Using Deep Learning on Retinal Images to Classify the Severity of Diabetic Retinopathy

Shereen A. El-aal[1], Rania Salah El-Sayed[2]*, Abdulellah Abdullah Alsulaiman[3], Mohammed Abdel Razek[4]
Department of Mathematics & Computer Science-Faculty of Science-Al-Azhar University, Cairo, Egypt[1, 2, 4]
Department of Educational Technology-College of Education-King AbdulAziz University, Saudi Arabia[3]

***Abstract*—Diabetic retinopathy (DR) is a leading cause of blindness worldwide, particularly among working-age individuals. With the increasing prevalence of diabetes, there is an urgent need to address the public health burden posed by DR. This research paper aims to develop a clinical decision support approach that integrates automated DR detection and classifying the grade of severity in DR. A three-stage deep learning model for DR detection is proposed. First, incorporating preprocessing, image enhancement, and augmenting the DR images using three different color space transformations and a filtering technique: BGR to RGB, RGR to LAB, and Gaussian Blur Filter. Secondly, feature extraction and representation learning are based on CNN with various layers. Thirdly, classification is based on SVM. The implementation and evaluation of the proposed model on a dataset containing five stages of DR are essential steps towards validating its performance and assessing its potential for clinical applications. Through thorough dataset preprocessing, model training, performance analysis, comparison with baseline methods, and generalization tests, we can gain insights into the model's classification and staging capabilities. This research makes a significant contribution to the field of DR severity detection, ultimately leading to enhanced diagnostic capabilities. The developed models demonstrated an accuracy rate of 94.72%, indicating their efficacy in accurately assessing the severity of the condition.**

Keywords*—Deep learning; diabetic retinopathy (DR); Gaussian Blur Filter; support vector machine (SVM); color space; performance evaluations

I. Introduction

Diabetic Retinopathy (DR) is an ocular disorder that can lead to visual impairment and complete blindness in individuals with diabetes. This condition specifically impacts the blood vessels located in the retina, which is the light-sensitive tissue situated at the rear of the eye. Early intervention in the treatment of DR can significantly alleviate the burden of vision loss attributed to this condition, so making it a crucial area of study, particularly in light of the creation of new diagnostic instruments [1].

Several studies aimed at detecting Parkinson's disease early were presented. Yasashvini R. et al. [2] presented DR Classification using convolution neural network (CNN), hybrid CNN with DenseNet 2.1, and hybrid CNN with ResNet are utilized to extract the features of the eye. The author's model used 3662 train images and 1928 test images after applying the image augmentation technique, divided into 5-classes. Sayan Das and Sanjoy Kumar Saha [3] introduced DR detection model using CNN based on genetic algorithm for extract features and support vector machine (SVM) for classification. The model was tested on a dataset that contains 1200 retinal fundus images divided into 4- classes. Raja Chandrasekaran and Balaji Loganathan [4] presented an approach that combines deep learning techniques with wavelet analysis with Hyper-analyticWavelet phase activations. The reported results in DR classification offer better generalization ability and improved learning of feature maps from wavelet sub-bands.

Thippa Reddy Gadekallu et al. [5] used DNN based on Principal Component Analysis (PCA) for dimensonality reduction used firefly optimization algorithm. The DenseNet architecture has demonstrated exceptional performance in the task of image feature extraction, resulting in optimal accuracy for image classification tasks [6]. Mohamed M. Farag et al. [7], presented a severity detection model based on DenseNet169's encoder that was used for feature extraction then followed by Convolutional Block Attention Module (CBAM) for feature refinement. The author model used 3296 training and 366 testing images, divided into 5-classes. Gergo Bogacsovics et al. [8], presented a model based on hand-crafted features sequentially AlexNet, MobileNetv3, and Resnet-50, respectively, in automated fundus image classification. The authors applied their model to three datasets: the IDRiD, Kaggle DR, and Messidor datasets. Fernando C. Monteiro [9] proposed blended Deep Learing (DL) model by training several DL models (VGG16, VGG19, ResNet50, ResNet101, Inception-V3, Incep.ResNet, Xception, DenseNet201, DarkNet53, and EfficientNetB0) using 5-f) using validation that mean 50 (10 architectures x 5 folds).

Zongyun Gu. et al. [10] proposed a classification model of fundus images for DR stages. The author's model used a transformer encoder for feature extraction, and multiple fractional tensors were generated via different 1 × 1 convolutions that were used for grading prediction. The author's model was applied to DDR dataset consisting of 13,673 fundus images with 6835 training, 2733 validation, and 4105 testing, divided into 6 classes. Ghadah Alwakid et al. [11] presented two RD classification models, one without and one with image augmentation. Auther models used DenseNet-121 that were applied on APTOS and DDR datasets, divided into 5-classes. Isoon Kanjanasurat et al. [12] introduced DR fundus grading model. In a single training session, the author's model employed 27 pre-trained CNNs and divided the DR Dataset into two groups (no DR and DR). The author's used (APTOS2019) dataset consists of 3662 color retinal images, divided into 5-classes.

*Corresponding Author

Zhan Wu et al. [13] proposed CF-DRNet model consists of two stage, first of them is Coarse Network performs that was used to classify data into two-class including No DR and DR. Second of them is Fine network is proposed to classify four-stage DR severity grades of the grade DR. Rajaa, and L. Balajib [14] presented diabetic detection in retinal images, which used adaptive histogram equalization (AHE) for preprocessing followed by CNN and fuzzy c-means clustering (FCM), respectively. The author's model was applied on a dataset containing 76 retinal images which includes normal and abnormal retinal images. Angel Ayala et al. [15], introduced a convolutional neural network model to process a fundus oculi image to recognize the eyeball structure and determine the presence of DR.

Our contribution to this research is: 1) Utilizing efficient image preprocessing including BGR to RGB color space conversion, RGB to LAB color space transformation, and Gaussian blur filtering to preprocess and enhance the (DR) images, 2) designing a CNN-based architecture that can automatically learn and extract relevant features from the preprocessed DR images, capturing the intricate patterns and anomalies associated with different stages of the disease, 3) classifying and staging diabetic retinopathy using SVM and DNN models in accordance with the CNN-extracted features, 4) comparing and investigating the optimal model according to the evaluation metrics, and compare the results with datasets that have higher accuracy, as the dataset used in this research has a lower accuracy.

The subsequent sections of this paper will be structured as follows: Section II briefly introduces the preprocessing operation and CCN layers which were used in the proposed model. Section III explains the research methodology (dataset description and architecture of the proposed model), the experimental environment, and the procedure of the proposed model are illustrated in Section IV. In Section V. Comparative study and discussion of results. Sections VI and VII serve as the concluding section of the paper, summarizing the key findings and insights obtained throughout the research. Additionally, it outlines the scope and potential avenues for future activities and investigations in the field.

II. Preliminaries

This section introduces three image processing techniques utilized for dataset augmentation, along with an overview of different types of CNN layers.

A. Preprocessing Operation

The input image undergoes various preprocessing procedures before the feature extraction stage. Image processing plays a crucial role in enhancing the quality and diversity of the images, leading to improved performance of machine learning models. In this subsection three preprocessing techniques are discussed.

- BGR Color Space to RGB: The default color space used in many image processing applications, is the BGR color space [16]. However, most computer vision tasks and deep learning models utilize the RGB color space. Therefore, converting images from BGR to RGB is a fundamental step in preprocessing. By performing this conversion, we ensure compatibility with various algorithms and frameworks, facilitating seamless integration into deep learning architectures. Additionally, RGB images often exhibit better visual interpretability and can capture more accurate color information, enhancing the overall quality of the dataset.
- RGR Color Space to the LAB: Another preprocessing operation involves converting images from the RGB color space to the LAB color space, the LAB color space separates the luminance (L) component from the color information [16]. This separation provides a perceptually uniform color representation, enabling better discrimination of color variations. By incorporating LAB images into the dataset additional diversity is introduced, as the model can learn to extract meaningful features from different color channels independently.
- Gaussian Blur Filter (GBF): GBF is a widely used technique in image processing [17]. It applies a convolution operation using a Gaussian kernel, resulting in a blurring effect on the image. This filter introduces controlled levels of blurriness to the images, simulating different degrees of focus and sharpness. By incorporating blurred images into the dataset, the model can learn to handle and generalize better to such instances, improving its overall performance.

B. CNN and Layer Types

Convolutional Neural Networks (CNNs) create a network architecture in a more reasonable way by utilizing the structure of the input image. Three dimensions; width, height, and depth—are used to organize the layers of a CNN in a 3D volume; depth is the third dimension of the volume, which can be the number of channels in an image or the number of filters in a layer [18].

CNNs are composed of various layers, each serving a specific purpose in the network's architecture. Convolutional Layer (CONV) is the fundamental building block of a CNN. It performs a mathematical operation known as convolution, which involves applying a set of filters to the input data. These filters help to extract relevant features from the input image, such as edges, textures, and shapes. The output of this layer is a feature map, which represents the learned features. Pooling layers are used to reduce the spatial dimensions of the feature maps generated by previous layers. They achieve this by downsampling the feature maps, effectively reducing the amount of information to be processed in subsequent layers. Activation layers help the network to learn complex patterns and make predictions such as Rectified Linear Unit (ReLU) [19].

Fully connected layers, also known as dense layers are responsible for making predictions based on the learned features. Dropout layers are used to prevent overfitting in CNNs. Batch normalization layers are used to improve the training speed and stability of CNNs [20]. The softmax layer is often used as the final layer in CNNs for classification tasks. Fig.1 shows the fundamental architecture of CNN.

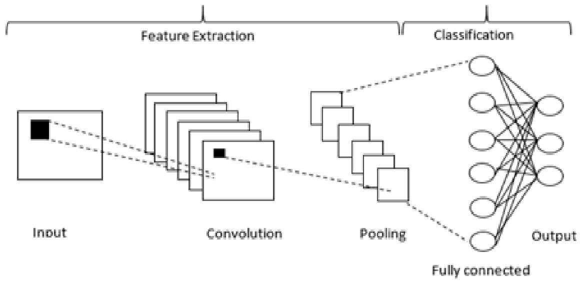

Fig. 1. The fundamental architecture of CNN.

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III. Research Methodology

A. Dataset Description

All the experimental work conducted in this research utilized the DR Dataset as the primary test bed [21]. It encompasses five distinct classes, namely Healthy, Mild DR, Moderate DR, Proliferative DR, and Severe DR. The distribution of images across these classes is presented in Table I. The dataset provides a comprehensive representation of different stages of DR, ranging from healthy retinas to severe cases. The availability of images across various classes allows for a thorough analysis and evaluation of the proposed model's performance in detecting and classifying DR [22].

TABLE I. Distribution of Images in DR Dataset

Class	# Original Images
Healthy	1000
Mild DR	370
Moderate DR	900
Proliferative DR	290
Severe DR	190

B. Architecture of the Proposed Model

In this section, we present the architecture of the proposed model for classifying the severity of DR. The model's architecture plays a critical role in its ability to extract relevant features from retinal images and make accurate predictions regarding the severity levels of DR. As shown in Fig. 2. a general overview of the proposed model for DR classification is provided.

1) Preprocessing operation and dataset augmentation: The proposed methodology of image processing is based on enhancing the contrast of images, it consists of two stages aimed at increasing the number of images and introducing diversity into the dataset.

The first stage focuses on augmenting the DR images by converting them from the default BGR color space to RGB. This conversion effectively doubles the number of images available for analysis or training.

In the second stage, the original images are transformed from the RGB color space to the LAB color space, generating a new set of images. By introducing LAB images into the dataset, a broader range of variations is incorporated, enhancing the diversity of the data. This augmentation technique benefits the model by enabling it to capture subtle color variations more effectively, thus improving its performance in accurately detecting and classifying different stages of DR. To further enhance the diversity of the dataset, a Gaussian Blur filter is applied to the augmented images. Table II shows the number of images in each class after augmentation.

TABLE II. Distribution of Augmented Images in each Class

Class	# original images+ RGB	# original images+ RGB +LAB
Healthy	2000	3000
Mild DR	740	1110
Moderate DR	1800	2700
Proliferative DR	580	870
Severe DR	380	570

2) Proposed learning model: To prepare the dataset, the enhanced input image dimensions are standardized to 224 x 224 pixels, and the corresponding category is assigned to each image. Table III presents the proposed model for classifying the severity of DR adopts a CNN-based architecture. The image classification stage consists of six convolutional layers, activation functions, pooling layers, and fully connected layers, the model effectively extracts and learns meaningful features from retinal images. This architecture enables the model to make accurate predictions regarding the severity levels of DR, contributing to improved diagnosis and management of this condition. The architecture, illustrated in Table III consists of CNN layers that play a crucial role in extracting relevant features from retinal images. The table also provides names for the operations performed in each layer, providing a clear understanding of the network's structure. The model is compiled using the Adam optimizer with a learning rate of 0.001 and the categorical cross-entropy loss function is utilized to measure the difference between the predicted class probabilities and the true labels. It undergoes 100 epochs of training, with a batch size of 32.

TABLE III. CNN MODEL ARCHITECTURE

Layer No.	Operation Name	Name	Setting
1	Convolutional	conv2d	Filter 32, kernel size (3x3), activation(ReLU)
1	Convolutional	conv2d	Filter 32, kernel size (3x3), activation(ReLU)
2	Batch Normalization	batch_normalization	Maintains the mean output close to 0 and the output standard deviation close to 1.
3	Convolutional	conv2d_1	Filter 32, kernel size (3x3), activation(ReLU)
4	Batch Normalization	batch_normalization_1	Maintains the mean output close to 0 and the output standard deviation close to 1.
5	MaxPooling2D	max_pooling2d	pool_size=(2, 2) to reduce the spatial dimensions of the feature maps.
6	Dropout	dropout	Rate=0.25
7	Convolutional	conv2d_2	Filter 64, kernel size (3x3), activation(ReLU)
8	Batch Normalization	batch_normalization_2	Maintains the mean output close to 0 and the output standard deviation close to 1.
9	Convolutional	conv2d_3	Filter 64, kernel size (3x3), activation(ReLU)
10	Batch Normalization	batch_normalization_3	Maintains the mean output close to 0 and the output standard deviation close to 1.
11	MaxPooling2D	max_pooling2d_1	pool_size=(2, 2)
12	Dropout	Dropout_1	Rate=0.25
13	Convolutional	conv2d_4	Filter 128, kernel size (3x3), activation(ReLU)
14	Batch Normalization	batch_normalization_4	Maintains the mean output close to 0 and the output standard deviation close to 1.
15	Convolutional	conv2d_5	Filter 128, kernel size (3x3), activation(ReLU)
16	Batch Normalization	batch_normalization_5	Maintains the mean output close to 0 and the output standard deviation close to 1.
17	MaxPooling2D	max_pooling2d_2	pool_size=(2, 2)
18	Dropout	Dropout_2	Rate=0.25
19	Flatten	flatten	adds an extra channel dimension and output shape is (batch, 1).
20	Dense	dense	Units=256, activation(ReLU)
21	Batch Normalization	batch_normalization_6	Maintains the mean output close to 0 and the output standard deviation close to 1.
22	Dropout	dropout_3	Rate=0.5
23	Dense	dense_1	Units=5, activation(Softmax)

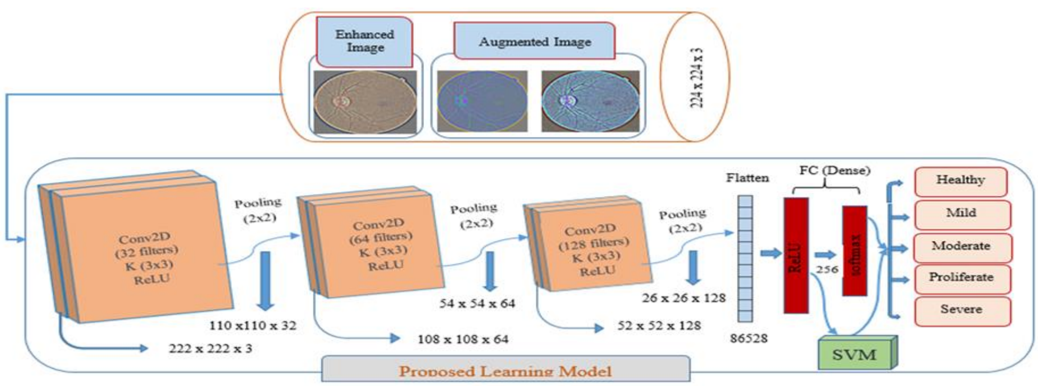


Fig. 2. Architecture of proposed learning model.

IV. EXPERIMENTAL RESULTS

The experimental setup utilized an Intel(R) Core i7 processor running at 2 GHz, with 8GB of RAM. The system operated on a 64-bit architecture. The dataset is split into training and testing sets, with a test size of 20% and the validation set was assigned 20% of the training set. This ensures a separate and unbiased dataset for evaluating the model's performance.

A. Deep Learning Model for Classifying Severity of DR Dataset

In this section, we present the evaluation results of the proposed model for classifying the severity of DR using Softmax and SVM classifiers. The original DR dataset as shown in Table I, comprising a collection of retinal images, is utilized for this evaluation. The objective is to assess the performance of the proposed model when employing these two commonly used classifiers in the field of deep learning. Table IV presents the distribution of samples used for training, validation, and testing in the experimental setup. Additionally, we provide insights into the performance of the CNN model by analyzing the classification accuracy and loss for the training and validation images across different numbers of epochs as shows in Fig. 3 and 4.

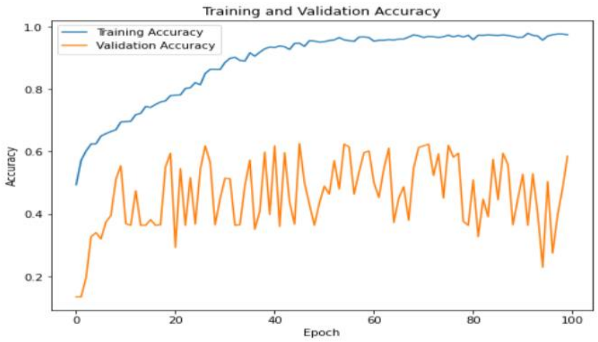


Fig. 3. Classification accuracy for CNN model on an orginal DR dataset with different no. of epochs.

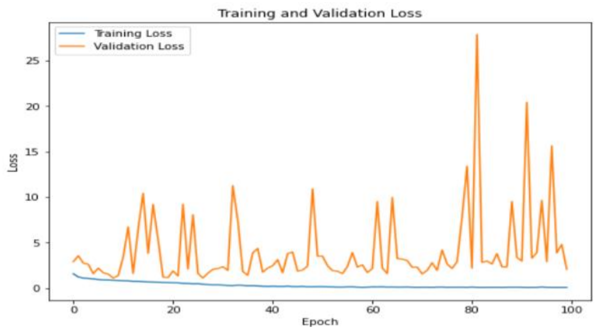


Fig. 4. Loss for CNN model on an orginal DR dataset with different no. of epochs.

TABLE IV. THE DISTRIBUTION OF SAMPLES

Class Name	Training	Validation	Testing
Healthy	640	160	200
Mild DR	237	59	74
Moderate DR	576	144	180
Proliferative DR	186	46	58
Severe DR	121	31	38

Table V and VI presents the performance measures obtained by applying the Softmax and SVM classification methods on the extracted features from the original DR test images using a CNN model.

TABLE V. THE PERFORMANCE MEASURES OBTAINED BY APPLYING A CNN MODEL ON THE ORIGINAL DR DATASET

Class Name	Accuracy %	Precision%	Recall%	F1 Score%
Healthy	90.55	91	82	86
Mild DR	84	41	43	42
Moderate DR	70.73	55	59	57
Proliferative DR	80.91	16	19	17
Severe DR	90.91	27	18	38

TABLE VI. THE PERFORMANCE MEASURES OBTAINED BY APPLYING A CNN MODEL AND SVM CLASSIFIER ON THE ORIGINAL DR DATASET

Class Name	Accuracy %	Precision %	Recall %	F1 Score %
Healthy	94	90	94	92
Mild DR	85.27	44	34	38
Moderate DR	72.18	57	61	59
Proliferative DR	83.82	22	21	21
Severe DR	88.73	18	18	18

B. *Improving DL Model for Classifying Severity of DR based on Enhancement Technique*

In this section, we employed the DR dataset as the test bed after applying enhancement preprocessing operations. We applied a contrast enhancement technique by multiplying the pixel intensities by a factor of 1.5, thereby effectively increasing the image's contrast. The distribution of samples after applying the enactment technique used for training, validation, and testing in the experimental setup as in Table IV. Fig. 5 and 6 illustrate respectively the classification accuracy and loss of the CNN model for the training and validation images across different numbers of epochs. It provides insights into how the accuracy improves or stabilizes as the training progresses. Table VII and VIII present the performance measures obtained by applying the Softmax and SVM classification methods on the extracted features from the DR test images using a CNN model based on enhancement technique.

TABLE VII. THE PERFORMANCE MEASURES OBTAINED BY APPLYING A CNN MODEL ON THE DR DATASET BASED ON ENHANCEMENT TECHNIQUE

Class Name	Accuracy %	Precision %	Recall %	F1 Score %
Healthy	87.09	74	98	85
Mild DR	87.64	60	24	35
Moderate DR	74.91	63	57	60
Proliferative DR	84.55	27	28	27
Severe DR	90.19	26	24	25

TABLE VIII. THE PERFORMANCE MEASURES OBTAINED BY APPLYING A CNN MODEL AND SVM CLASSIFIER ON THE DR DATASET BASED ON ENHANCEMENT TECHNIQUE

Class Name	Accuracy %	Precision %	Recall %	F1 Score%
Healthy	93.82	87	98	92
Mild DR	87.64	56	38	45
Moderate DR	75.09	59	75	66
Proliferative DR	87.45	31	16	21
Severe DR	92	33	16	21

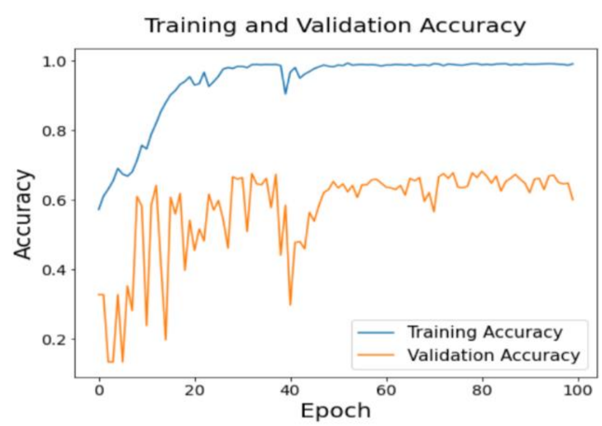


Fig. 5. Classification accuracy for CNN model on DR dataset with different no. of epochs.

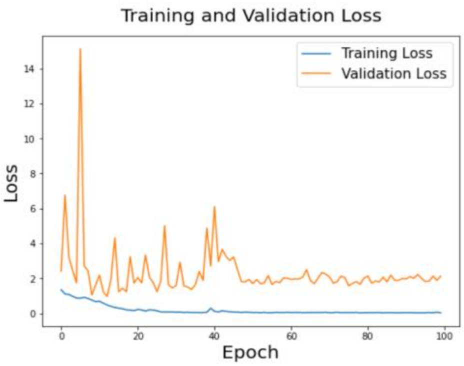


Fig. 6. Loss for CNN model on DR dataset with different no. of epochs.

C. Improving Feature Extraction using DL Model based on Augmented BGR2RGB

In this paper, we investigate the impact of using an augmented BGR2RGB color space on the feature extraction capabilities of deep learning models. BGR2RGB color space conversion refers to converting an image from the BGR (Blue, Green, Red) color space commonly used in computer vision applications to the RGB (Red, Green, Blue) color space, often used in other domains. Table IX presents the distribution of samples used for training, validation, and testing in the experimental setup after an augmented BGR2RGB. Fig. 7 is the plot visually demonstrates the performance of the model as the number of epochs increases. It shows how well the model learns from the training data and its ability to generalize to unseen validation data. Fig. 8 demonstrates the reduction in loss as the model optimizes its parameters during training. The validation loss, demonstrates how the loss changes on unseen validation data as the model undergoes training.

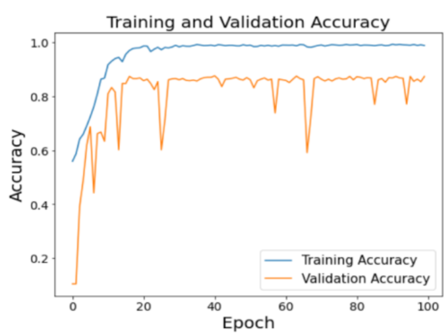


Fig. 7. Classification accuracy for CNN model based on augmented BGR2RGB with different no. of epochs.

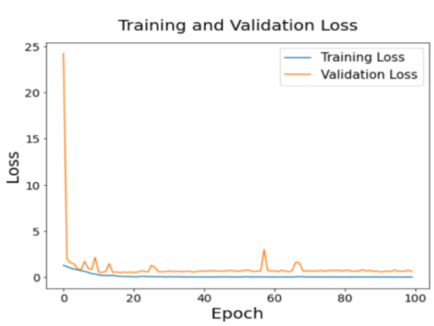


Fig. 8. Loss for CNN model based on augmented BGR2RGB with different no. of epochs.

TABLE IX. THE DISTRIBUTION OF SAMPLES USING AN AUGMENTED BGR2RGB

Class Name	Training	Validation	Testing
Healthy	1280	320	400
Mild DR	474	118	148
Moderate DR	1152	288	360
Proliferative DR	273	92	116
Severe DR	242	62	76

TABLE X. THE PERFORMANCE MEASURES OBTAINED BY APPLYING A CNN MODEL AND SVM CLASSIFIER ON THE DR DATASET AFTER UTILIZING AN AUGMENTED BGR2RGB

Class Name	Accuracy%	Precision %	Recall %	F1 Score%
Healthy	97.27	94	99	96
Mild DR	94.18	82	73	77
Moderate DR	89.09	81	87	84
Proliferative DR	94.36	76	67	72
Severe DR	96.55	84	62	71

D. Improving Feature Extraction using DL Models based on Augmented BGR2RGB and RGB2LAB Color Space Conversions

We investigate the efficacy of improving feature extraction using DL models based on augmented BGR2RGB and RGB2LAB color space conversions. RGB2LAB conversion converts images from the RGB color space to the LAB color space, which separates color information from brightness. We hypothesize that leveraging these augmented color space conversions can enhance the models' ability to capture meaningful patterns and improve generalization performance. Table XI. the distribution of samples used for training, validation, and testing in our experimental setup after applying both augmented BGR2RGB and RGB2LAB color space conversions. Fig. 9 and 10 would present the classification accuracy and loss for the CNN model based on augmented BGR2RGB and RGB2LAB color space conversions during the training and validation stages.

TABLE XI. THE DISTRIBUTION OF SAMPLES USING AN AUGMENTED BGR2RGB AND RGB2LAB

Class Name	Training	Validation	Testing
Healthy	1920	480	600
Mild DR	711	177	222
Moderate DR	1728	432	540
Proliferative DR	558	138	174
Severe DR	363	93	114

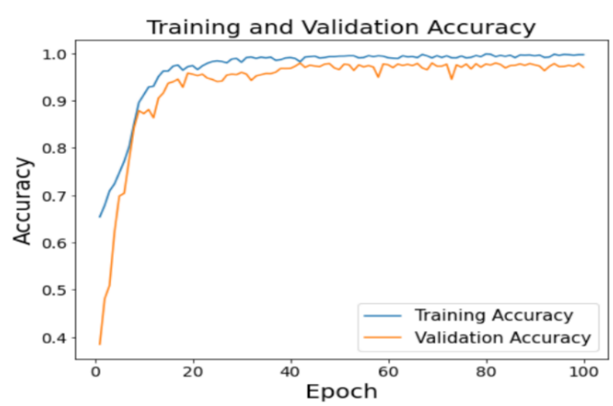


Fig. 9. Classification accuracy for CNN model based on augmented BGR2RGB and RGB2LAB with different no. of epochs.

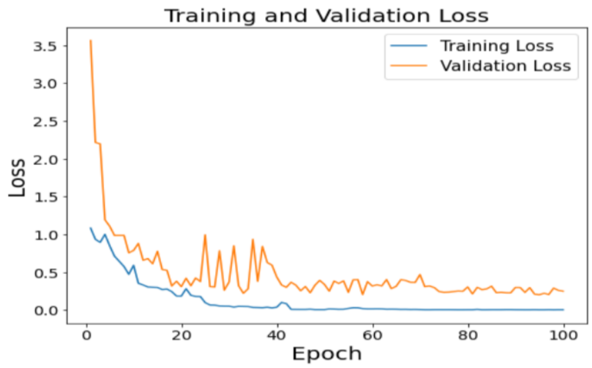


Fig. 10. Loss for CNN model based on augmented BGR2RGB and RGB2LAB with different no. of epochs.

Table XII and Table X display the performance measures obtained by applying the Softmax and SVM classification methods on the extracted features after utilizing an augmented BGR2RGB color space conversion on the DR test images using a CNN model. The performance measures include accuracy, precision, recall, and F1-score.

TABLE XII. THE PERFORMANCE MEASURES OBTAINED BY APPLYING A CNN MODEL ON THE DR DATASET AFTER UTILIZING AN AUGMENTED BGR2RGB

Class Name	Accuracy %	Precision%	Recall %	F1 Score %
Healthy	96.73	93	99	96
Mild DR	94.36	86	69	77
Moderate DR	89.09	80	89	84
Proliferative DR	94.55	79	66	72
Severe DR	96.36	81	62	70

In Tables XIII and XIV, we present the performance measures obtained by applying the Softmax and SVM classification methods on the extracted features, following the utilization of an augmented BGR2RGB and RGB2LAB color space conversion on the DR test images using a CNN model.

TABLE XIII. THE PERFORMANCE MEASURES OBTAINED BY APPLYING A CNN MODEL ON THE DR DATASET AFTER UTILIZING AN AUGMENTED BGR2RGB AND RGB2LAB

Class Name	Accuracy (%)	Precision (%)	Recall (%)	F1 Score %
Healthy	98.79	97	97	98
Mild DR	97.94	92	92	92
Moderate DR	95.33	91	95	93
Proliferative DR	96.73	89	78	83
Severe DR	98.12	94	78	85

TABLE XIV. THE PERFORMANCE MEASURES OBTAINED BY APPLYING A CNN MODEL AND SVM CLASSIFIER ON THE DR DATASET AFTER UTILIZING AN AUGMENTED BGR2RGB AND RGB2LAB

Class Name	Accuracy (%)	Precision (%)	Recall (%)	F1 Score %
Healthy	99.45	99	99	99
Mild DR	98.12	93	93	93
Moderate DR	96.42	94	95	95
Proliferative DR	97.33	88	87	87
Severe DR	98.12	90	82	86

V. COMPARATIVE STUDY AND DISCUSSION OF RESULTS

To gain deeper insights into the effectiveness of the proposed model, a comparative analysis is conducted by evaluating different architectures commonly adopted for DR detection and classification. Each architecture is trained, validation and tested using the same dataset and evaluation metrics as the proposed model. Table XV and XVI the training and testing overall accuracy of the CNN and the proposed model using original, enhanced, an augmented BGR2RGB and an augmented BGR2RGB +RGB2LAB datasets. These tables allow for a comparative analysis of the models' performance, providing insights into the effectiveness of the proposed model and the impact of preprocessing stage on the overall accuracy for DR detection and classification. The proposed model using SoftMax and SVM classifiers achieved an overall accuracy of approximately 93.45% and 94.72% respectively for testing and 96.6% and 99.36% for training DR classification. The confusion matrices obtained from different techniques on the DR Dataset are analyzed and compared in Table XIX. These findings contribute to the understanding of the proposed model's effectiveness and can guide future improvements in the classification of DR severity.

TABLE XV. THE OVERALL ACCURACY FOR TRAINING OF THE PROPOSED MODEL AND COMPARATIVE RESULTS ON THE DR

Techniques	Overall Accuracy for Training			
	CNN based on an original dataset	CNN based on an enhancement technique	CNN based on an augmented BGR2RGB	CNN based on an augmented BGR2RGB and RGB2LAB
CNN Model	88.7%	93.9%	95.6%	96.6%
CNN+SVM (Proposed)	99%	68%	95.3%	99.36%

TABLE XVI. THE OVERALL ACCURACY FOR TESTING OF THE PROPOSED MODEL AND COMPARATIVE RESULTS ON THE DR

Techniques	Overall Accuracy for Testing			
	CNN based on an original dataset	CNN based on an enhancement technique	CNN based on an augmented BGR2RGB	CNN based on an augmented BGR2RGB and RGB2LAB
CNN Model	58.5%	62%	85.55%	93.45%
CNN+SVM (Proposed)	62%	68%	85.73%	94.72%

Table XVII presents the loss values obtained during the testing process of the CNN model and the SVM classifier on the DR dataset. These loss values serve as crucial indicators of convergence and performance for each classifier.

TABLE XVII. THE LOSS VALUES OF THE PROPOSED MODEL AND COMPARATIVE RESULTS ON THE DR

Techniques	Loss Values for Testing			
	CNN based on an original dataset	CNN based on an enhancement technique	CNN based on an augmented BGR2RGB	CNN based on an augmented BGR2RGB and RGB2LAB
CNN Model	2.1	1.8	0.7104	0.2131
CNN+SVM (Proposed)	0.9	0.32	0.1427	0.1199

Table XVIII illustrates the overall accuracy values of the proposed model, considering the enhancement technique, in comparison with a related approach. In study [2], the authors employed a CNN with DenseNet 2.1 to extract eye features for effective classification. When applied to the DR Dataset, as shown in Fig. 11(a), they reported an overall accuracy of 66.9%. However, when utilizing the dataset depicted in Fig.

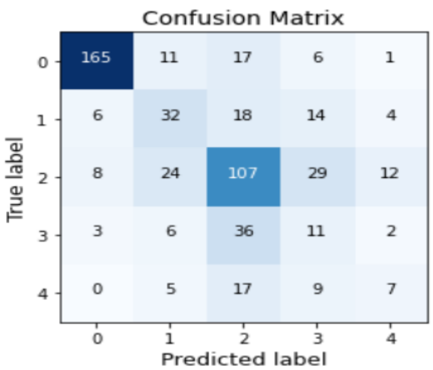
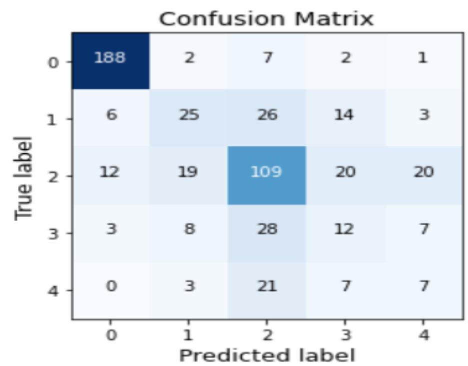
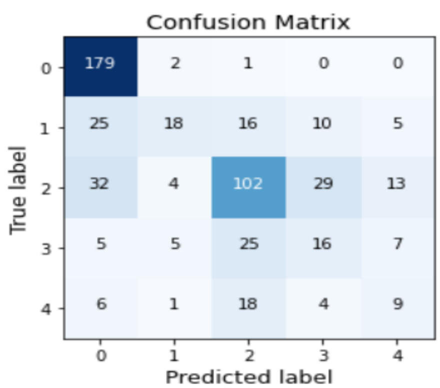
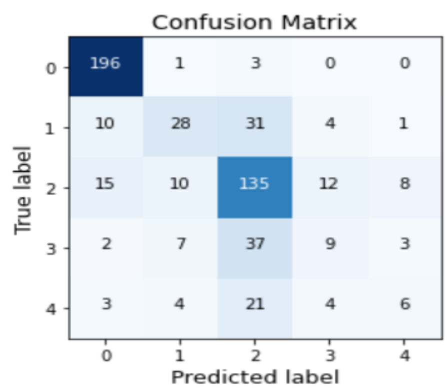
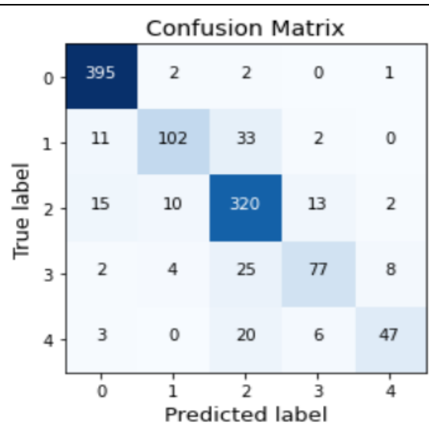
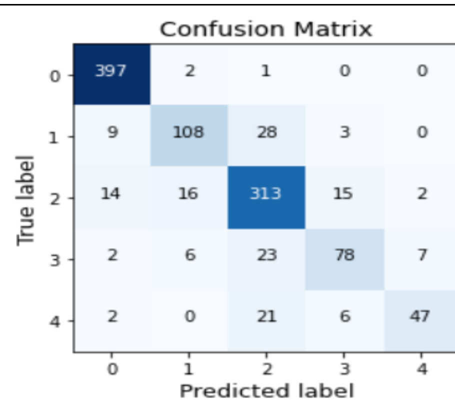
11(b) as per study [2], they achieved an overall accuracy of 93.18%. This difference in accuracy can be attributed to variations in image resolution between the two datasets.

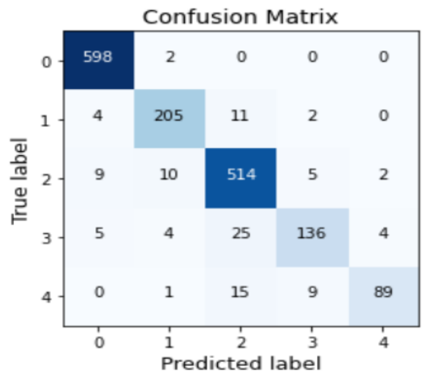
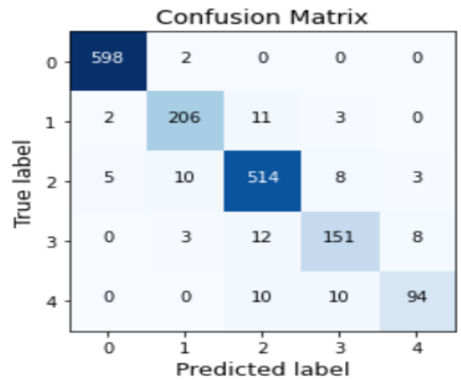
The overall accuracy attained by the proposed model serves as a crucial indicator of its effectiveness in classifying the severity of DR. A higher overall accuracy value of 94.72% demonstrates the model's ability to make accurate predictions, thereby providing valuable assistance to healthcare professionals in diagnosing and managing this condition as show in Table XVI.

TABLE XVIII. OVERALL ACCURACIES FOR THE MODEL BASED ON ENHANCEMENT AND SOME RELATED ONES BASED ON DR DATASET (A)

Techniques	Classifier	Overall Accuracy
CNN + DenseNet [2]	SoftMax	66.9%
CNN based on an enhancement technique	SoftMax	62%
	SVM	68%

TABLE XIX. COMPARATIVE ANALYSIS OF CONFUSION MATRICES ON THE DR DATASET USING DIFFERENT TECHNIQUES

<table>
<tr><th>Techniques</th><th>SoftMax</th><th>SVM</th></tr>
<tr><td>CNN based on an original dataset</td><td>
</td><td>
</td></tr>
<tr><td>Overall Accuracy</td><td>58.5%</td><td>62%</td></tr>
<tr><td>CNN based on an enhancement technique</td><td>
</td><td>
</td></tr>
<tr><td>Overall Accuracy</td><td>62%</td><td>68%</td></tr>
<tr><td>CNN based on an augmented BGR2RGB</td><td>
</td><td>
</td></tr>
<tr><td>Overall Accuracy</td><td>85.55%</td><td>85.73%</td></tr>
</table>

CNN based on an augmented BGR2RGB and RGB2LAB		
Overall Accuracy	93.45%	94.72%

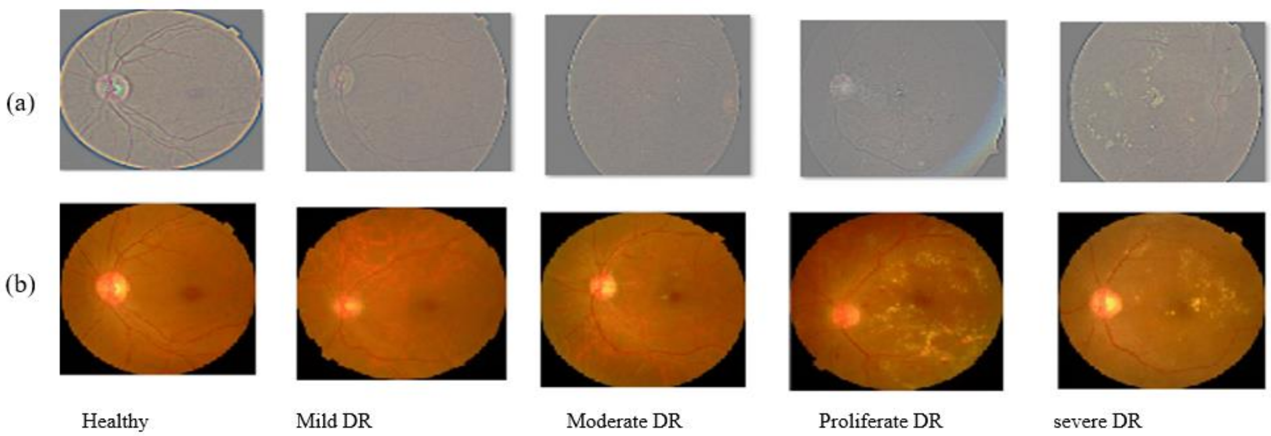


Fig. 11. Samples from two datasets: (a) the dataset specifically used in this paper, and (b) the dataset applied in the study [2].

VI. Recommended Prototype

Fig. 12 illustrates the recommended prototype for effectively classifying new DR images using a proposed learning model. The process begins by enhancing the contrast of the input image, as depicted in figure. This enhancement step aims to improve the visual quality and highlight important features in the image. Then, additional transformation is performed including applying BGR2RGB and RGB2LAB conversions, which further augment the image and help extract relevant information for classification purposes. Finally, the enhanced and the augmented images are passed to the proposed learning model for classification.

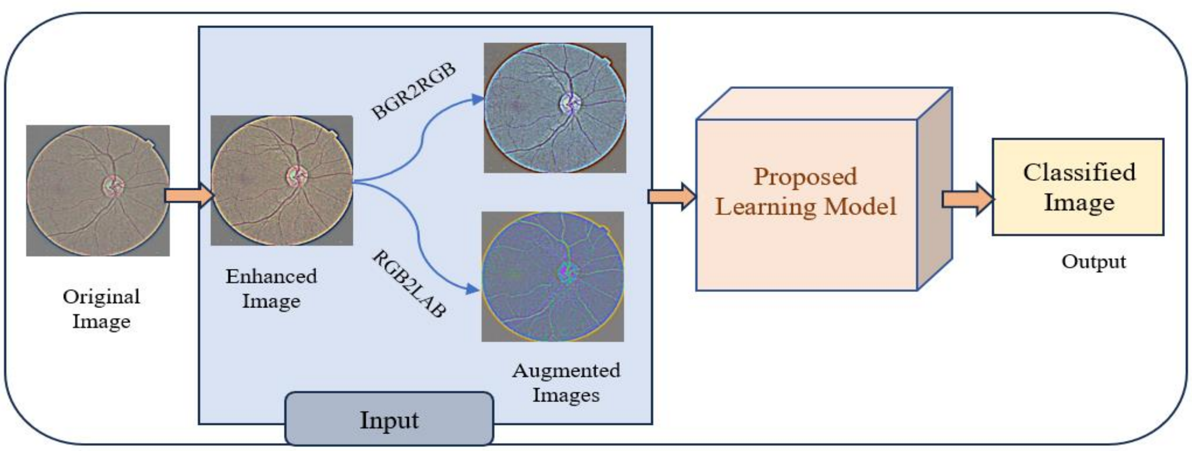


Fig. 12. Recommended prototype.

VII. Conclusion

In conclusion, DR has a significant global burden that requires immediate attention, as a primary cause of blindness among working-age populations globally. The main objective of this study was to develop a robust CDSS that combines automatic DR diagnosis and multistage classification module to make CDSS a comprehensive tool for ophthalmologists and help them make an accurate diagnosis. The proposed three-stage deep learning model for DR analysis encompasses several key steps. Firstly, preprocessing techniques, including image enhancement and augmentation, were implemented. In particular, the Gaussian Blur Filter was applied to augment the DR images, alongside the conversion from BGR to RGB and from RGB to LAB color spaces. Secondly, feature extraction and representation learning were performed using a CNN with various layers. This step allowed the model to learn discriminative features from the enhanced images dataset, including the augmented images from BGR to RGB and further augmented images from RGB to LAB. Lastly, by testing the SVM and deep learning models on different versions dataset iterations, the classification outcomes were determined. These versions included the enhanced images dataset, the enhanced images dataset combined with augmentation from BGR to RGB, and the enhanced images dataset augmented from BGR to RGB and further augmented from RGB to LAB. The evaluation metrics were employed to compare the performance of the models. Notably, the enhanced images dataset combined with augmentation from BGR to RGB and augmentation from RGB to LAB demonstrated superior results, achieving an overall accuracy about 95% by SVM classifier. This finding highlights the effectiveness of the proposed approach in accurately classifying and staging DR. While the proposed three-stage deep learning framework has demonstrated promising results in automated diabetic retinopathy grading, future research directions may include the exploration of more advanced neural network architectures to further enhance the feature extraction and classification capabilities.

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