights, etc.) from previously trained models for training newer models and even tackle problems like having less data for every task.

Transfer learning should enable us to utilize knowledge from previously learned tasks and apply it to newer and related ones. If we have significantly more data, we may utilize its learning and generalize this knowledge (features, weights) for tasks (which have significantly less data). In the case of problems in the computer vision domain, certain low-level features, such as edges, shapes, corners, and intensity, can be shared across tasks and thus enable knowledge transfer among tasks! Also, as we have depicted in the earlier figure, knowledge from an existing task acts as an additional input when learning a new target task.

2. LITERATURE SURVEY

Application of higher order spectra for the identification of diabetes retinopathy stages:
Feature extraction-based classification and DL have been used to classify DR. Acharya et al. 's higher order spectra technique was used to extract features from 300 fundus images and fed to a support vector machine classifier; it classifies the images into 5 classes with a sensitivity of 82% and specificity of 88%. Different algorithms were developed to extract DR lesions, such as blood vessels, exudates, and microaneurysms. Exudates have to be extracted for DR grading. A support vector machine was used to classify the DIABETDB1 dataset into positive and negative classes using the area and number of microaneurysms as features. **Rethinking the inception architecture for computer vision**:
Feature extraction-based classification methods need expert knowledge to detect the required features, and they also involve a time-consuming process of feature selection, identification, and extraction. Furthermore, DL-based systems such as CNN have been seen to outperform feature extraction-based methods. DL training for DR classification has been performed in two major categories: learning from scratch and transfer learning.

Development and validation of a deep learning algorithm for the detection of diabetic retinopathy in retinal fundus photographs:
A convolutional neural network (CNN) was trained to classify a dataset of 128,175 fundus images into 2 classes, where the first class contains images with severity levels 0 and 1, and the second class contains levels 2, 3, and 4. An operating cut point picked for high sensitivity had a sensitivity of 97.5% and specificity of 93.4% on the EyePACS-1 dataset, which consists of 9963 images; it cored a sensitivity of 96.1% and a specificity of 93.9% on the Messidor-2
dataset; and in an evaluation cut point selected for high specificity, the sensitivity and specificity were 90.3% and 98.1% on the EyePACS-1, while 87% and 98.5% were scored on the Messidor-2, consecutively.

Convolutional neural networks for diabetic retinopathy:
Using a training dataset of over 70,000 fundus images, Pratt et al. trained a CNN using a stochastic gradient descent algorithm to classify DR into 5 classes, and it achieved 95% specificity, 75% accuracy, and 30% sensitivity. A DL model was trained from scratch on the MESSIDOR-2 dataset for the automatic detection of DR, and a 96.8% sensitivity and 87% specificity were scored. Automated identification of diabetic retinopathy using deep learning A CNN was trained from scratch to classify fundus images from the Kaggle dataset into referable and non-referable classes, and it scored a sensitivity of 96.2% and a specificity of 66.6%. A dataset of 71896 fundus images was used to train a CNN DR classifier, resulting in a sensitivity of 90.5% and specificity of 91.6%. A DL model was designed and trained on a dataset of 75137 fundus images and resulted in sensitivity and specificity scores of 94% and 98%, respectively. **Comparative Study of Fine-Tuning of Pretrained CNN for Diabetic Retinopathy Screening**:
To avoid the time and resources consumed during DL, Mohammadian et al. fine-tuned the
Inception-V3 and Exception pre-trained models to classify the Kaggle data set into two classes. After using data augmentation to balance the dataset, we reached an accuracy score of 87.12% on the inception-V3 and 74.49% on the Exception model. Deep convolutional neural networks for diabetic retinopathy detection by image classification Wan et al.
Implemented transfer learning and hyperparameter tuning on the pre-trained models, VggNet [Visual Geometry Group Network] are VggNet-16, VggNet-19, GoogleNet, and the ResNet using the Kaggle dataset and compared their performances. The highest accuracy score was that of the

VggNet-s model, which reached 95.68% when training with hyperparameter tuning. Transfer learning was used to work around the problem of insufficient training datasets for retinal vessel segmentation. An inception-V4 model-based DR classification scored higher sensitivity when compared with human expert graders on 25,326 retinal images of patients with diabetes from Thailand.

Deep-learning-based automatic computer-aided diagnosis system for diabetic retinopathy:
Mansour put to use the Kaggle dataset to train a deep convolutional neural network using transfer learning for feature extraction when building a computer-aided diagnosis for DR. In Dutta et al 2000, fundus images were selected from the Kaggle dataset to train a shallow feed-forward neural network, deep neural network, and VggNet16 model. On a test dataset of 300 images, the shallow neural network scored an accuracy of 41%, the deep neural network scored 86.3%, and the VggNet16 scored 78.3%. Diagnosis of Diabetic Retinopathy Using Deep Neural Networks A training dataset of size 4476 was collected and labeled into 4 classes depending on abnormalities and required treatment; they resized input images into 600x600 and cut every image into four 300x300 images, and fed these images into separate pre-trained Inception-V3 models, which they called the Inception@4. After it was seen that the accuracy result of the Inception@4 surpassed the VggNet and Res Net models, it was deployed on a web-based DR classification system.

Multi-Cell Multi-Task Convolutional Neural Networks for Diabetic Retinopathy Grading:
A multi-cell and multitask convolutional neural network that uses a combination of cross entropy and mean square error was developed to classify images from the Kaggle dataset into 5DR degrees. A binary tree-based multi-class VggNet classifier was trained on the Kaggle dataset in Adly et al., and it scored an accuracy of 83.2%, a sensitivity of 81.8%, and a specificity of 89.3% on a validation dataset of 6000 fundus images. Fundus Image Classification Using VGG-19 Architecture with PCA and SVD By making use of SVMs with fully connected layers based on the VggNet- 19model, Mateen et al. reached an accuracy of 98.34% when classifying DR on the Kaggle dataset. The Kaggle dataset, which contains 35126 label fundus images, has been exhaustively used for DL-based classification of DR research purposes.

3. REQUIREMENT ANALYSIS

1. Dataset

- **Dataset Selection:** You will need a dataset containing labeled retinal images for diabetic retinopathy. A widely used dataset for this purpose is the Kaggle Diabetic Retinopathy Detection dataset. This dataset consists of thousands of retina images with labels for different stages of DR.
- **Preprocessing**: Resize images to a consistent size (e.g., 224x224 or 512x512). Normalize pixel values (scale the values to a range of 0 to 1 or - 1 to 1). Data augmentation techniques (like rotation, flipping, and zooming) to increase the robustness of the model and reduce overfitting. Possibly convert the images to grayscale if the color does not add significant value.

2. Deep Learning Model

- **CNN Architecture:** Convolutional Neural Networks (CNNs) are the backbone of deep learning image classification tasks. A typical CNN consists of Convolutional layers to extract features (edges, textures, patterns) from images. Activation functions (e.g., ReLU) to introduce nonlinearity. Pooling layers (MaxPooling) reduce the spatial dimensions of feature maps and decrease the computational complexity. Fully connected (dense) layers at the end to perform classification.
- **Model Choices:** Basic CNN Architecture: You can start with a simple architecture consisting of several convolutional layers followed by maxpooling and fully connected layers. Transfer Learning with Pre-trained Models: For better performance, you may consider using pre-trained models like ResNet, VGG16/19, or InceptionV3, which have already been trained on large image datasets (such as ImageNet), and fine-tune them on the diabetic retinopathy dataset. **3. Model Evaluation and Metrics**
- **Loss Function:**

If it's a classification task, categorical cross-entropy can be used.

- **Optimization Algorithm:** Adam optimizer is commonly used for training deep learning models.
- **Metrics: Accuracy:** Percentage of correct classifications. Precision, Recall, F1-Score: These metrics help evaluate the model's performance in imbalanced datasets.
- **Confusion Matrix:** To analyze the performance across different classes (severity levels of DR).
  AUC-ROC curve: To visualize the trade-off between true positive rate and false positive rate.

4. Training the Model Data Augmentation:

You should apply data augmentation techniques such as random rotations, shifts, flips, and zooms to increase the size and diversity of the training dataset, which can help in generalizing the model better. **Learning Rate Scheduling:**

You might want to decrease the learning rate as the number of epochs increases, which helps the model converge more smoothly. Early Stopping: To prevent overfitting, early stopping can be applied based on validation performance.

5. Hardware Requirement

To effectively handle the computational demands of deep learning, a robust hardware setup is essential. At the core of the hardware requirements is a high-performance Graphics Processing Unit (GPU), which accelerates the training of complex CNN models. Additionally, a minimum of 32 GB of RAM is recommended to manage large volumes of data and ensure smooth execution of the training processes.

- System : Pentium IV 2.4 GHz.
- Hard Disk: 40 GB.
- Floppy Drive: 1.44 Mb.
- Monitor: 15 VGA Color.
- Mouse: Logitech.
- RAM: 512 Mb.

6. Software and Tools Operating System:

Windows We use Operating systems such as Windows 10 or newer, 64-bitmaps OS 10.13+, or Linux, including
Ubuntu, Red Hat, CentOS 6+, and others.
System architecture: Windows-64-bitx 86, 32bitx 86; MacOS-64-bitx86; Linux64-bit x86, 64bitPower8/Power9.

Environment: Python 2.7 or above version Hardware configuration Processor: Intel core i5 or above Ram: 8GB (OR) above and Storage Minimum 5GB disk space to download and install.

7. Deployment

- After the model has been trained, you might want to deploy it as a web application or API for real-time DR detection.
- You can use frameworks such as **Flask** (for Python) or **FastAPI** to build a RESTful API, where users can upload retinal images, and the model can return the predicted DR classification.

4. FLOW CHART

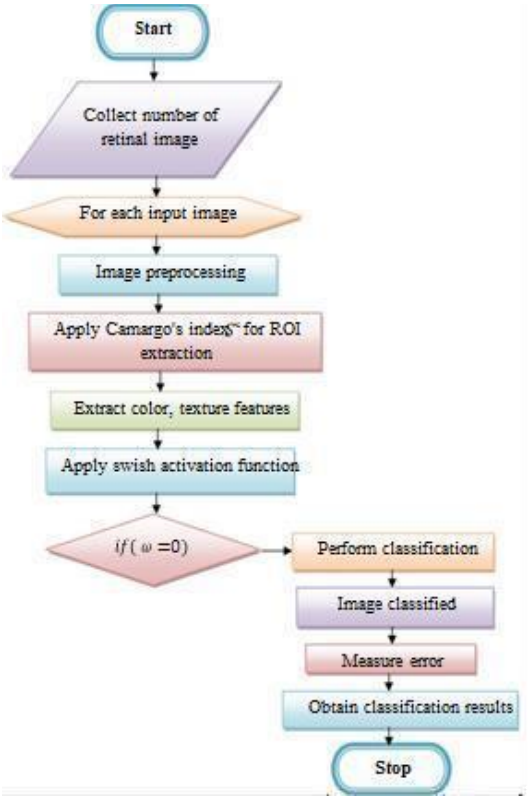

Figure: Flow chart of deep learning

5. DESIGN AND IMPLEMENTATION

DATA COLLECTION AND PREPARATION

In Pre-processing, there are 4 submodules: Data preparation, Exploratory Data Analysis, Metric, and Preprocessing.

Data preparation

We collect all the fundus images from the APTOS (Asia Pacific Tele-Ophthalmology Society) dataset. In this Fig1.1: Flow chart of deep learning dataset, the fundus images are labeled as 0,1,2,3 and
4 for Normal, Mild DR, Moderate DR, Severe DR, Prolific DR respectively.[3] This dataset provides 4657 fundus images in total. Among these, 3662 (stored in Train.csv with image ID and its diagnosis label) were used for model training, and the remaining 995(stored in Test.csv with image ID and its diagnosis label) were used for model testing.

Exploratory Data Analysis

We think one should at least examine the label distribution, the images before pre-preprocessing, and the images after Pre-processing.

Data Collection

For training a deep learning model, you will need a labeled dataset of retinal images with annotations indicating the severity of diabetic retinopathy.

Public Datasets:

Kaggle Diabetic Retinopathy Detection Dataset: A large dataset containing retinal images with labels for each stage of DR.
EyePACS: This is another dataset available on Kaggle.

Messidor: A French dataset with retinal images labeled according to DR severity.

You will typically work with **fundus photographs**, which are colored images of the retina. The images should be pre-processed to ensure that they are normalized and standardized for deep learning models.

Data Preprocessing

Data preprocessing is a critical step in preparing the dataset for deep learning. The following operations can be performed on the retinal images:

Resizing: Resize all images to a consistent size, e.g., 224x224 or 256x256 pixels, to match the input size expected by the neural network.
Normalization: Scale pixel values to the range [0, 1] by dividing by 255 (standard for RGB images).

Model Design

For diabetic retinopathy detection, we can use a **Convolutional Neural Network (CNN)**, which is excellent for image classification tasks. A common architecture for this task is based on popular models like **ResNet** (Residual Networks), **VGG16**, **InceptionV3**, or **EfficientNet**. These models are trained on large image datasets like ImageNet and can be fine-tuned on the DR dataset.

1. **CNN Architecture**:

Convolutional Layers: Extract features from the image. These layers use filters/kernels that detect patterns such as edges, textures, and more complex patterns.

Pooling Layers: Pooling reduces the spatial dimensions (width and height) of the image, allowing the model to focus on high-level features.

Fully Connected Layers: After convolution and pooling, the feature maps are flattened and passed through fully connected layers for classification.

Activation Function: Use ReLU(Rectified Linear Unit) for nonlinearity in hidden layers and softmax for classification in the output layer.

2. **Output Layer**: Since DR is a multi-class classification problem (with 5 stages), the output layer will have 5 nodes, each corresponding to a stage of DR. Softmax activation will be applied to these nodes to output the probability distribution over the classes.

3. **Loss Function**: The cross-entropy loss function is typically used for multi-class classification problems.

4. **Optimization**: Optimizers like Adam or SGD (Stochastic Gradient Descent) are commonly used for training the model.

Deployment

Once the model is trained and evaluated, it can be deployed for real-time prediction on new retinal images.

Deployment Approaches:

1. **API-Based Deployment**: Use Flask or Fast API to create a REST API that allows users to upload retinal images and get predictions.
2. **Mobile or Web Application**: Implement the model in a mobile app or web application using frameworks like TensorFlow Lite (for mobile) or TensorFlow.js (for web).

Effective Net Architecture

The effectiveness of model scaling also relies heavily on the baseline network. So, to further improve performance, we have also developed a new baseline network by performing a neural architecture search using the Auto MLMNAS framework, which optimizes both accuracy and efficiency (FLOPS). The resulting architecture uses mobile inverted bottleneck convolution (MB Conv), similar to MobileNetV2 and Mas Net, but is slightly larger due to an increased FLOP budget. We then scale up the baseline network to obtain a family of models called Effective Net. The architecture for our baseline network, EfficientNet-B0, is simple and clean, making it

easier to scale and generalize. Below is the architecture of Efficient b0architecture.

Efficient Net Performance

We have compared our Efficient Nets with other existing CNNs on Image Net. In general, the Efficient Net models achieve both higher accuracy and better efficiency over existing CNNs, reducing parameter size and FLOPS by an order of magnitude. For example, in the high-accuracy regime, our EfficientNet-B7 reaches state-of-the-art 84.4% top-1 / 97.1% top-5 accuracy on ImageNet while being 8.4x smaller and 6.1x faster on CPU inference than the previous G pipe. Compared with the widely used ResNet50, our EfficientNet-B4 uses similar FLOPS while improving the top-1 1accuracyfrom 76.3% of ResNet-50 to 82.6% (+6.3%).

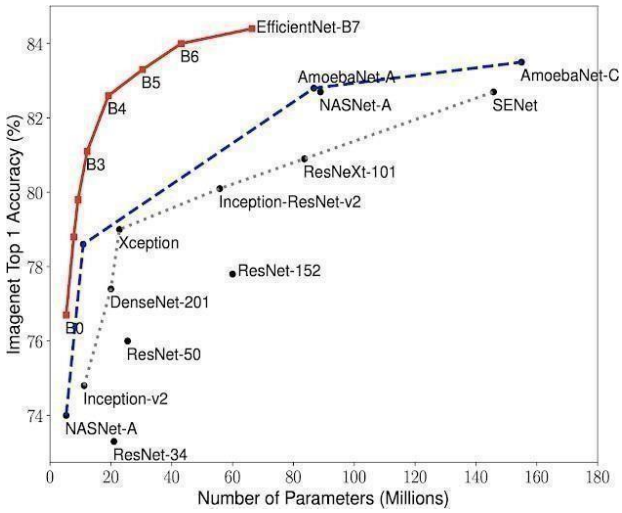

Figure 2: Efficient net performance of Net-B5 architecture

EfficientNet-B0 is the baseline network developed by Auto MLMNAS, while Efficient-B1 to B7 are obtained by scaling up the baseline network. In particular, our EfficientNet-B7 achieves new state-of-the-art 84.4% top-1 / 96.2% top-5 accuracy while being 8.4 times smaller than the best existing CNN.

Exploratory Data Analysis

Exploratory Data Analysis (EDA) is an essential first step in understanding the dataset, identifying patterns, detecting outliers, and ensuring that the data is ready for deep learning model training. The goal is to explore the structure and distribution of the data before training a Convolutional Neural Network (CNN) for diabetic retinopathy (DR) detection. In this case, we'll be working with a typical diabetic retinopathy dataset like the **Kaggle Diabetic Retinopathy Detection** dataset or **EyePACS**, which contains retinal images along with labels indicating the severity of diabetic retinopathy.

1. Dataset Overview

The dataset typically consists of two main components:

Images: Retinal fundus images of various resolutions.

Labels: An associated label for each image indicating the severity of diabetic Retinopathy, usually on a scale from 0 to 4:

0: No DR

1: Mild DR

2: Moderate DR

3: Severe DR

4: Proliferative DR

We think one should at least examine the label distribution, the images before Pre- pre-processing, and the images after the Preselected training algorithm, which is batch gradient descent with ascending learning rate, and the quadratic weighted kappa loss function. Deep learning techniques that can learn from small datasets to categorize medical images should be utilized to classify DR, as this can be transferred to other medical image classification problems facing the challenge of insufficient training data. Experiments should be done to compare the performances of the other pre-trained deep convolutional Networks.

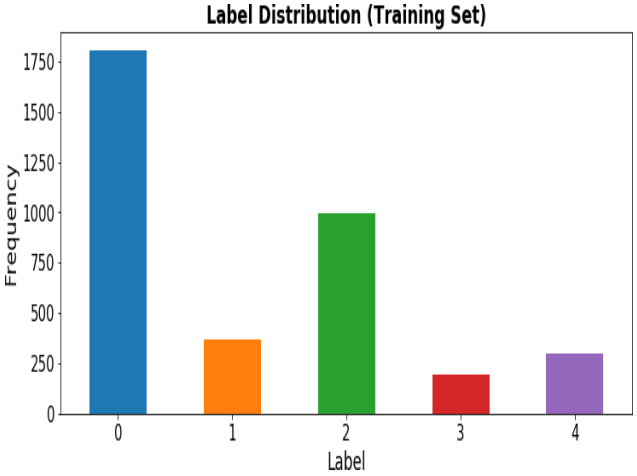

Figure 3: Label distribution

The above graph shows the label on the x-axis denotes the stages of DR, and the height of the histogram denotes the number of images present in that stage.

CONCLUSION

In this project, deep learning is implemented to classify DR into 5 classes with much-reduced training data than other previous DR classification techniques employed. This was done to design a way to train a DL model that performs well on unseen data by efficiently learning from a small dataset because training data is limited in health care. Our model has reached an accuracy that is higher than other techniques that have used transfer learning on the whole Kaggle DR challenge dataset for multiclass classification.

REFERENCE

[1] S. Rykov, D. Chugaiev, and S. Ziablitsev, "Blood select in levels as a predictive factor for diabetic retinopathy and diabetic macular edema in IJISAE, 2024, 12(3), 2599–2606 | 2606

[2] N. u. Huda, A. A. Salam, N. S. Alghamdi, J. Zeb, and M. U. Akram, "Proliferative diabetic retinopathy diagnosis using varying scales filter banks and double-layered thresholding," Diagnostics, vol. 13, no. 13, p.2231, 2023.

[3] A. Shanthini, G. Manogaran, G. Vadivu, K. Kottilingam, P. Nithyakani, and C. Fancy, "Threshold segmentation-based multi-layer analysis for detecting diabetic retinopathy using convolution neural network," Journal of Ambient Intelligence and Humanized Computing, pp. 1–15, 2022.

[4] S. Burewar, A. B. Gonde, and S. K. Vipparthi, "Diabetic retinopathy detection by retinal segmentation with region merging using CNN," in 2024. IEEE 13th International Conference on Industrial and Information Systems (ICIIS). IEEE, 2018, pp. 136–142.

[5] P. H. N. Castro, G. C. Fortuna, R. A. B. de Queiroz, and G. J. P. Moreira, "Regularization through simultaneous learning: A case study for hop classification," arXiv preprint arXiv: 2305. 13447, 2023.

[6] R. Vignesh, N. Muthukumaran, and M. P. Austin, "Detection of diabetic retinopathy image analysis using convolution graph neural network," in 2023 International Conference on Inventive Computation Technologies (ICICT). IEEE, 2023, pp. 921–929.

[7] K. Swarnalatha, U. A. Nayak, N. A. Benny,H. Bharath, D. Shetty, and S. D. Kumar, "Detection of diabetic retinopathy using convolution neural network," in Emerging Research in Computing, Information, Communication, and Applications: Proceedings of ERCICA 2022. Springer, 2022, pp. 427–439.

[8] D. Mane, S. Sangve, P. Kumbharkar, S. Ratnaparkhi, G. Upadhye, and S. Borde, "A diabetic retinopathy detection using customized convolutional neural network.

[9] Al-Antary MT, Arafa Y (2023) Multi-Scale Attention Network for Diabetic Retinopathy Classification.IEEE Access 9:54190–54200 Ashir AM, Ibrahim S, Abdulghani M, Ibrahim AA, Anwar MS, (2023) Diabetic Retinopathy Detection Using Local [10] Extrema Quantized Haralick Features with Long Short-Term Memory Network. Int JBiomed Imaging. T, Charoen larpnopparut C, Mahapakulchai S (2023) Deep learning-based hemorrhage detection for diabetic retinopathy screening. Sci Rep 13(1):1479. https:// doi. org/ 10. 1038/ s41598- 023- 28680-3.

[11] Muthusamy D, Sathyamoorthy S (2023) Feature Sampling based on Multilayer Perceptive Neural Network for image quality assessment, Engineering Applications of Artificial Intelligence. Elsevier 121:106015. https:// doi. org/ 10. 1016/j. engap pai. 2023. 106015.