RESEARCH PAPER

An Integrated Deep Learning Framework for Diabetic Retinopathy: Channel and Spatial Attention U-Net for Lesion Segmentation and CNN-Based Fundus Image Denoising with Ensemble Feature Classification

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ABSTRACT

Diabetic retinopathy is thought to be the primary cause of visual loss. It is a microvascular illness that specifically affects the retina, causing vessel obstruction that deprives the retinal tissues of nourishment. Early detection is key to effective treatment, since advanced stages might result in irreversible blindness or loss of vision. Therefore, efforts are made to build automatic detection systems that would both speed up and lower the cost of the identification process. Our study presents a deep learning architecture based on UNet for the segmentation of blood vessels, exudates, and microaneurysms in diabetic retinopathy. However, because to the small number of credible datasets, the accuracy of the current prediction algorithms is not yet good enough for eye specialists to rely on them as trustworthy diagnosis tools. In addition, a variety of noise kinds are included in the recorded data. Eliminating the noise thus becomes a crucial undertaking for this study. For filtering and classification, we thus looked into an approach that coupled denoising with ensemble-based learning. Noise is identified by residual noise mapping, a feature of CNN-based architecture used for filtering. Using an ensemble classifier, we categorize the features acquired in the following stage, which presents a CNN-based feature extraction model.

Keywords – Diabetic retinopathy, Segmentation, Denoising, Filtering, Classification.

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1. INTRODUCTION:

This article offers a thorough analysis of diabetic retinal disease (DR), a serious, progressive vascular and neurodegenerative disorder that kills retinal cells without causing noticeable vision loss and is initially challenging to identify. Diabetic retinopathy (DR), a condition that gradually deteriorates eyesight, can be brought on by uncontrolled blood sugar levels. Thus, early detection of DR is crucial to prevent retinal damage that might ultimately lead to blindness. In line with a study that Saeedi et al. [1] reported. Approximately 463 million individuals worldwide have DR as of 2019, 31 million of them live in the United States. Researchers estimate that by 2030, this number will increase to 578 million (34.4 million in the US), and by 2045, it will reach 700 million (367 million in the US). Furthermore, the occurrence of DR has been estimated at 4.1 million in the United States, according to the Centers for Disease Control and Prevention (CDC) [2]. Additionally, the U.S. spends around $500 million annually owing to diabetes-related blindness [2]. There are 899,000 blind people in the United States. Therefore, it is essential to identify DR as soon as possible.

The eye is one of the body's essential organs, and the human body has many other sense organs as well. In the medical field, ocular pathology is becoming a major concern. One of the primary problems with eye pathology is blindness. Numerous eye conditions, including glaucoma, macular degeneration, and diabetic retinopathy, can cause it. But in order to diagnose these silent conditions, regular ocular examinations are necessary. Diabetes is widely prevalent worldwide and is regarded as one of the most chronic diseases. An estimated 463 million adults worldwide, aged 20 to 79, suffer from diabetes, according to a recent study presented in [1]. Similarly, authors in [2,3] reported that by 2040 diabetic patients are expected to increase by 600 million. Figure 1 depict the current statues of diabetes in worldwide scenario.

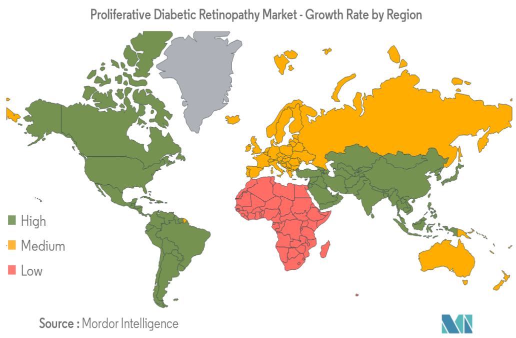


Fig.1.worldwide prevalence of diabetes

According to Tripathy et al. [4], China leads the world in the quantity of diabetic cases, with India coming in second. According to a survey conducted by the International Diabetes Federation [5], India is expected to have 77,005,600 diabetics in 2019. Diabetes mellitus, also referred to as diabetes, is a metabolic disease that is associated with hyperglycemia, or elevated blood sugar. The insulin hormone in the human body is in charge of transferring sugar from the blood to the cells where it can be stored and utilized as fuel. However, diabetes abnormalities interfere with this process, causing the body to either not produce enough insulin or not use it to its full potential. The inability to produce enough insulin and the difficulty in using it for peripheral purposes. Below given figure 2 depicts the classification of different types of diabetes which includes type -1, type-2 and gestational diabetes.

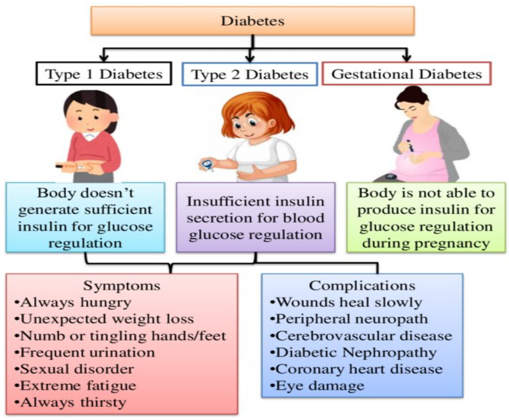


Fig.2. Diabetes categories

Due to metabolic abnormalities, diabetic patients are extremely susceptible to a wide range of short- and long-term complications.These complications can harm the organ system and exacerbate potentially fatal conditions like retinopathy, neuropathy, nephropathy, and macrovascular complications. Within this framework, diabetic retinopathy is regarded as one of the most frequently occurring microvascular complications, resulting from elevated blood sugar levels that impact the blood vessels within the retina [6]. Blindness could result from the worsening diabetic retinopathy conditions. Recent studies estimate that the population of the DR was 126.6 million in 2010 and is projected to increase to 191 million by 2030. It has a major negative influence on a person's life and is one of the main causes of adult vision loss worldwide. Generally speaking, DR is categorized as non-proliferative DR (NPDR), which is an early stage and mild phase. Microaneurysms are a hallmark of the early stages of DR. Proliferative DR (PDR), on the other hand, is a different kind that is in a moderate stage and can cause a significant loss of vision. However, Type-1 and Type-2 diabetes are the primary causes of these DRs, so it's critical to recognize and treat diabetes early on. Preventing vision loss can be achieved through routine DR screening.

2. Proposed Model

The deep learning-based approach for diabetic retinopathy segmentation is presented in this section. As was previously mentioned, UNet is thought to be among the most promising methods for obtaining dependable segmentation results.

2.1 Basics of UNet

Designed in 2015, Unet is a deep learning network for biomedical image segmentation. The conventional Unet model processes the input image through two paths—a downsampling path and an upsampling path—to perform segmentation. The four main blocks that make up the downsampling path are shown in figure3 below. Leaky ReLu is used in each of these blocks to perform 3x3 unpadded convolutions. The value of α is regarded as 0.3. Moreover, it employs a 2x2 max pooling operation with a stride of 2. Once the first block is processed, there are twice as many feature channels.

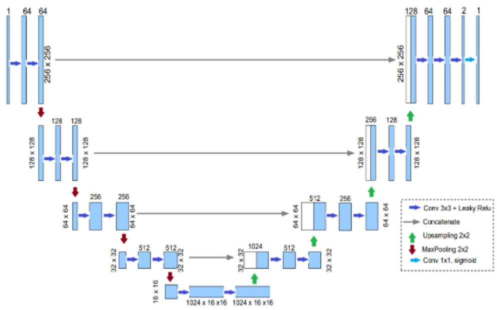


Fig.3. UNet architecture

In a similar manner, the upsampling path uses four blocks, as shown in figure 4. These blocks' primary functions include upsampling feature maps and applying 2x2 convolution to feature channels. Leaky ReLu and the feature maps from the downsampling path are concatenated with these feature maps to perform a 3x3 convolution operation. The feature vector is mapped into two classes with the aid of the final layer's 1x1 convolution using the softmax function. Additionally, to produce the final output, it optimizes Adam using a loss function during the training phase.

2.2 Proposed architecture for segmentation

In this area of segmenting biomedical images, UNet offers a number of benefits. Nevertheless, it has a number of drawbacks, including the inability to handle organ segmentation heterogeneity when the ROI is inconsistent. As the source of the ROI irregularity in our instance, we concentrate on blood vessel segmentation, hard exudates, soft exudates, and microaneurysms. The original image and matching ground truth for vessel segmentation are shown in the given figure below. This demonstrates how these inconsistencies must be handled by the segmented architecture.

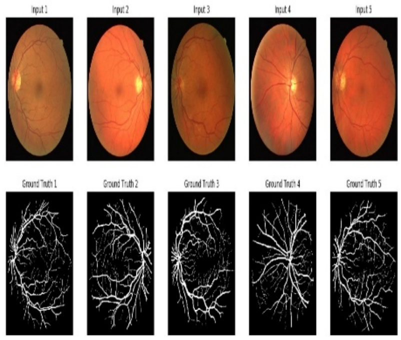


Fig.4. Blood vessel segmentation (original and groundtruth sample images)

Moreover, a large number of parameters are needed for training in traditional UNet architectures. These architectures make use of residual blocks, where redundant features are stored by the convolution layer, leading to inaccurate feature map generation. Low-quality feature maps are produced as a result of these layers discarding the low-layer features of earlier layers. Conventional UNet models are unable to effectively retrieve data from several receptive scales. Several studies have been conducted to address these problems, but they are unable to manage the various modalities and variations

[18]. We present a new deep learning based architecture for diabetic retinopathy images to address these issues. Although the suggested method is based on the UNet architecture, we have made a number of changes to enhance the segmentation performance, including changing the UNet encoder model, taking

into account the convolution's output features, using dilated convolution, and adding a skip connection model. To further enhance system performance, we have added spatial and channel attention models. The general architecture of the suggested model is shown in figure 5, which is provided below. This model has four encoder and decoder units, just like the conventional UNet.

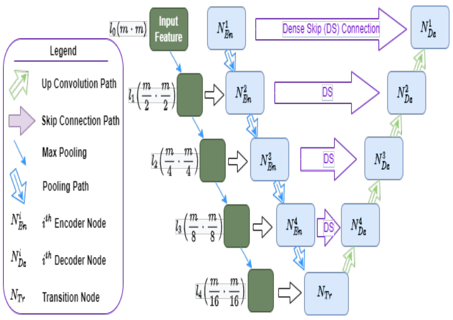


Fig.5. Proposed UNet Architecture

2.3.1 CNN based feature extraction for classification :

The different attributes are obtained by the proposed AEM taking into account the sparse mechanism. It also aids in lessening the network's depth. Additionally, the acquired features are processed via the enhancement block, which fuses the attributes to improve the quality of the features. This combination aids in handling both the noise present in the real world and other unidentified noise kinds. The suppression block reduces the computational cost by distilling the features from the obtained attributes. Afterwards, the low resolution image is cleaned using the reconstruction block, and the final clean image is produced by processing it further using the post processing block.

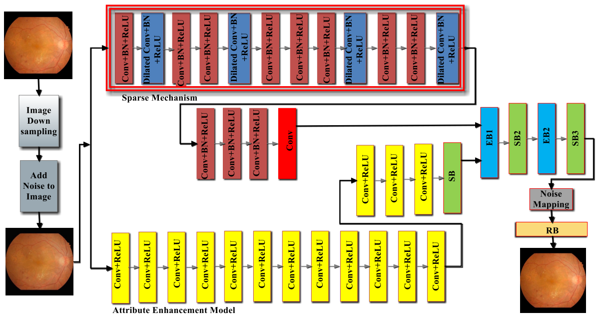


Fig6. Overall architecture flow

The suggested method for fundus image denoising using deep learning-based schemes was covered in the previous section. Our goal at this point is to apply a deep learning scheme for reliable feature extraction that can be applied to other processes. The suggested method makes use of max pooling, batch normalization, and convolution layers in that order. Batch normalization works by rescaling and recentering the layers, which increases system speed.

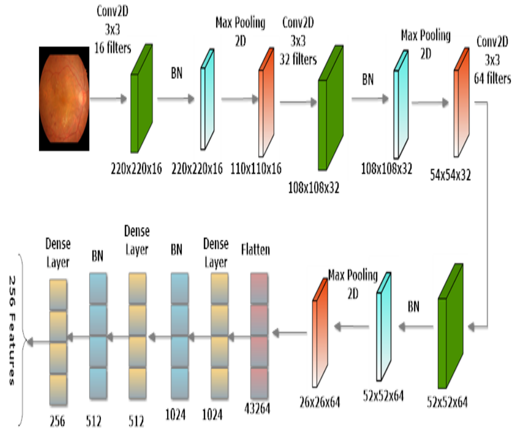


Fig. 7 CNN based feature extraction

According to this figure the data is processed through a 2D convolution layer of size 3x3 with filter size of 16, later BN, Max Pooling and 2D convolution operations are performed. However, the size of input filters is varied at each stage as 16, 32 and 64 filters. The max pooling operation helps to capture the largest value from the considered patch, dropout helps to reduce the overfitting and improves the training speed. Further, this model uses Adam optimizer. Finally, the dense layer generates the list of all features.Below given table shows the layer configuration used in this network. This figure shows that the data is first processed through a 3x3 2D convolution layer with a 16-filter size. Afterwards, BN, Max Pooling, and 2D convolution operations are carried out. Nonetheless, there are variations in the input filter sizes of 16, 32, and 64 at each step. While dropout helps to lessen overfitting and increase training speed, max pooling helps to extract the maximum value from the patch under consideration. This model also makes use of the Adam optimizer. Ultimately, the list of all features is generated by the dense layer. The layer configuration used in this network is displayed in the table below.

Table 1. Layer configuration

Layer	Shape	Parameters
Input Layer (Conv2D)	[(None, 224, 224,3)]	0
Conv2D	[(None, 220, 220,16)]	1216
Batch Normalization	[(None, 220, 220,16)]	64
Activation	[(None, 220, 220,16)]	0
Max Pooling	[(None, 110, 110,16)]	0
Conv2D_1	(None,108,108,32)	4640
Batch Normalization 2	[(None, 108, 108,32)]	128
Activation	[(None, 108, 108,32)]	0
Max pooling2d	[(None, 54, 54,32)]	0
Conv2D_2	(None,52,52,64)	18496
Batch Normalization 3	(None,52,52,64)	256
Activation_2	(None,52,52,64)	0
Max pooling 2d 2	(None,26,26,64)	0
Flatten	(None, 43264)	0
Dense	(None, 1024)	44303360
Batch normalization 4	(None, 1024)	4096
Activation 3	(None, 1024)	0
Dropout	(None, 1024)	0
Dense 1	(None, 512)	524800
Batch normalization 5	(None, 512)	2048
Activation 4	(None, 512)	0
Dropout	(None, 512)	0
Feature extractor	(None, 256)	131328

2 Results and discussion

This section presents the complete experimental analysis of proposed approach where we evaluate the performance of proposed approach and compare its performance with the existing schemes.

Table 2. Comparative performance for DRIVE dataset

Method	Se	Sp	Acc	AUC
Khan[32]	0.7381	0.967	0.95	0.853
Khan [33]	0.7821	0.972	0.953	0.877
Soomro [28]	0.7455	0.91	0.94	0.831
Ngo[34]	0.746	0.984	0.954	0.865
Biswal. [35]	0.7	0.978	0.96	0.8
Yan [36]	0.765	0.9852	0.954	0.874
Oliveria [37]	0.803	0.980	0.957	0.892
Wan [38]	0.764	0.981	0.954	0.873
Feng . [29]	0.762	0.980	0.952	0.871
Ribeiro [39]	0.788	0.981	0.956	0.885
Dharmawan[40]	0.831	0.972	-	0.90
Saroj . [27]	0.730	0.976	0.954	0.853
Dash and Senapati[41]	0.740	0.990	0.966	0.865
Biswas[42]	0.782	0.981	0.956	0.881
Budak[43]	0.743	0.990	0.968	0.867
Ma [26]	0.874	0.962	0.954	0.918
AbdelMaksoud[45]	62.4	98.7	95.6	-
B-COSFIRE filter [46]	76	97.0	94.	96
Gao [47]	70	98.	96.	97
Adapa[48]	69	98.	94	93
AbdelMaksoud [44]	72.5	98.	96.5	97.8
Proposed approach	89.9	98.9	98.1	98

This comparison analysis demonstrates that, in terms of Sensitivity, Specificity, Accuracy, and AUC, respectively, the suggested approach achieves an overall performance of 89.96%, 98.96%, 98.15%, and 98.50%. In a similar manner, we assess the performance for the STARE dataset and contrast the results with those of other systems. Table 3 below displays the STARE dataset performance.

Table 3. Comparative analysis for STARE dataset

Method	Se	Sp	Acc	AUC
Khan [32]	0.735	0.97	0.950	0.853
Khan [33]	0.772	0.964	0.951	0.868
Soomro[28]	0.74	0.92	0.94	0.83
Yan [36]	0.758	0.984	0.961	0.871
Oliveria. [37]	0.831	0.985	0.969	0.908
Wang [38]	0.752	0.9	0.966	0.870
Feng [29]	0.770	0.984	0.963	0.877
Dharmawan [40]	0.792	0.982	-	0.887
Saroj[27]	0.727	0.972	0.950	0.850
AbdelMaksoud [44]	0.890	0.974	0.969	0.932
Proposed model	0.925	0.984	0.985	0.964

This experiment shows that the suggested method performs as follows: Sensitivity, Specificity, accuracy, and AUC are all achieved at 0.9256, 0.9840, 0.9854, and 0.9640, respectively. Additionally, we provide the CHASE_DB1 dataset experimental analysis and contrast the results with current systems. Table 4 below displays the comparative performance.

Table 4. Comparative analysis for CHASE_DB1 dataset

Method	Se	Sp	ACC	AUC
Biswal [35]	0.77	0.98	-	0.86
Yan [36]	0.763	0.980	0.961	0.872
Oliveria [37]	0.777	0.986	0.965	0.882
Wang [38]	0.773	0.979	0.96	0.876
Soomro [28]	0.802	0.96	0.89	0.88
AbdelMaksoud [44]	0.891	0.959	0.956	0.92
Proposed approach	0.956	0.968	0.90	0.971

The average performance for blood vessel segmentation is presented in below given table where we compare the performance of proposed approach with state-of-art segmentation techniques.

Table 5. Average performance for blood vessel segmentation for different dataset

Method	DB	Acc	AUC	Sn	Sp	PPV	DSC
AbdelMaksoud . [45]	DRIVE	95.61	-	62.45	98.79	-	71
Soares		94.6	95.9	-	-	-	-
BCOSFIRE filter		94.4	96.1	76.5	97.04	-	-
Gao		96.3	97.7	78	98.7	89	-
Adapa		94.5	93.9	69.9	98.1	-	-
AbdelMaksoud [44]		96.58	97.84	72.58	98.89	86.29	78.84
B-COSFIRE filter	CHASEDB1	93.8	94.8	75.8	95.8	-	-
AbdelMaksoud [44]		96.17	95.08	56.75	98.94	79.05	69.04
Proposed approach		98.20	96.30	85.30	99.10	89.80	85.21
B-COSFIRE filter	HRF	96.4	95	75	97.40	-	-
AbdelMaksoud. [44]		95.6	95.30	70.14	98.25	85.1	76.2
Proposed approach		98.50	96.30	84.20	99.50	91.20	82.50

Table 6. Comparative analysis for Ex and MA segmentation for different dataset

Technique	Dataset Used	Lesion type	Accuracy	AUC	Sn	Sp	PPV	DSC
Kou et al	IDRiD	Ex	99	98.6	95	93.9	-	-
		MA	99	98.01	92.9	93.5	-	-
Abdelmaksoud	IDRiD	Ex	99	-	100	100	-	100
		MA	97.8	-	100	80	-	98.7
Khojasteh	DIARETDB1	Ex	99	-	95	98.2	95	-
		MA	95	-	85	96.45	86	-
Yan	DIARETDB1	Ex	-	96.3	89	98.6	-	-
		MA	-	96.3	97	95.6	-	-
Abdelmaksoud [44]	IDRiD	Ex	99					
		MA	99					
	DIARETDB1	Ex	98					
		MA	98					
Proposed Approach	IDRiD	Ex	99.8					
		MA	99					
	DIARETDB1	Ex	99.8					
		MA	98.					

This experiment demonstrates that the suggested method achieves 99.86 accuracy for exudate detection on the IDRiD dataset and 99.9% accuracy for MA identification; for the DIARETDB1 dataset, the corresponding results are 99.80 and 98.56 for EX and MA detection, respectively.

Classification performance for binary classifier and multiclass scenario

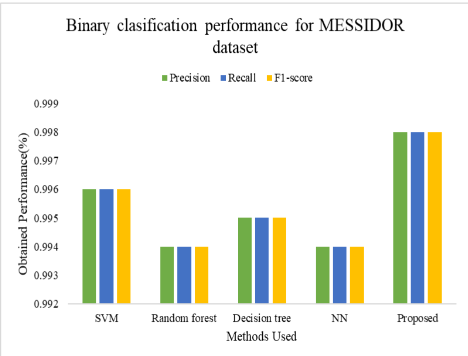
As was previously indicated, the aforementioned dataset also includes pictures for binary categorization. Consequently, we compare the acquired performance with several classifiers and quantify the performance for binary classification. The comparative performance for the MESSIDOR Database is displayed in table 7 below.

Table 7. Binary classification performance measurement for MESSIDOR database

Classifier	Specificity	Precision	Recall	F1-score
SVM	0.004	0.996	0.996	0.996
Random forest	0.006	0.994	0.994	0.994
Decision tree	0.005	0.995	0.995	0.995
NN	0.006	0.994	0.994	0.994
Inception-V3	0.9435	0.9512	NA	0.9299
GoogLeNet	0.9375	0.923	NA	0.903

AlexNet	0.9234	0.92	NA	0.9181
ResNet	0.937	0.9415	NA	0.9365
5-Layered CNN	0.9787	0.9815	NA	0.9894
Modified Alexnet	0.9745	92.35	NA	NA
CLAHE+ResNet-101-DELM	0.9819	0.9820	98.20	NA
Proposed	0.989	0.998	0.998	0.998

The traditional InceptionV3 scheme suffer from overfitting and computational complexity leads to increase the training time. Similarly, GoogLeNet also uses Inception modules and it also suffers from vanishing gradient problem which affects the convergence and training stability of the network. The AlexNet is shallower and narrower, which might have limited its ability to capture hierarchical features at various scales.

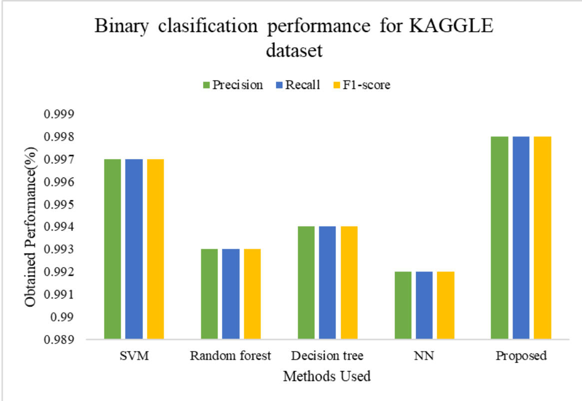


Similarly, we measure the performance of binary classifier for Kaggle dataset and the obtained performance is presented in given table 8.

Table 8. Binary classification performance measurement for KAGGLE database

Classifier	Specificity	Precision	Recall	F1-score
SVM	0.003	0.997	0.997	0.997
Random forest	0.007	0.993	0.993	0.993
Decision tree	0.006	0.994	0.994	0.994
NN	0.008	0.992	0.992	0.992
Proposed	0.002	0.998	0.998	0.998

The comparative study presented for MESSIDOR and KAGGLE shows that the proposed approach achieves better classification performance in terms of Specificity, Precision, Recall, and F1-score.

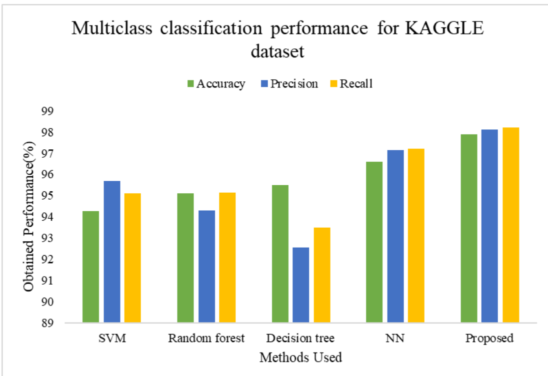


Further, we present the comparative study for multiclass scenario and compared the obtained performance with other methods. Below given table 9 shows the comparative performance in terms of classification accuracy.

Table 9. Multiclass classification performance measurement for KAGGLE database

Classifier	Accuracy	Precision	Recall
SVM	94.25	95.7	95.10
Random forest	95.10	94.30	95.15
Decision tree	95.50	92.55	93.50
NN	96.58	97.15	97.20
Proposed	97.89	98.1	98.20

The complete experimental analysis shows that the proposed approach achieves better performance for image denoising and classification as average classification accuracy is obtained as 99.80% and 97.89% for binary and multiclass classifier.



Similarly, we measure the performance of proposed approach for DDR dataset and compared its performance with existing deeplearning based schemes below given table 10 demonstrates the comparative analysis.

Table 10. Multiclass classification performance measurement for DDR database

Model	Class - 0	Class - 1	Class - 2	Class - 3	Class - 4	Class - 5	Avg. Accuracy
VGG-16	0.9537	0.0423	0.5625	0.3944	0.6436	0.9422	0.5898
ResNet	0.9548	0.0582	0.622	0.3662	0.5818 0	0.9133	0.5827
GoogLeNet	0.9574	0.0265	0.5759	0.3380	0.5782	0.9162	0.5654
Proposed Model	0.9623	0.9785	0.8012	0.9915	0.9868	0.9811	0.95.02

The comparative analysis for DDR dataset reported that proposed approach has reported the average accuracy of 93.55% which is better than the state of art DL based methods.

3. Conclusion

The research community is becoming more aware of the diabetes pandemic due to its growing global impact and the alarming rise in cases of diabetic retinopathy. Many methods for DR detection have been proposed; however, directly applying machine learning schemes to the raw images does not yield a consistent result. In order to help physicians and other medical professionals diagnose patients more accurately, segmentation is crucial. Deep learning-based segmentation techniques have been the main focus of this work. Although we have altered the UNet architecture to include skip connection, channel attention, and spatial attention, the suggested method is still based on the well-known UNet segmentation model. The generation of rich feature maps is aided by the skip connection. Moreover, the final semantic feature map is also generated by the attention mechanism and connected to the upsampling layers.The CNN-based architecture used in the denoising scheme creates the filtered image through residual image mapping. In the following stage, we extract features using a CNN-based model and feed the resulting features into an ensemble classifier to produce the final classification result. The suggested method has been trained for segmenting microaneurysms, detecting exudates, and identifying blood vessels. The IDRiD, DIARETDB1, STARE, ChaseDB1, DRIVE, and HRF datasets are among the publicly accessible datasets used to test this methodology. The comparative analysis demonstrates that the suggested strategy improves segmentation accuracy for cases of diabetic retinopathy.Similarly, classification study shows that the proposed approach obtained the average classification accuracy as 98.9%, 97.89% and 95.02% for MESSIDOR, KAGGLE and DDR datasets, respectively.

Compliance and Ethical Standards

Funding: No funding received for this research work.

***Conflict of interest*: The authors declare there is no conflict of Interest**

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