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Diabetic Retinopathy Classification and Symptom Analysis Using Convolutional Neural Networks

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Abstract: In this study, we are focus on Diabetic Retinopathy (DR) classification and symptom analysis using Convolutional Neural Networks (CNNs). The methodology begins with preprocessing steps including image resizing to ensure uniformity, conversion to grayscale, noise removal using Median Filtering. Histogram Equalization and contrast adjustment further enhance image quality for improved feature extraction. Segmentation is performed using k-means clustering to isolate regions of interest indicative of DR severity. Training options are carefully selected to maximize classification accuracy, evaluated using a confusion matrix. The classification outputs include Mild DR, Moderate DR, No DR, Proliferative DR, and Severe DR stages. Additionally, symptoms analysis aids in understanding disease progression and severity. The study aims to achieve high accuracy in DR diagnosis, facilitating early intervention and personalized treatment strategies.

Keywords: Diabetic Retinopathy Dataset, Pre-Processing, Convolution Neural Network, Deep learning, Classification, Symptoms, Accuracy.

I.INTRODUCTION

Diabetic Retinopathy (DR) poses a significant trouble to vision among diabetic individualities, manifesting as progressive damage to the retina due to diabetes- related complications. As one of the leading causes of blindness worldwide, early discovery and bracket of DR are pivotal for effective treatment and operation. Traditional styles for DR opinion have reckoned on homemade examination of retinal images, which can be time- consuming and private. With the arrival of deep literacy ways, particularly DenseNet classifiers, there has been a paradigm shift towards automated and more accurate DR bracket. This system involves a methodical approach starting with the accession of retinal images, followed by resizing for uniformity, conversion to grayscale to simplify processing, and operation of advanced ways similar as noise junking and discrepancy improvement to ameliorate image clarity. Segmentation farther isolates areas of interest reflective of DR inflexibility, allowing the DenseNet classifier to classify images into stages ranging from Mild DR to Severe DR with high perfection.

Diabetic retinopathy is an eye complaint that affects people living with diabetes. It develops when high blood sugar damages the bitsy blood vessels in the retina. This causes a variety of symptoms like vague vision and vision loss.

II.LITERATURE REVIEW

[1] Diabetic Retinopathy Classification Using CNN and Hybrid Deep Convolutional Neural Networks. Symmetry 2022, 14, 1932.

Diabetic Retinopathy (DR) is an eye condition that mainly affects individuals who have diabetes and is one of the important causes of blindness in adults. As the infection progresses, it may lead to permanent loss of vision. Diagnosing diabetic retinopathy manually with the help of an ophthalmologist has been a tedious and a very laborious procedure. This paper not only focuses on diabetic retinopathy detection but also on the analysis of different DR stages, which is performed with the help of Deep Learning (DL) and transfer learning algorithms. CNN, hybrid CNN with ResNet, hybrid CNN with DenseNet are used on a huge dataset with around 3662 train images to automatically detect which stage DR has progressed. Five DR stages, which are 0 (No DR), 1 (Mild DR), 2 (Moderate), 3 (Severe) and 4 (Proliferative DR) are processed in the proposed work. The patient's eye images are fed as input to the model. The proposed deep learning architectures like CNN, hybrid CNN with ResNet, hybrid CNN with DenseNet 2.1 are used to extract the features of the eye for effective classification.

[2] Chazhoor, A.; Sarobin, V.R. Intelligent automation of invoice parsing using computer vision techniques. Multimed. Tools Appl.2022, 81, 29383-29403. [CrossRef].

Manual parsing of invoices is a tedious, arduous and error-prone task. Due to the academic and business importance of this problem, it has attracted the attention of machine learning enthusiasts. There are several complexities and challenges in the automated parsing of invoices. Some of them include a paucity of useful datasets, eclectic template formats, and poor performance of algorithms in real life scenarios. This problem can be solved by the automatic traversal of the invoices by object detection algorithms such as YOLO, SSD and R-CNN. These state-of-the-art algorithms will be trained to detect various fields or entities present in an invoice. In this paper, a dataset of 315 invoices has been generated using web testing tools. The dataset has been annotated for eight entities: billing address, shipping address, invoice date, invoice number, product name, price, quantity, and total amount. The text boxes detected by the models is converted to machine encoded text, using text extraction methods such as Optical Character Recognition (OCR). Hyperparameter tuning has been performed to improve model accuracy. The models have been evaluated on myriad metrics such as mean Average Precision (mAP), common objects in context (COCO) evaluation metrics and total loss during training and validation. The loss vs iteration graph has been visualized using Tensor board. A front-end application encapsulates all the functions of the research paper and allows testing of various models

[3] Jiang, H.; Yang, K.; Gao, M.; Zhang, D.; Ma, H.; Qian, W. An Interpretable Ensemble Deep Learning Model for Diabetic Retinopathy Disease Classification. In Proceedings of the 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Berlin, Germany, 23-27 July 2019; pp. 2045-2048.

Diabetic retinopathy (DR) is one kind of eye disease that is caused by overtime diabetes. Lots of patients around the world suffered from DR which may bring about blindness. Early detection of DR is a rigid quest which can remind the DR patients to seek corresponding treatments in time. This paper presents an automatic image-level DR detection system using multiple well-trained deep learning models. Besides, several deep learning models are integrated using the Adaboost algorithm to reduce the bias of each single model. To explain the results of DR detection, this paper provides weighted class activation maps (CAMs) that can illustrate the suspected position of lesions. In the pre-processing stage, eight image transformation ways are also introduced to help augment the diversity of fundus images. Experiments demonstrate that the method proposed by this paper has stronger robustness and acquires more excellent performance than that of individual deep learning model.

[4] Sanket, S.; Vergin Raja Sarobin, M.; Jani Anbarasi, L.; Thakor, J.; Singh, U. Narayanan, S.
Detection of novel coronavirus from chest X-rays using deep convolutional neural networks. Multimed.
Tools Appl. 2022, 81, 22263-22288. [CrossRef] [PubMed].

With over 172 million people infected with the novel coronavirus (COVID-19) globally and with the numbers increasing exponentially, the dire need of a fast diagnostic system keeps on surging. With shortage of kits, and deadly underlying disease due to its vastly mutating and contagious properties, the tired physicians need a fast diagnostic method to cater the requirements of the soaring number of infected patients. Laboratory testing has turned out to be an arduous, cost-ineffective and requiring a well-equipped laboratory for analysis. This paper proposes a convolutional neural network (CNN) based model for analysis/detection of COVID-19, dubbed as CovCNN, which uses the patient's chest X-ray images for the diagnosis of COVID-19 with an aim to assist the medical practitioners to expedite the diagnostic process amongst high workload conditions. In the proposed CovCNN model, a novel deep-CNN based architecture has been incorporated with multiple folds of CNN. These models utilize depth wise convolution with varying dilation rates for efficiently extracting diversified features from chest X-rays. 657 chest X-rays of which 219 were X-ray images of patients infected from COVID-19, and the remaining were the images of non-COVID-19 (i.e. normal or COVID-19 negative) patients. Further, performance evaluation on the dataset using different pre-trained models has been analyzed based on the loss and accuracy curve. The experimental results show that the highest classification accuracy (98.4%) is achieved using the proposed CovCNN model.

III.PROPOSED METHOD

The methodology for diabetic retinopathy bracket and symptom analysis utilizes Convolutional Neural Networks (CNNs) for robust image processing and bracket. original way involves preprocessing the input images resizing for uniformity, converting to grayscale, and applying Median Filtering for noise junking. Histogram Equalization and discrepancy improvement optimize image quality. Segmentation is performed using k- means clustering to insulate applicable regions indicating DR inflexibility. A mongrel CNN armature is employed, incorporating multiple layers for effective point birth and bracket into orders Mild DR, Moderate DR, No DR, Proliferative DR, and Severe DR. The dataset is stoked to diversify training samples, enhancing model conception. Training options are fine- tuned for optimal performance, estimated through a confusion matrix to measure bracket delicacy. Symptoms analysis complements the bracket results, furnishing perceptivity into complaint progression. This methodology aims to achieve high individual delicacy, easing early discovery and substantiated treatment strategies for diabetic retinopathy.

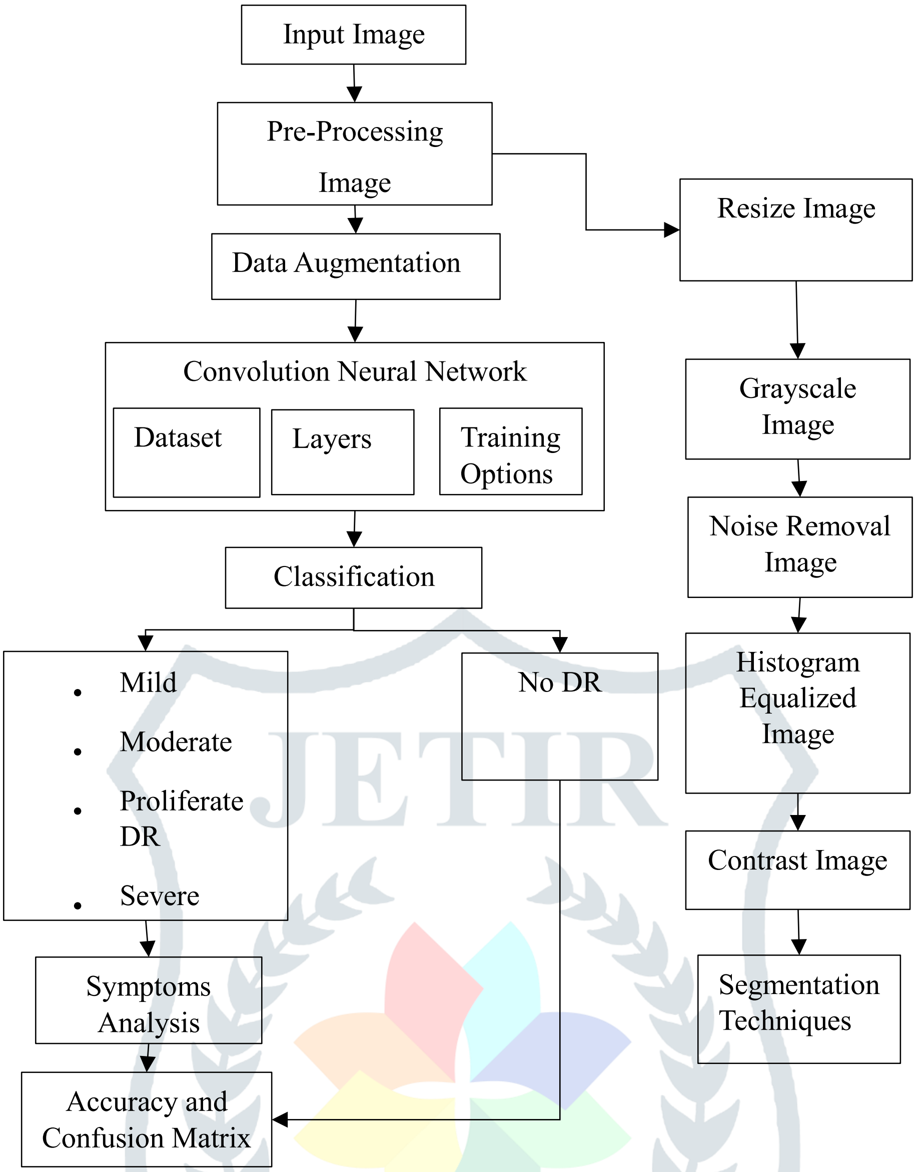


Fig 1: Block Diagram of Proposed Model

- **Image Resize:**

Image resizing is a fundamental task in image processing, often necessary for standardizing images to a specific dimension for further analysis or processing.

- **Gray scale Image:**

Grayscale image processing in MATLAB is a fundamental technique used in various image processing applications. A grayscale image, unlike a colour image, contains only shades of Gray and is represented by a single intensity channel, making it simpler and faster to process.

- **Noise Removal:**

Noise removal is a critical step in image processing, particularly in medical imaging where clarity and accuracy are paramount.

- **Contrast Image:**

In MATLAB, enhancing image contrast is a fundamental task in image processing aimed at improving the visual quality and making important details more discernible. Contrast adjustment involves modifying the distribution of pixel intensities across the image, effectively stretching or compressing the intensity range.

- **Segmentation technique:**

Segmentation techniques in MATLAB encompass a diverse set of methodologies crucial for extracting meaningful information from images by partitioning them into distinct regions.

➢ **Convolutional Neural Network:**

Convolutional Neural Networks (CNNs) stand as a foundation in the realm of deep literacy, revolutionizing colourful fields, particularly computer vision, with their unequalled capability to comprehend and prize intricate patterns from visual data. In MATLAB, CNNs have garnered significant attention due to their exceptional capacity to reuse complex image- grounded information. At its core, a CNN mimics the visual cortex's armature, composed of multiple layers that precipitously learn and abstract hierarchical features from raw pixel inputs. This hierarchical point birth enables CNNs to automatically descry essential details like edges, textures, and shapes, making them largely complete at tasks similar as image bracket, object discovery, and image segmentation.

- **Convolutional Layer:**

A 2- D convolutional subcaste applies sliding convolutional pollutants to 2- D input. produce a 2- D convolutional subcaste using convolution2dLayer. The convolutional subcaste consists of colourful factors.

- **Filters and Stride**:

A convolutional subcaste consists of neurons that connect to subregions of the input images or the labours of the former subcaste. The subcaste learns the features localized by these regions while surveying through an image. When creating a subcaste using the convolution2dLayer function, you can specify the size of these regions using the sludge Size input argument.

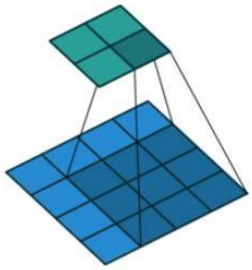


Fig 2: Filters and Stride

- **Dilated Convolution:**

A dilated complication is a complication in which the adulterants are expanded by spaces fitted between the rudiments of the sludge. Use dilated complications to increase the open field of the caste without adding the number of parameters or computation.

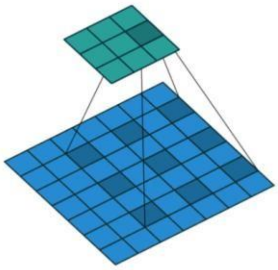


Fig 3: Dilated Convolution

- **Point Charts:**

As a sludge moves along the input, it uses the same set of weights and the same bias for the complication, forming a point chart. Each point chart is the result of a complication using a different set of weights and a different bias. Hence, the number of point charts is equal to the number of pollutants. The total number of parameters in a convolutional subcaste is ((h * w * c 1) * Number of Pollutants), where 1 is the bias.

- **Padding:**

You can also apply padding to input image borders vertically and horizontally using the' Padding' name value brace argument. Padding is values added to the borders of the input to increase its size. By conforming the padding, you can control the affair size of the subcaste.

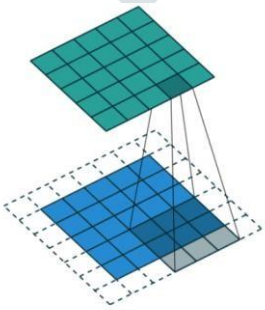


Fig 4: Padding

- **Affair Size:**

The affair height and range of a convolutional subcaste is (Input Size – ((Filter Size – 1) * Dilation Factor 1) 2 * Padding)/ Stride 1. This value must be an integer for the whole image to be completely covered.

still, the software by dereliction ignores the remaining part of the image along the right and nethermost edges in the complication, If the combination of these options does n't lead the image to be completely covered.

- **Number of Neurons:**

The product of the affair height and range gives the total number of neurons in a point chart, say Chart Size. The total number of neurons (affair size) in a convolutional subcaste is Chart Size * Number of Pollutants.

- **Learning Parameters:**

You can acclimate the literacy rates and regularization options for the subcaste using name- value brace arguments while defining the convolutional layer. However, also train Network uses the global training options defined with the training Options serve, If you choose not to specify these options.

- **Number of Layers:**

A convolutional neural network can correspond of one or multiple convolutional layers. The number of convolutional layers depends on the quantum and complexity of the data.

- **Accuracy:**

In MATLAB, "Accuracy" is a common performance metric used to evaluate the overall effectiveness of a classification model, particularly in binary or multi-class classification tasks. It measures the proportion of correctly classified samples over the total number of samples in the dataset. To understand Accuracy, it's essential to know the concepts of True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN):

- True Positives (TP): The number of samples correctly classified as positive by the classifier.
- False Positives (FP): The number of negative samples that were incorrectly classified as positive by the classifier.
- True Negatives (TN): The number of samples correctly classified as negative by the classifier.
- False Negatives (FN): The number of positive samples that were incorrectly classified as negative by the classifier.

Accuracy is calculated using the following formula:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

In other words, Accuracy is the ratio of the correctly classified samples (both positive and negative) to the total number of samples in the dataset.

IV.RESULTS

The image taken from http://www.kaggle.com/competitions/aptos2019-blinnessdetection/data?select=test

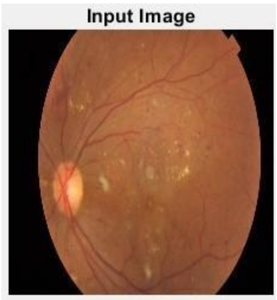


Fig 5: input image

Fig 6: resized image

Fig 7: grayscale image

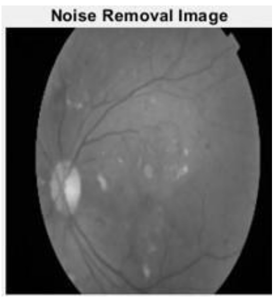


Fig 8: noise removal image

Fig 9: histogram equalized image

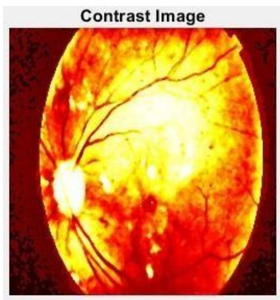


Fig 10: Contrast image

Figures illustrate the preprocessing steps applied to input images, including resizing, grayscale conversion, noise removal, and contrast enhancement. Example visual outputs (e.g., Figures showing grayscale and noise-removed images) demonstrate improvements in image clarity, which help in isolating DR-relevant regions.

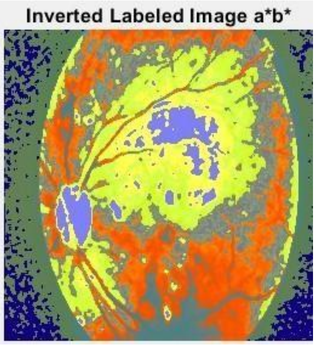


Fig 11: inverted labelled Image

This image, titled "Inverted Labelled Image a*b*," seems to be a processed version of a retinal image, likely segmented for analysing different regions related to diabetic retinopathy.
In this color-coded representation:

- Yellow and green areas may indicate regions of interest where potential symptoms or features of diabetic retinopathy are prominent.
- Blue areas could represent blood vessels or areas with no signs of diabetic retinopathy.
- Red and orange regions may signify areas of abnormality or concern, such as haemorrhages, exudates, or other indicators of retinopathy progression.

Fig 12: Classification Results Image

```
The classified output is : 98.997500
Symptoms of Severe DR: Major blood vessel blockages, large bleeds, severe vision loss, eye swelling
Precision: 81.8182
Recall: 90.0000
F1 Score: 85.7143
```

Fig 13: Metric Values image

Classification Results image and Metric values image shown the output and symptoms. In shown values are Precision, Recall and F1 Score.

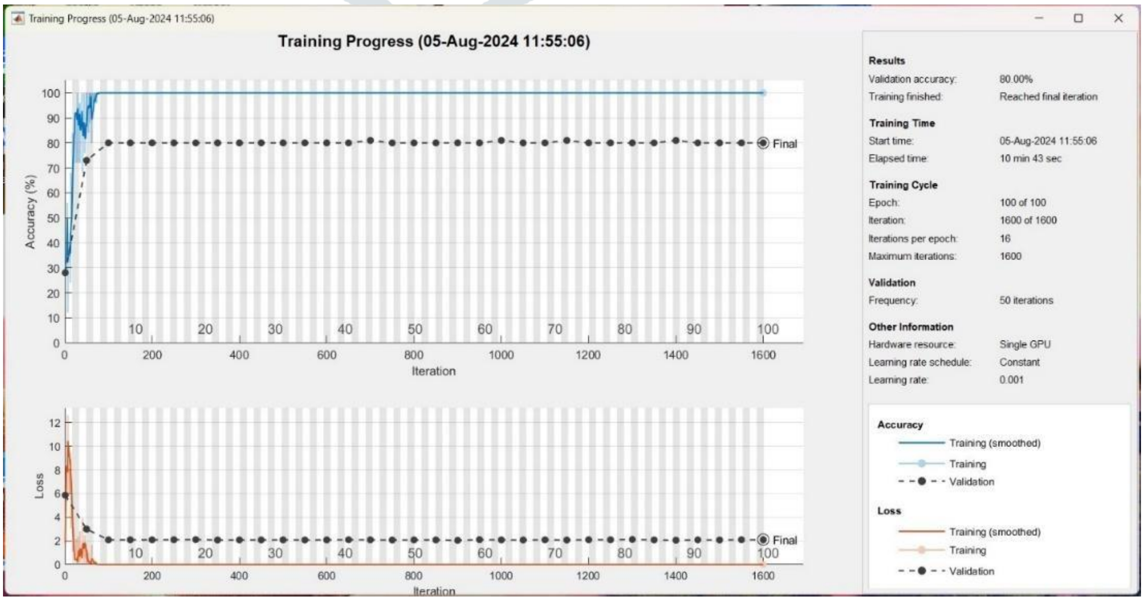


Fig 14: Training progress image

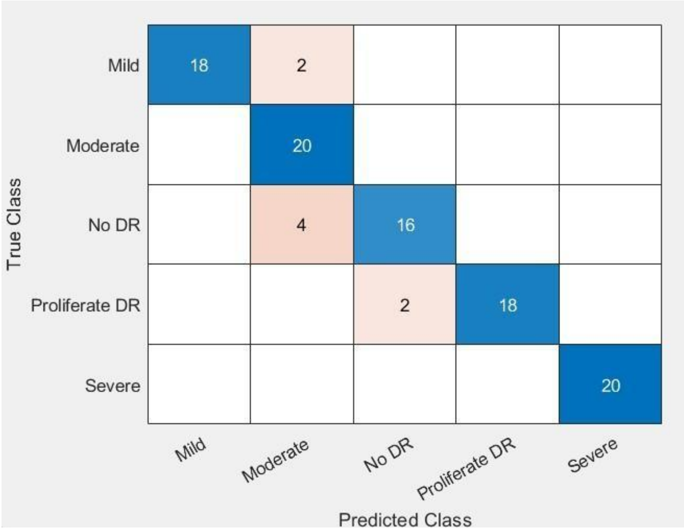


Fig 15: Confusion Matrix Image

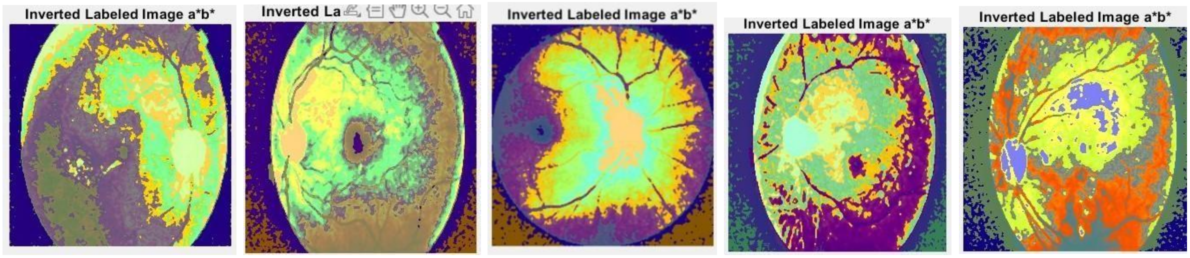
Segmentation is performed using k-means clustering to isolate regions of interest indicative of DR severity. Training options are carefully selected to maximize classification accuracy, evaluated using a confusion matrix. The classification outputs include Mild DR, Moderate DR, No DR, Proliferative DR, and Severe DR stages.

Command Window Editor - main.m

Training on single GPU.
Initializing input data normalization.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss	Base Learning Rate
1	1	00:00:05	28.00%	28.00%	1.7983	5.8708	0.0010
4	50	00:00:22	88.00%	73.00%	1.0450	2.9977	0.0010
7	100	00:00:38	100.00%	80.00%	5.3934e-06	2.0956	0.0010
10	150	00:00:55	100.00%	80.00%	4.4346e-07	2.0965	0.0010
13	200	00:01:13	100.00%	80.00%	-0.0000e+00	2.0942	0.0010
16	250	00:01:30	100.00%	80.00%	-0.0000e+00	2.1064	0.0010
19	300	00:01:47	100.00%	80.00%	6.2471e-06	2.1170	0.0010
22	350	00:02:07	100.00%	80.00%	4.6924e-06	2.0811	0.0010
25	400	00:02:32	100.00%	80.00%	-0.0000e+00	2.0863	0.0010
29	450	00:02:52	100.00%	80.00%	-0.0000e+00	2.0878	0.0010
32	500	00:03:14	100.00%	80.00%	-0.0000e+00	2.0931	0.0010
35	550	00:03:36	100.00%	80.00%	7.6294e-08	2.0841	0.0010
38	600	00:03:59	100.00%	80.00%	-0.0000e+00	2.0892	0.0010
41	650	00:04:23	100.00%	80.00%	9.5367e-09	2.1052	0.0010
44	700	00:04:42	100.00%	81.00%	4.2915e-08	2.0951	0.0010
47	750	00:05:02	100.00%	80.00%	1.1110e-06	2.0789	0.0010
50	800	00:05:22	100.00%	80.00%	2.3700e-06	2.0902	0.0010
54	850	00:05:42	100.00%	80.00%	6.4472e-06	2.0869	0.0010
57	900	00:06:02	100.00%	80.00%	4.7684e-09	2.0540	0.0010
60	950	00:06:25	100.00%	80.00%	1.9073e-08	2.1098	0.0010
63	1000	00:06:45	100.00%	81.00%	2.3842e-08	2.0900	0.0010
66	1050	00:07:08	100.00%	80.00%	1.4305e-08	2.0809	0.0010
69	1100	00:07:28	100.00%	80.00%	3.3094e-06	2.0972	0.0010
72	1150	00:07:46	100.00%	81.00%	1.0729e-06	2.0778	0.0010
75	1200	00:08:05	100.00%	80.00%	1.3304e-06	2.1041	0.0010
79	1250	00:08:24	100.00%	80.00%	1.3876e-06	2.1026	0.0010
82	1300	00:08:52	100.00%	80.00%	-0.0000e+00	2.1293	0.0010
85	1350	00:09:11	100.00%	80.00%	-0.0000e+00	2.0878	0.0010
88	1400	00:09:29	100.00%	81.00%	1.2016e-06	2.0623	0.0010
91	1450	00:09:48	100.00%	80.00%	2.1840e-06	2.0913	0.0010
94	1500	00:10:06	100.00%	80.00%	6.1989e-08	2.0807	0.0010
97	1550	00:10:24	100.00%	80.00%	-0.0000e+00	2.1052	0.0010
100	1600	00:10:43	100.00%	80.00%	1.4019e-06	2.0905	0.0010

Fig 16: Training Iterations Image



a) b) c) d) e)

Fig 17: a) MILD, b) MODERATE, c) NO DR, d) PROLIFERATE, e) SEVERE

Table-1 (List of Symptom, Output, Precision, Recall, F1 Score)

S.NO	Symptom	OUTPUT	Precision	Recall	F1 Score
a	Mild	98.932	90.909	100.000	95.238
b	Moderate	99.005	71.428	100.000	83.333
c	No DR	99.017	75.000	90.000	81.818
d	Proliferate	98.827	100.000	80.000	88.888
e	Severe	98.997	81.818	90.000	85.714

Comparison Table-2: Existing method and Proposed method comparison

S. No	Existing Method Training Loss	Proposed Method Training Loss
1	1.03296	0.128543
2	1.03296	0.128543
3	1.03296	0.128543
4	1.03296	0.128543
5	1.03296	0.128543

Comparison Graph:

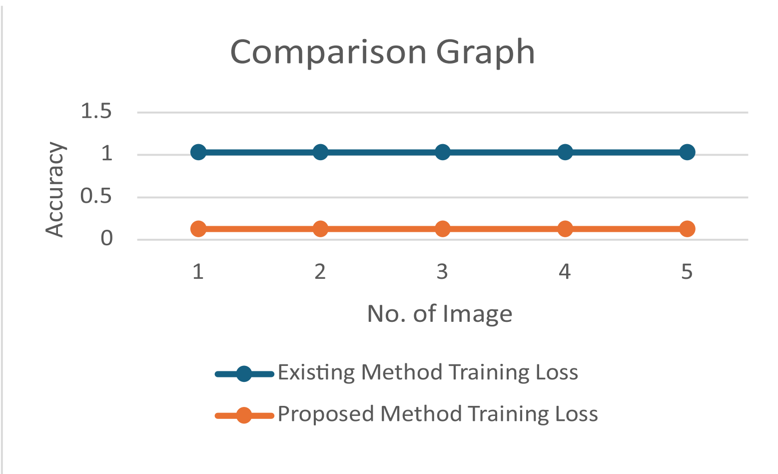


Fig 18: comparison graph

V.CONCLUSION:

In conclusion, our study demonstrates the efficacy of Convolutional Neural Networks (CNNs) in diabetic retinopathy (DR) classification and symptom analysis. By employing a robust methodology that includes preprocessing, segmentation, and a Hybrid CNN architecture, we have achieved accurate classification into multiple DR stages. The use of techniques such as image resizing, grayscale conversion, and k-means clustering ensures precise feature extraction and severity assessment. Augmenting the dataset enhances model generalization, crucial for reliable diagnosis. Our approach not only focuses on achieving high classification accuracy but also integrates symptoms analysis to provide deeper insights into disease progression and severity. This comprehensive approach aims to support early detection and personalized treatment strategies, ultimately enhancing patient care outcomes in diabetic retinopathy management. By leveraging advanced CNN techniques, this research contributes to advancing diagnostic capabilities, empowering healthcare professionals with a tool for efficient and effective DR diagnosis and intervention.

VI.FUTURE SCOPE:

Improved Model Accuracy in Utilizing deeper CNN architectures, Vision Transformers, and multimodal data for enhanced classification. Interpretability to Developing explainable models to support clinicians with symptom-focused heatmaps. In Real-Time Diagnostics Integrating with portable diagnostic tools and automated workflows for remote and clinic use. Predicting DR progression to tailor personalized treatment. Combining CNNs with RNNs and using transfer learning for robust performance on diverse datasets. Deploying CNN-based tools in telehealth apps for remote monitoring and patient education.

ACKNOWLEDGMENT:

The satisfaction that accompanies the successful completion of this model would be incomplete without acknowledging the individuals whose constant guidance and encouragement made it possible. Their unwavering support has crowned our efforts with success, and for that, we are sincerely grateful.

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