Educational Administration: Theory and Practice
2024, 30(5), 7306-7315
ISSN:2148-2403
https://kuey.net/
Research Article

Detection Of Diabetic Retinopathy Using Machine Learning & Image Processing

Shubhangi G. Dhawase[1*], Dr. Asmita Manna[2]

[1*]Department of Computer Engineering Pimpri Chinchwad Education Trust Pimpri Chinchwad College of Engineering, Nigdi, Pune-411044, Maharashtra, India. sgdhawase@gmail.com
[2]Department of Computer Engineering Pimpri Chinchwad Education Trust Pimpri Chinchwad College of Engineering, Nigdi, Pune-411044, Maharashtra, India. asmita.manna@pccoepune.org

Citation: Shubhangi G. Dhawase, et al (2024), Detection Of Diabetic Retinopathy Using Machine Learning & Image Processing, *Educational Administration: Theory and Practice*, *30*(5), 7306-7315, Doi: 10.53555/kuey.v30i5.4056

ARTICLE INFO	ABSTRACT
	This research proposes a comprehensive framework for diabetic retinopathy detection, encompassing five key stages: image passing, data preprocessing, data augmentation, feature extraction, and classification. The initiation is done with the acquisition of the retinal images that undergo the thorough data preprocessing procedures that are geared towards the enhancement of the quality and clarity. Afterward, the data augmentation process is initiated to diversify the dataset, augmenting its size and ensuring robust model training. Feature extraction follows, utilizing advanced algorithms to identify distinctive characteristics associated with diabetic retinopathy. Each stage is accompanied by rigorous evaluation, yielding results that highlight the effectiveness of the proposed methods. The final classification stage employs machine learning models, particularly deep learning techniques namely VGG16, to categorize retinal images based on identified features. The comprehensive nature of this framework, from image acquisition to classification, contributes to the development of an automated system for diabetic retinopathy detection. Results demonstrate the system's efficacy in accurately identifying and classifying diabetic retinopathy, showcasing its potential for widespread clinical application and enhancing early diagnosis for improved patient outcomes. The proposed pre-trained VGG16 model confirmed better accuracy by using the Adam optimizer in DR detection when applied with the approach of transfer learning (TL). The model is not overfitted and it provides the more accurate results. **Keywords—**Diabetic retinopathy, Deep learning, Retinal images, Early detection, VGG16, Adam optimizer, Transfer learning

I. Introduction

Diabetic retinopathy (DR) is one of the major illnesses that can result in blindness, if not treated at the initial stage. Therefore, early detection and treatment are crucial to prevent irreversible vision loss. Traditionally, the same can be detected by ophthalmologists from the retinal fundus snapshots. Considering that, half of the Indian population not having access to the proper healthcare system, diabetic retinopathy goes unnoticed in its early stages. Even if the detection happens, manual intervention in time-consuming, subjective, and quite difficult in resource-constrained settings.

In this paper, one such image processing and machine learning based framework for the automatic detection of modern-day diabetic retinopathy is proposed. The goal of the same is to propose a robust and scalable solution for DR detection that may be deployed in diverse healthcare system, including remote or underserved regions where there is a scarcity of specialist ophthalmologist. The novelty of the study is that, with the help of transfer learning, where a pre-trained VGG16 model is fine-tuned on a new selected dataset [35] including 5 labelled classes for detection of diabetic retinopathy so that it can be easily curable in the early stage.

In this work, pre-trained VGG16 model is used on the assembled dataset [35] consisting of high-decision retinal pictures, obtained from diverse populations with various degrees of contemporary DR severity is considered. This dataset consists of 31877 images and the total number of classes included in it is 5 i.e. Mild, Moderate, No_DR, Proliferate_DR and Severe. With the help of fully connected layers (Dense connection), the input and output layer are added to the transfer learning model. The output layer is generating results by using SoftMax+Relu, it works as the activation function.

This paper's main research objectives are as follows:
(a) Apply image resizing, data augmentation methods to preprocess retinal images before classification.
(b) Implement classification algorithms to classify retinal images for diabetic retinopathy detection.
(c) To optimize model performance and improving the accuracy using VGG16 in order to make it lightweight.

Section II of this paper presents the literature survey to find the gap in the existing approaches; Section III presents the complete architecture of proposed system and methodology; Section IV shows the experimental results and, finally Section V concludes the paper.

II. LITERATURE REVIEW

The integration of machine learning (ML) and image processing techniques has recently caused a transformative shift in the field of diabetic retinopathy (DR) detection. The literature review on diabetic retinopathy detection using machine learning and image processing techniques encompasses a diverse range of methodologies, strengths, and weaknesses.

In a recent study (1), a two-stage framework employing ensemble learning demonstrated high classification accuracy (0.99), F1-score, precision, specificity, and sensitivity, with an AUC of 1.00. However, challenges include the requirement for large annotated datasets and interpretability issues associated with ensemble models.

Another approach (2) focused on optical system-based data classification, achieving a commendable 98% classification accuracy and showing potential for diabetic retinopathy detection. Nevertheless, further optimization is needed to enhance sensitivity and address integration challenges with real-world clinical systems.

In a study from 2021 [3], a machine learning approach integrates weighted k-nearest neighbors (KNN), cubic support vector machines (SVM), and decision trees for analyzing retinal images. The work combines image processing and machine learning, utilizing standard databases (DIARETDB0 and DIARETDB1). However, a limitation is noted in the lack of detailed information regarding the dataset's size and diversity, and the specific machine learning algorithms employed are not explicitly specified.

A 2022 study explores image processing techniques for detecting hemorrhages in retinal images. The methodology involves basic preprocessing and hemorrhage segmentation using morphological operations, utilizing the STARE & DRIVE datasets. However, the study provides limited context on the source and quality of retinal images [4].

The authors of [5] focused on retinal image defects to determine the severity of the sickness. The article described a lesion localization model and a patch-based technique using a deep neural network for various layers of patches, which were used to localise the red lesions. The results showed an improvement in AUC, sensitivity, and specificity measures.

The study [6] used deep learning technologies to easily identify retinal illness. To achieve better results, the image preprocessing techniques used principal component analysis (PCA) to lower the image's dimensions while also eliminating noisy data. The data in the study was normalised using the firefly method and typical scalar procedures.

The study in [7] proposed automatic diagnosis algorithms that use retinal pictures to determine the severity of the condition. The proposed machine learning approach trains and tests the inception network architecture on the EYEPACS dataset to classify fundus images. These approaches produced higher accuracy outcomes than standard approaches.

According to the authors of [8], DR is one of the most complex disorders that causes eye impairment over the globe. This work also focused on improving image quality by utilising a contrast-constrained adaptive histogram equalisation model for image segmentation. The image was optimised using a Bayesian method, and the hyperparameter tuning inception-v4 model improved the evaluation findings.

The authors [9] described an image classification approach that employed CLAHE (contrast limited adaptive histogram equalisation) and HE (Histogram Equalisation) algorithms. The MESSIDOR dataset was used to test the image screening approach with CNN.

The improvement in CNN design addressed the CNN pooling layer's low accuracy issue while specifying image view attributes. CapsNet architectural features on the MESSIDOR dataset demonstrate matrix multiplication, dynamic routing, and squashing functions for improved outcomes [10].

In [11], machine learning methods such as SVM, KNN (K-nearest neighbour), and bagging trees were applied to diabetic patients' physical health records to quickly identify diabetic retinopathy. Using the bagged trees prediction method, the model achieved a high level of accuracy.

The authors in [12] developed a collective intelligence strategy (human+eye) for increased results in identifying diabetic retinopathy categories compared to existing AI techniques. The proposed method improved the accuracy of previously trained images by using EfficientNetB3, EfficientNetB4, and EfficientNetB5. Because of the variability and volume of data distribution, this strategy limits the training dataset to a lower size.

These studies broaden the perspective, emphasizing the need for benchmarking and the potential of ontological frameworks in enhancing model accuracy and interpretability. Benchmarking studies provide insights into the performance metrics of different ML algorithms, crucial for discerning their efficacy in real-world applications. The journey from the exploration of deep learning in diverse medical applications to the focused efforts on lesion localization and ensemble learning in diabetic retinopathy detection signifies a broader paradigm shift towards a more comprehensive and interpretable approach to medical diagnostics. Diabetic retinopathy (DR) detection has been significantly influenced by the machine learning (ML) and image processing techniques. As these advancements continue to unfold, collaborative efforts between clinicians, data scientists, and industry stakeholders will be pivotal in translating these research strides into tangible clinical benefits, ultimately improving the lives of individuals affected by diabetic retinopathy worldwide.

The papers studied during the survey included the largest public dataset for DR classification, but the results were provided for only a few numbers of diabetic retinopathy classes. The dataset used for comparison of the transfer learning models i.e VGG16 in the study included total 5 classes according the severity and the size was also large enough which ensured proper training and testing of the models to provide the maximum output from the models.

A comparative analysis of the discussed approaches is presented in Table 1.

TABLE I. PRIOR RESEARCH RELATED TO DIABETIC RETINOPATHY DETECTION**Ref. & Year**	**Methodology**	**Dataset Used/Dataset Size/Number of Images/Type of Images**	**Result/Accuracy/ Sensitivity**	**Loopholes**
[1] 2023	ML framework for DR diagnosis and disease-stage identification from fundus images	The database was selected from Kaggle EyePACS, which offers the largest public dataset for DR classification	High classification accuracy (0.99), High F1-score and precision, High specificity and sensitivity (0.99), AUC of 1.00	Requires large annotated datasets, Interpretability challenges of ensemble models
[2] 2023	Center Resnet-50 classifies images for color fundus detection	Dataset consist of the ensemble pulse coupled filtering and green histogram channel equalization-based adaptive filtering segment this picture for blood vessel characterization	Achieved a classification accuracy of 98%	Requires further optimization to improve sensitivity and AUC, Integration challenges with real-world clinical systems
[3] 2021	The Machine Learning algorithms that are used for result analysis are Weighted KNN, Cubic SVM and Simple Tree	Uses standard databases (DIARETDB0 and DIARETDB1)	Optimizable KNN achieved an accuracy of 97.97%, with a precision of 0.99	Lacks detailed information on the size and diversity of the dataset, Specific machine learning algorithms used are not specified
[4] 2022	Basic preprocessing, hemorrhage segmentation using morphological operations and connected components labelling	STARE & DRIVE Dataset	Accuracy = 85%, Specificity = 82%, Sensitivity = 89%	Utilizes advanced image processing techniques & limited context on the source and quality of retinal images

[5] 2020	DNN patch-based approach	Seven datasets were used: Calibration level 0 (DIARETDB0) & Calibration level 1 (DIARETDB1) [23] are the Standard DR Database, Kaggle, Messidor [24], Messidor-2, Indian Diabetic Retinopathy Image Dataset (IDRiD) [25], and DDR [26]. DIARETDB0 [27] contains 130 fundus images: 20 are normal and 110 show symptoms of DR	Accuracy = 97%, Specificity = 95%, Sensitivity = 92%	Use of limited data leading to enhanced cost
[6] 2020	PCA with firefly algorithm using DNN	Selected debrecen dataset from UCI machine learning repository-MESSIDOR-2 dataset. The diabetic retinopathy dataset used in this study had 1151 instances and 20 attributes	Accuracy = 97%, Specificity = 95%, Sensitivity = 92%, Precision = 96%, Recall = 96%	Low-dimensional data are not considered
[7] 2021	Deep CNN with inception method	EyePACS dataset	Accuracy = 92%, Specificity = 94%, Sensitivity = 81%, Precision = 93%	Automated image prognosis method is not implemented
[8] 2020	HPTI (hyperparameter tuning inception)-V4 model	MESSIDOR database	Accuracy = 99%, Specificity = 98%, Sensitivity = 99%, Precision = 97%	Implementation of different classification are models not included
[9] 2020	Histogram equalization and limited adaptive histogram equalization methods	MESSIDOR database with 400 images	Accuracy = 97%, Specificity = 98%, Sensitivity = 94%, Precision = 97%, F1 score = 94%, G-Means = 94%	Alternative medical databases are not considered for performance evaluation
[10] 2021	Capsule network architecture	MESSIDOR dataset	Accuracy = 95%	Training of limited image features. All the classes of image datasets depend on the severity are not trained in Caps Net
[11] 2020	PCA (principal component analysis) and linear regression	Data collected from patients in central India	Accuracy = 92%	Larger datasets are not considered
[12] 2020	Gaussian filters and Efficient Net	Eye PACS dataset	AUC = 0.68, Kappa score = 0.36	Exclusion of balanced dataset leading to reduced efficiency

III. Proposed Work

The principal aim is to carry out diabetes prediction tasks on the basis of the input data, the VGG16 pre-trained model is adopted. The transfer learning model is used as feature extractors. The dataset used contains a total of 13877 images. The total number of classes included in the dataset is 5. Using the ADAM optimizer algorithm, precision of the model can be improved to produce high quality forecasts regarding the risk of developing diabetes.

The architecture of proposed system is depicted in Fig. 1 and described in detail thereafter.

A. Datasets

The dataset contains 31877 images which included five labelled directories (Size-155 MB) . The detailed description image count as per diagnostic measurements is Mild - 6972 images, Moderate - 6541 images, No_DR - 6869 images, Proliferate_DR - 5346 images & Severe - 6149 images. Based on specific diagnostic metrics included in the dataset, the main aims to diagnostically predict the presence or absence of diabetes in a patient.

A dataset is available on the kaggle [35] which is used for both the training and testing purposes. Dataset is splitted into Train :- 80%(25499 images), Test:- 20%(3193 images) & Val:- 20%(3185 images).

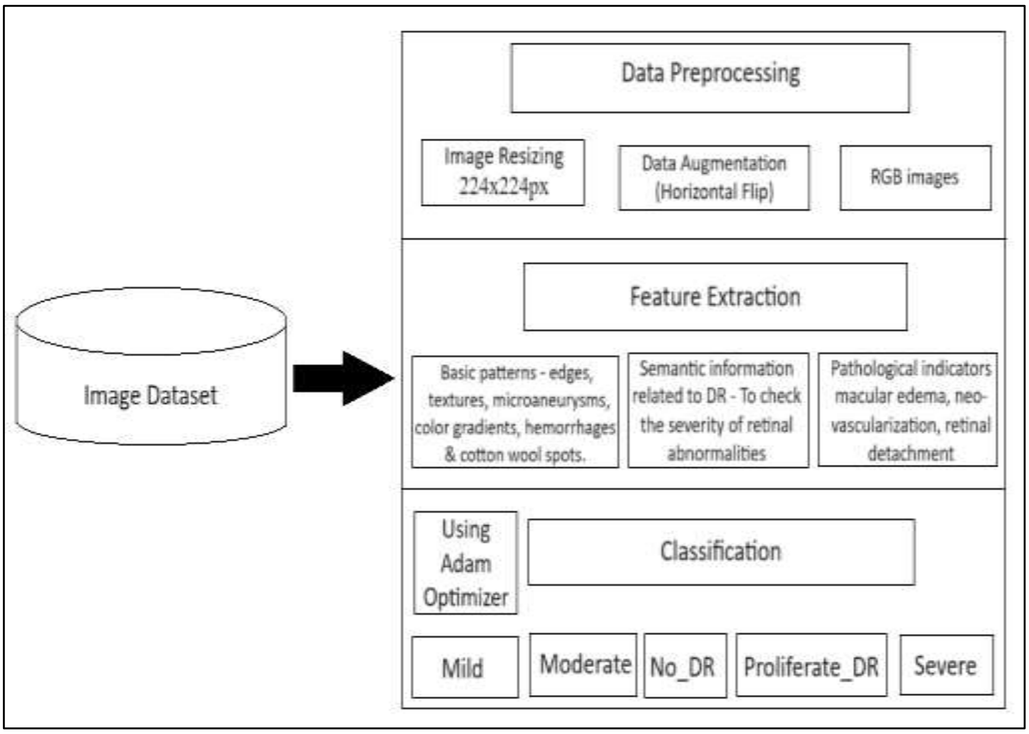

Fig 1. Complete Architecture of Proposed System

B. Data Pre-processing

Initially, the data had to be prepared in order to maximise the model's performance. This involves resizing the images to the desired input size (e.g., 224x224px), normalization to scale pixel values to a certain range & data augmentation
(horizontal flip). Then we constructed batches to train the model in stages. A batch size of 32 images was generated. The batch size refers to the number of samples processed prior to model updates. This is required because after training from batches, expected results can be compared to actual results to calculate the error, which is then used to update the algorithm and improve the model. All the images used are RGB images but they are not in the same size hence resizing is done. So, the dimension of images used is (224x224x3).

C. Transfer Learning Approach

We used the VGG16 pre-train model from keras library. At every stage of addition of layers, the features extracted may capture basic patterns such as edges, textures, color gradients, microaneurysms, hemorrhages, exudates and cotton wool spots. Semantic information related to diabetic retinopathy, such as the presence or absence of pathological changes, the severity of retinal abnormalities, and the likelihood of disease progression. The top layers of the VGG16 model may capture specific pathological indicators of diabetic retinopathy, including features indicative of diabetic macular edema, neovascularization, retinal detachment, and other clinically significant findings. These features enable the model to make accurate predictions about the presence and severity of diabetic retinopathy.

All images from the dataset were scaled to 224 × 224 pixels. The deep learning library TensorFlow 2.4 with Keras API was used to create and implement the VGG16 model. The categorical cross-entropy loss function was used to train the model and assess its performance. We then used the Adam optimizer with a learning rate of 0.001 to reduce the loss function and increase efficacy.

D. Training

Providing summary outlines the architecture of a neural network VGG16 model. This layer represents the VGG16 convolutional base used for feature extraction. Sequential Model, it adds the layers sequentially. First, we add the base_model as the first layer in our new model. This allows us to use all of its pre-trained features. Next, we flatten the output from the base_model into a 1-dimensional array using Flatten (Flatten). This prepares it for input into fully connected layers. Then, add three Dense layers ((Dense (Dense)-1024 Neurons), (Dense_1(Dense)-512 Neurons), (Dense_2(Dense)-256 Neurons)) i.e. (with different numbers of neurons and activation functions (relu). These are fully connected layers that will learn additional features specific to dataset. After each Dense layer, there is also a Dropout layer (Dropout (Dropout)) with a dropout rate of (.3). This randomly drops out 30% of the connections between neurons during training. This helps prevent overfitting by forcing different paths through the network to be learned instead of relying on one path too heavily. Dense_3(Dense)-128 Neurons, again we add the dense layer with the activation functions relu. The goal of ReLU is to add nonlinearity into the network, helping it to understand complicated patterns and correlations in the input. ReLU sets all negative values to zero while leaving positive values unaltered, resulting in a thresholding effect. Finally, there is an output Dense layer (Dense_4(Dense)) with 5 neurons (equal to number of classes) and softmax activation function. Softmax, ensures that all outputs sum up to 1 so they can be interpreted as probabilities for each class.

Overall, this neural network architecture consists of multiple dense layers following a pre-trained VGG16 convolutional base, with dropout regularization applied to improve generalization performance. The model is designed for a classification task with 5 output classes.

E. Adam Optimizer Algorithm

Explaining the role of Adam Classifier Algorithm as below:

- Model Optimization: Adam optimizer adapts the learning rate for each parameter separately. This is why it can cover more ground and converge faster during the training stage.
- Gradient Descent: By using the best of AdaGrad and RMSProp, Adam is constructed of the first and second moments of the gradients that allows learning rate to be custom-tailored.
- Convergence: Adam does this by varying the learning rate dynamically, therefore it becomes easier to prevent the model from being stuck and it also accelerates convergence, which is vital for high accuracy in diabetic retinopathy detection.
- Performance: Utilizing Adam as the optimizer enhances the overall performance of the classifier model, leading to more accurate predictions and better generalization to unseen data.

This is especially important to adjust the learning rate when diagnosing diabetic retinopathy, as a better diagnosis can be achieved by ensuring that the model converges efficiently, avoids poor local minima and reach global minima if we get stuck while training and performs well in generalization to unseen data and avoid the overfitting.

F. Classification

A testing dataset of 3193 images is provided for testing the trained model. 82.52% accuracy is obtained to evaluate the performance of the VGG16 model using the testing dataset. For prediction, the image which is to be classified is obtained from the user and it is first processed. It is converted into an image of 224x224px that is best suited for the model and then classification is done.

IV. EXPERIMENTAL RESULTS

The results are checked based on the accuracy provided by VGG16 model. The accuracy and loss curves are also plotted to better understand the training process of the model. This gives an idea about the accuracy and loss of the model over each 25 epochs.

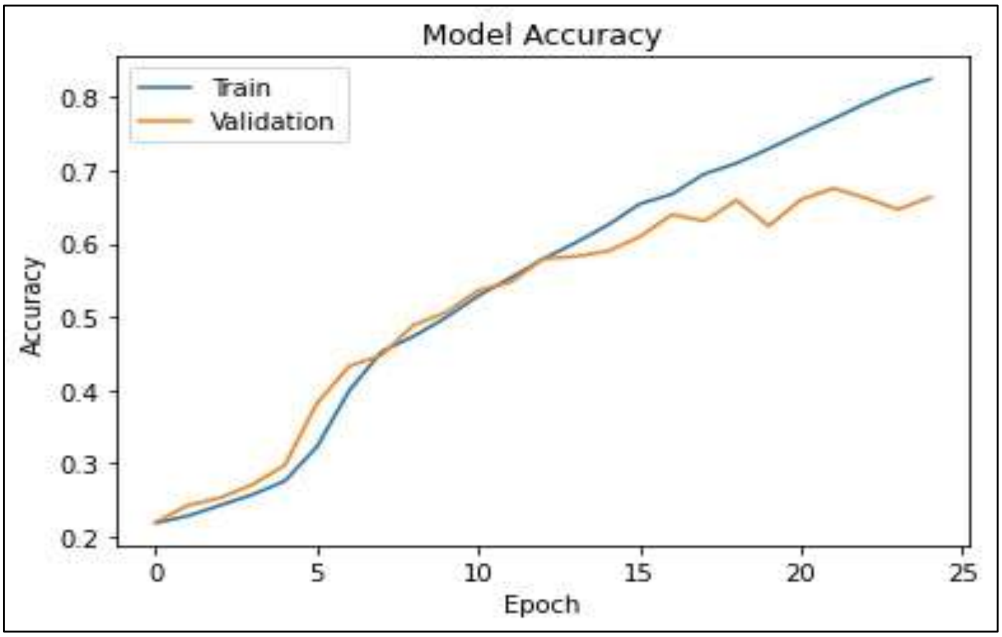

Fig 2. Model Accuracy

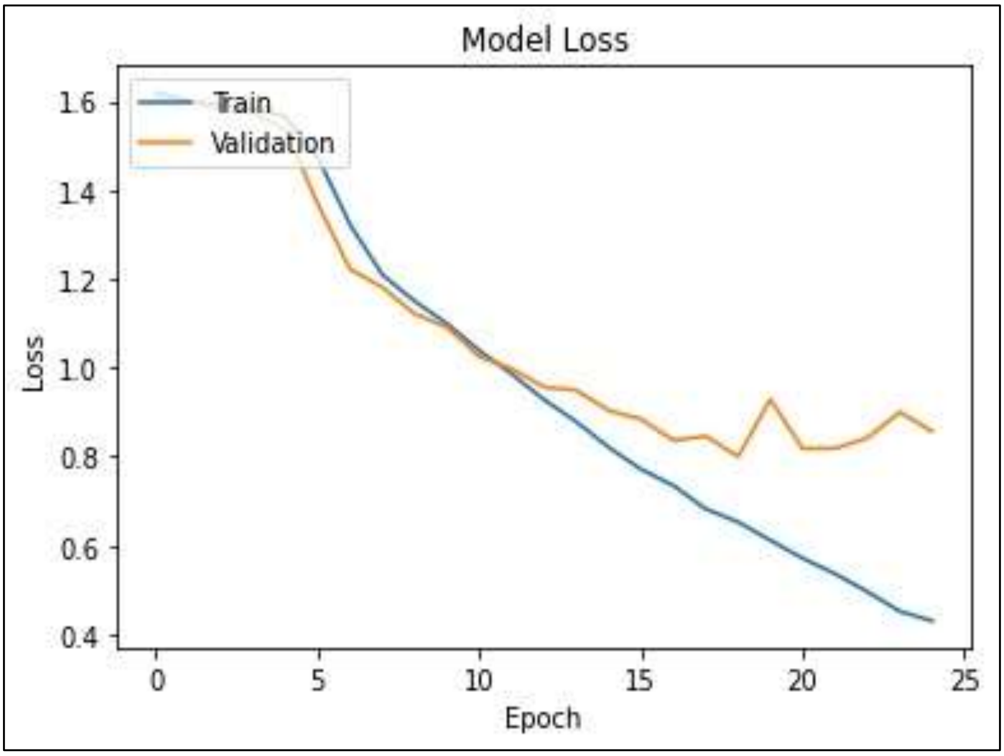

Fig 3. Model Loss

When loss and accuracy are taken into consideration for VGG16 model, it is observed that the graph shows loss values for both training & validation is continuously decreasing with each 25 epochs as the model learns and improves performance. However, accuracy values for both training & validation is continuously increasing.

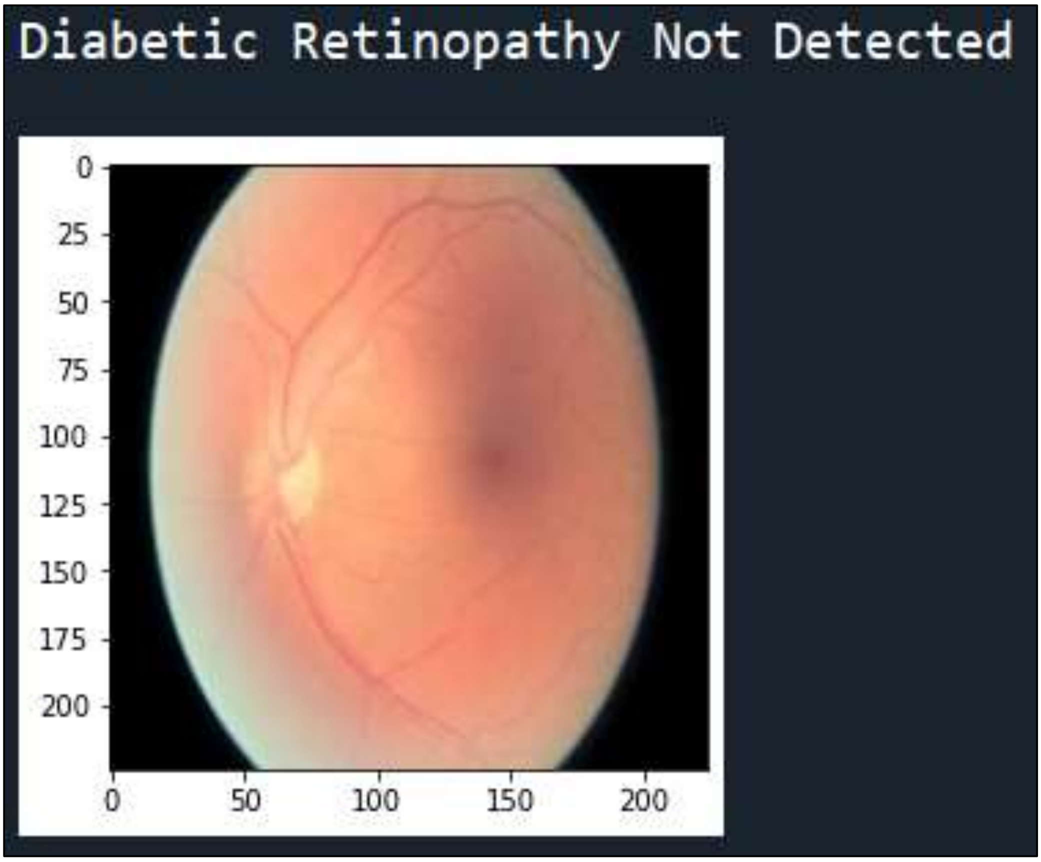

Fig. 4. DR Not Detected

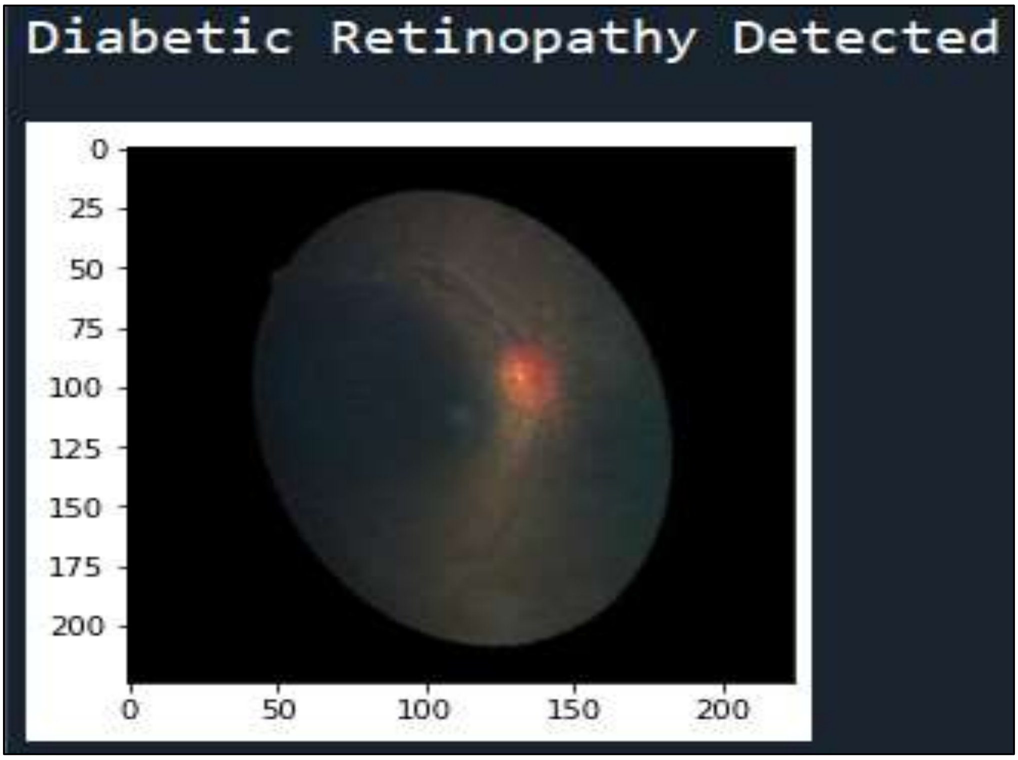

Fig. 5. DR Detected

In this present work, retinal images are preprocessed and augmented to enhance quality and dataset diversity. Using an Adam optimizer, a pre-trained VGG16 model is fine-tuned for diagnosis prediction. The VGG16 model was executed for diabetic retinopathy detection i.e., 'diabetic retinopathy detected' and 'diabetic retinopathy not detected' in the specific input image. The VGG16 model weights were assigned from 'imagenet'. As we are aimed at binary classification, the output layer was flattened into a 1-dimensional array. The 'relu' and 'softmax' activation functions were used with 1024 hidden units and a drop rate of 0.3. This approach facilitates analysis and classification of images according to their severity levels and ensures robustness and generalization, vital for accurate diagnosis in retinal imaging tasks.

V. Conclusion and future work

In this paper, a pre-trained VGG16 model for diabetic retinopathy detection has been studied. It has been understood that mostly the existing systems have used deep learning models or transfer learning models with smaller datasets and standard databases which are publicly available. Therefore, an elaborate dataset consisting of 31877 images [35] of 5 classes depend on the severity has been identified for this work. By employing the Adam optimizer has yielded promising results in the multi classification of retinal images for Diabetic Retinopathy detection. Over 25 epochs, VGG16 model achieved notable accuracy of 82.52%. Further optimization and exploration of advanced techniques hold potential for enhancing real-world applications in medical image analysis. The model's performance could benefit from continuous fine-tuning for better accuracy and better identification of DR. For fine-tuning, the number of epochs may be increased or some of the layers of the transfer learning models can be unfrozen. Furthermore, considering interpretability and explain ability in the model's decisions would be crucial for gaining trust in the medical community. Collaborating with healthcare professionals and integrating the system into clinical workflows would be pivotal for its real-world impact.

References

1. Alshayeji Mohammad H., Abed Sa'Ed and Sindhu Silpa Chandrabhasi, "Two-stage framework for diabetic retinopathy diagnosis and disease stage screening with ensemble learning", Expert Systems with Applications, vol. 225, p. 120206, Apr (2023), doi: 10.1016/j.eswa.2023.120206.
2. Malik S., Gupta S., Rajora C. S. and Srinivasan S., "Optical system-based data classification for diabetic retinopathy detection using machine learning with artificial intelligence", Optical and Quantum Electronics, vol. 55, no. 10, Aug (2023), DOI: 10.1007/s11082-023-05193-x.
3. Sharma, S. Shinde, S. Rani, I. I. Shaikh and Vyas M., "Machine Learning Approach for Detection of Diabetic Retinopathy with Improved Pre-Processing", (2021), International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), 19-20 February (2021), DOI: 10.1109/ICCCIS51004.2021.9397115.

4. Padmapriya M., Pasupathy S. and Punitha V., "Image Processing Techniques in the Detection of Hemorrhages in Retinal Images (STARE & DRIVE)", (2022), International Conference on Inventive Computation Technologies (ICICT), Nepal, pp. 197-201, doi: 10.1109/ICICT54344.2022.9850841.
5. Zago G. T., Andrea˜o R. V., Teatini Salles E. O. and Dorizzi B., "Diabetic retinopathy detection using red lesion localization and convolutional neural networks. Computers in Biology & Medicine", (2020), doi: 10.1016/j.compbiomed.2019.103537.103537.
6. Gadekallu T. R., Bhattacharya S., Khare N., et al., "Early detection of diabetic retinopathy using pca-firefly based deep learning model", Electronics, (2020), doi: 10.3390/electronics9020274.
7. Reddy A. J., Dang A., Dao A. A., Arakji G., Cherian J. and Brahmbhatt H., "A substantive narrative review on the usage of lidocaine in cataract surgery", Cureus, (2021), doi: 10.7759/cureus.19138.19138.
8. K. Shankar, Yiwei Liu, Ling Wu, Chi-Hua Chen and Yizhuo Zhang, "Hyperparameter tuning deep learning for diabetic retinopathy fundus image classification", IEEE Access, (2020), doi: 10.1109/access.2020.3005152.118164.
9. Jude Hemanth D., Deperlioglu Omer and Kose Utku, "An enhanced diabetic retinopathy detection and classification approach using deep convolutional neural network", Neural Computing & Applications, (2020), doi: 10.1007/s00521-018-03974-0.
10. Kalyani G., Prasad L. V. N., Janakiramaiah B. and Karuna A., "Diabetic retinopathy detection and classification using capsule networks", Com- plex & Intelligent Systems, (2021), doi: 10.1007/s40747-021-00318-9.
11. Rathi M. P., D. S. and Padmavati Shrivastava, "Prediction of diabetic retinopathy using classification techniques", Solid State Technology, (2020).
12. Bhatter P., Frisch E., Duhaime E., Jain A and Fischetti C., "Diabetic retinopathy detection using collective intelligence", Journal of Scientific Innovation in Medicine, (2020), doi: 10.29024/jsim.47.
13. Pravin R. Kshirsagar, Hariprasath Manoharan, S. Shitharth, Abdulrhman M. Alshareef and Nabeel Albishry, "Deep learning approaches for prognosis of automated skin disease", (2022).
14. Hariprasath Manoharan, Shitharth Selvarajan, Ayman Yafoz, Hassan A. Alterazi, Mueen Uddin, Chin-Ling Chen, et al., "Deep conviction systems for biomedical applications using intuiting procedures with cross point approach", (2022), doi: 10.3389/fpubh.2022.909628.
15. Gabriel Tozatto Zago, Rodrigo Varejão Andreão, Bernadette Dorizzi and Evandro Ottoni Teatini Salles, "Diabetic retinopathy detection using red lesion localization and convolutional neural networks", (2020).
16. U. Köse and O. Deperlioglu, "Diagnosis of diabetic retinopathy using image processing and convolutional neural network", (2018).
17. Fatima, Imran Muhammad, Ullah Anayat, Arif Muhammad and Noor Rida, "A unified technique for entropy enhancement based diabetic retinopathy detection using hybrid neural network", (2022).
18. V. Purna Chandra Reddy and Kiran Kumar Gurrala, "Optimal feature selection-based hybrid graph convolutional network model for joint DR-DME classification", (2022).
19. Abbas Q., Fondon I., Alemany P., Jiménez S. and Sarmiento Auxilia., "Automatic recognition of severity level for diagnosis of diabetic retinopathy using deep visual features", (2017).
20. Yuhao N., Lin G., Yitian Z and Feng L., "Explainable diabetic retinopathy detection and retinal image generation", (2022).
21. Zineb Sabouri, Noreddine Gherabi and Maleh Yassine, "Benchmarking Classification Algorithms for Measuring the Performance on Maintainable Applications", Advances in Information, Communication and Cybersecurity, Cham, (2022), pp. 173–179, doi: 10.1007/978-3-030-91738-8 17.
22. Hakim El. M., Sajida M., Zineb S. and Noreddine G., "Ontology Based Machine Learning to Predict Diabetes Patients", Advances in Information, Communication and Cybersecurity, Cham, (2022), pp. 437–445, doi: 10.1007/978-3-030-91738-8 40.
23. Abbas M. Al-Bakry and Fayroza Alaa Khaleel, "Diagnosis of diabetes using machine learning algorithms", Mater, Today Proc., Jul (2021), doi: 10 .1016/j.matpr.2021.07.196.
24. Simon Y. Foo and Jobeda Jamal Khanam, "A comparison of machine learning algorithms for diabetes prediction", ICT Express, vol. 7, no. 4, pp. 432–439, Dec (2021), doi: 10.1016/j.icte.2021.02.004.
25. Coskun Hakan and Cihan Pınar, "Performance Comparison of Machine Learning Models for Diabetes Prediction", (2021), Signal Processing and Communications Applications 29th Conference (SIU), Jun (2021), pp. 1–4. doi: 10.1109/SIU53274.2021.9477824.
26. Wan S., Zhang Y and Liang Y., "Deep convolutional neural networks for diabetic retinopathy detection by image classification", Computers & Electrical Engineering 72(10):274-282, (2018).
27. G. Kalyani, B. Janakiramaiah, A. Karuna and L. V. Narasimha Prasad, "Diabetic retinopathy detection and classification using capsule networks", Com- plex & Intelligent Systems, (2021).
28. Suvajit Dutta, Bonthala C S Manideep, Ronnie D. Caytiles, N Ch Sriman Narayana Iyenger and Syed Muzamil Basha "Classification of diabetic retinopathy images by using deep learning models", International Journal of Grid and Distributed Computing, (2018).
29. Li T., Guo S., Liu H., Kang H., Gao Y. and Wang K., "Diagnostic assessment of deep learning algorithms for diabetic retinopathy screening", Information Sciences, (2019).
30. De la Torre Jordi, Valls Aida and Puig Domenec, "A deep learning interpretable classifier for diabetic retinopathy disease grading", Neurocomputing, (2020).

31. Junbin G., Tariq K., Manoranjan P., Ahmad Fadzil M. Hani and Mohammad A. U. K. and Toufique Ahmed S., "Computerised approaches for the detection of diabetic retinopathy using retinal fundus images", A survey, Pattern Analysis & Applications, (2017).
32. Varun G., Lily P., Marc C., Arunachalam N., Subhashini V., Rajiv R., et al., "Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs", (2016).
33. Gao Z., Li J., Guo J., Chen Y., Yi Z., and Zhong J., "Diagnosis of diabetic retinopathy using deep neural networks", (2019).
34. Shu-I Pao, Hong-Zin Lin, Ke-Hung Chien, Ming-Cheng Tai, Jiann-Torng Chen and Gen-Min Lin, "Detection of Diabetic Retinopathy Using Bichannel Convolutional Neural Network", Journal of Ophthalmology, (2020), doi: 10.1155/2020/9139713.9139713.
35. https://www.kaggle.com/datasets/praneshkumarm/diabetic-retinopathy.