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Diabetic Retinopathy Detection Using Morlet Wavelet Transform Based Residual Network

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Abstract: Early detection of Diabetic Retinopathy (DR) is crucial to prevent patients from the risk of blindness or vision loss which is caused by retinal damage in the eye due to long-term diabetic mellitus. However, existing detection models have several drawbacks to detect DR such as subtle differences between severity levels, and poor quality of images, which makes the detection process ineffective. To overcome these limitations, a Morlet Wavelet Transform-based Residual Network (MWT-ResNet) is to detect the DR accurately for early diagnosis. The MWT enable multi-scale analysis which helps to analyze retinal images at different frequencies and times that enhance the detection of lesions correctly. The retinal images are acquired from two benchmark datasets and preprocessed to improve the contrast of images for the detection of lesions precisely. Then, the preprocessed retinal photos are augmented by a data augmentation method to balance data in severity classes and segmented by a marker-controlled watershed segmentation method. Finally, the proposed MWT-based ResNet model detects DR accurately by learning relevant information from extracted multi-scale features. The experimental results of the proposed MWT-ResNet method achieved an accuracy of 98.36 % and 0.983 for IDRiD and Messidor datasets which is higher than the existing methods like Gradient Boosting-ResNet (GB-ResNet).

Keywords: Contrast limited Adaptive histogram equalization, Diabetic retinopathy, Marker controlled watershed segmentation, Morlet wavelet transform, Residual network.

1. Introduction

Diabetic Retinopathy (DR) is an eye disease due to retinal damage caused by the long-term illness of diabetes mellitus. Individuals with high blood sugar levels for long periods face an increased risk of developing this condition [1, 2]. Most people with high levels of diabetes which are not at a regular level for a long time, result in the weakening of the nephrons in kidneys and damage to neurons in the brain. [3, 4]. In recent years, doctors found that a high rise in sugar levels for a long period also affects blood vessels in the retina part of the eye which leads to blindness or vision loss. Thus, detection of DR presence and its difficulties using retinal images at an early stage helps to prevent its progression to advanced levels [5]. Based on the progression of lesions in the retina of the eye, DR is classified into Proliferative DR (PDR) and Non- PDR (NPDR), the NPDR is further categorized as 'Mild', 'Moderate', or 'Severe'. The mild class DR is the earliest stage at which microaneurysms are formed in the retinal portion of the eye. The symptoms for moderate levels are like mild class where the blood vessels start swelling and lead to form lesions according to the period the patients suffered from diabetes [6].

In PDR, the symptoms of the severe stage are the development of abnormal blood veins, extensive retinal fractures and detachment that results in vision loss [7]. However, the detection of DR based on the binary classification of DR and No DR without knowing the severity levels leads to the risk of vision loss. Hence, multi-class detection of DR levels is crucial for early diagnosis and to provide the right treatment [8]. In previous studies, researchers employed different Machine Learning (ML) and DL techniques for DR detection [9]. By using a single retinal image data set, the researchers obtained satisfactory results in binary class detection and classification [10, 11]. However, binary class detection using a combined dataset with images of different resolutions is difficult to diagnose and leads to risk [12]. Thus, DL approaches are widely used in medical image processing for accurate detection, classification, and recognition of diseases for early diagnosis [13, 14]. However, existing detection approaches based on DL models have several limitations such as inadequate quality of images and difficulty in distinguishing severity levels due to subtle differences leading to decreased detection accuracy [15]. To overcome these problems, a Morlet Wavelet Transform-based Residual Network (MWT-ResNet) is proposed to accurately detect DR and its severity levels.

The main contributions of this research are:

- MWT-ResNet is proposed for DR detection which efficiently detects DR with the feature map obtained by integration of the MWT method which captures complex details about various lesions of DR at different spatial and frequency levels.
- CLAHE is used to improve contrast in retinal images enhance image quality and increase detection accuracy, by enhancing the local contrasts and edges of retinal images without over-amplifying noise.
- For segmenting lesions in retinal images, a Marker-Controlled Watershed (MCW) segmentation method is employed to segment exudates, blood vessels and lesions which are often overlapped in the retinal images.

This research paper is organized as follows: Section 2 explains the literature review. Section 3 describes the methodologies implemented for this research. The experimental results are illustrated in Section 4 and Section 5 concludes the paper.

2. Literature review

The advantages and limitations of DL methods utilized for feature extraction and detection of DR are described in this section.

Bhutnal and Moparthi [16] designed an ensemble efficient with gazelle optimization (E-Effgaz) for DR classification. The designed E-EFFgaz model utilized a Dilation U-Net for segmentation and a convolutional swin transformer for feature extraction to enhance the classification of DR severity levels. An integration of gazelle optimization in EfficientNet reduced the delay and enhanced the early detection of DR based on retinal images. However, the gazelle optimization increased the speed of detection but failed to improve the accurate detection performance of DR severity levels due to similar features for mild and moderate classes.

Srinivasan and Rajagopal [17] represented a multihead attention mechanism in Gradient Boosting based ResNet (GB-ResNet) for DR classification. The represented GB-ResNet model utilized multiscale attention to method to extract high-level features at various scales to improve the classification performance of DR by ResNet. An advantage of the represented ResNet model was the integration of the gradient boost algorithm which aimed to adjust the model's errors and improve the detection of more complex cases of DR. However, the differentiation between severity grades due to subtle differences decreased the classification accuracy of ResNet.

Kalyani [18] explored the DL based Capsule Networks (CapsNet) model for DR detection and classification. The explored CapsNet model utilized a capsule layer that extracts the features from retinal fundus images and is classified by a softmax layer. The main advantage of the CapsNet was that presented a capsule layer that recognized the various DR lesions effectively by capturing spatial hierarchies from the retinal image. However, the explored CapsNet model failed to segment the accurately diseased portion because of several other substances like exudates, and blood vessels in retinal images.

Luo [19] designed a Deep Convolutional Neural Network (DCNN) for DR detection by mining local and long-range patches of retinal images. The correlations between long-range patches were used in DCNN framework to improve DR detection. The advantage of the DCNN model was to enhance the performance of DR detection by extraction of lesion features based on the interrelation between similar lesion patches in the feature map. However, the presented DCNN model failed to detect precisely due to inadequate quality and imbalanced datasets for severity level classes.

Rachapudi [20] presented an optimized Deep Neural Network (DNN) model for DR detection based on the Butterfly Optimization Algorithm (DNN-BOA). The presented DNN-BOA model utilized CLAHE to preprocess various techniques for the segmentation of blood vessels, exudates and optic discs in retinal images. The BOA model optimizes feature selection from extracted features, which helps DNN to focus on the most relevant features in DR images, which leads to improved classification accuracy. However, the limitation of the presented model was difficult to differentiate normal and mild levels of DR accurately due to imbalanced datasets.

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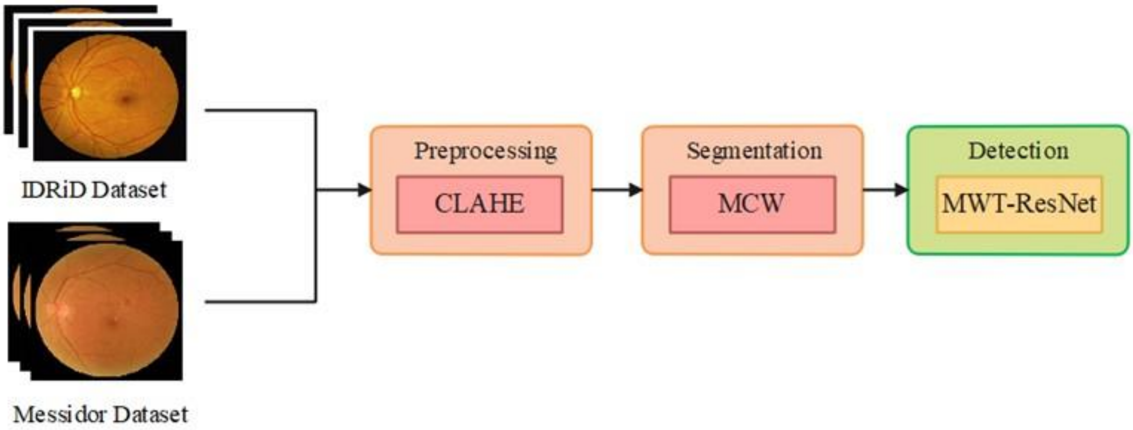

Figure. 1 Block diagram of Proposed DR detection using MWT-ResNet model

The above-mentioned existing approaches have limitations of poor segmentation, difficulty in distinguishing between normal and mild classes, imbalanced datasets, and inadequate quality of images. To overcome these limitations, a MWT-ResNet is proposed for effective DR detection using retinal images which extract the features of various DR levels including subtle differences that improve the DR detection. To enhance image quality, balance dataset and accurate segmentation CLAHE, data augmentation and MCW techniques are utilized for detection of DR.

3. Methodology

The proposed framework for DR detection includes four stages: Dataset, Preprocessing, Segmentation and Proposed Detection. The block diagram of the proposed DR detection is illustrated in Fig. 1. Initially, the retinal images are acquired from the two benchmark datasets of IDRiD and Messidor Datasets. Then, the quality of images is enhanced by the CLAHE approach and then augmented by several data augmentation techniques. After that, the diseased portions are segmented by the threshold-based segmentation method. Finally, the proposed MWT-ResNet is used to detect DR and severity levels of DR accurately.

3.1 Dataset

This research utilized two benchmark datasets for DR detection are IDRiD and Messidor-2.

3.1.1. IDRiD

The IDRiD dataset [21] consists of 516 retinal images with regular retinal structure is utilized in this research. This dataset includes 413 and 103 training and test images according to severity levels. Every sample image in the IDRiD dataset is annotated with DR and Diabetic Macular Edema severity grades at a pixel level. According to the severity scale, the DR levels are labelled into five classes on a scale of 0 – 3 categories.

3.1.2. Messidor

Messidor dataset [22] is a publicly available dataset that consists of 1200 RGB retinal images which are assimilated by three ophthalmologic departments. The retinal images are obtained with 8 bits per color and have resolutions of 1440 × 960, 2240 × 1488, or 2304 × 1536 pixels. The dataset consists of four levels 0, 1, 2, and 3 where 0 denotes normal or no DR. The remaining grades 1, 2, and 3 denote the severity levels with 1 as minimum and 3 as maximum. These retinal images are fed to the preprocessing phase to make a useful format for further processing.

3.2 Preprocessing

The raw data (retinal images) are fed to the preprocessing stage to enhance the quality of the images and increase the accurate detection performance of the proposed model. To enhance the quality of the retinal image in this research CLAHE technique is utilized for preprocessing. The CLAHE is an enhanced version of histogram equalization which is used to improve image contrast for achieving precise segmentation and classification of severity levels. The contrast intensity and cumulative probability density of retinal images are evaluated by clipping local histograms to a multiple cut-off value of the mean height of the histogram in contextual regions. This cumulative histogram of the contextual region is estimated in Eq. (1).

$$C_k = \frac{\sum_{j=0}^{k} h_j}{\sum_{k=0}^{L-1} n_k} \tag{1}$$

Where, C_k denotes cumulative histogram for intensity level k; $\sum_{k=0}^{L-1} n_k$ represents clipped pixels n for intensity level k . After enhancing the contrast and edges of retinal images, a data augmentation process is performed to balance the images in all severity classes equally.

3.2.1. Data augmentation

Data augmentation is a technique used to generate data like actual data by several augmentation techniques which helps balance the data in imbalanced datasets. Data augmentation techniques used for balancing the images in two datasets are rotating, shifting, and flipping (horizontally and vertically) [23]. These augmented images are further passed to the segmentation process to segment the diseased portion from retinal images for accurate detection.

3.3 Segmentation

The augmented images are further segmented using Marked–Controller Watershed (MCW) segmentation algorithm which identifies the target with the subject of interest and generates an image with the dark area known as a segmented object. Initially, the MCW algorithm estimates the foreground markers which are interconnection of clusters of pixels with every object. The markers in the MCW segmentation algorithm mark the target object (diseased portion) around the area first and guide for accurate lesion segmentation. The limitation in the existing watershed segmentation algorithm is addressed by utilizing only the regional minima [24] which is a modification in the segmentation function at foreground and background marker locations. The regional minima operator based on morphological operation and the segmentation process of the modified MCW algorithm is mathematically expressed as follows:

Regional minima for retinal images are given in Eq. (2)

$$I_N = RMIN\, I_{N-1} \tag{2}$$

Erosion based Gray scale image reconstruction is expressed in Eq. (3).

$$I_N \Delta_D f = \left(f \ominus_{I_N} D\right)^{\infty} \tag{3}$$

Dilation based Gray scale image reconstruction is expressed in Eq. (4).

$$I_N \Delta_D f = \left(f \oplus_{I_N} D\right)^{\infty} \tag{4}$$

Where, I_N represents a morphological reconstruction of the retinal image for N morphological operations; f denotes marker; D represents a flat structuring element.

The main steps of the MCW segmentation process are given below:

Step 1: Initially the retinal images are converted into greyscale images and Otsu thresholding is employed to set threshold values for segmenting image background from foreground.

Step 2: After that morphological operations like opening, closing and reconstruction are performed to eliminate noise for improving segmentation results.

Step 3: Then, the regional maxima are identified, and distance transform is applied to assign value for every pixel in the image.

Step 4: Finally, the watershed technique is applied to the distance transform image and labels are assigned for each region in the image based on intensity values and position. These segmented images are fed to the proposed MWT-ResNet model for accurate detection of DR.

3.4 Proposed MWT-ResNet

The Segmented images are fed to the proposed MWT-ResNet to detect the DR and its severity levels accurately for early diagnosis. An integration of MWT and ResNet enhanced the detection by extracting significant features from the retinal images that make the ResNet model able to differentiate and detect the severity levels accurately. The MWT performs a multiscale analysis by dividing an image into different scales that help to analyze and extract features across various resolutions. This makes the ResNet model easier to detect small lesions as well as larger structural changes in the retina, which are important for DR detection. In ResNet, residual blocks are used to mitigate vanishing/exploding gradient issues and employ a skip connection technique.

3.4.1. Morlet wavelet transform

The segmented image is fed as input to MWT which is developed from Gabor Wavelet which is a Gauss envelope complex wavelet for signal time-frequency analysis. The mathematical expression of MWT is expressed in Eqs. (5) and (6).

$$m(t) = e^{j\omega 0 t} e^{-\frac{t^2}{2}} \tag{5}$$

$$\widehat{m}(0) = \sqrt{2\pi} e^{-\omega_0^2/2} \neq 0 \tag{6}$$

Where, $m(t)$ denotes morlet wavelet which is a Fourier transform. The improved fundamental function wavelets are obtained as given in Eq. (7).

$$\varphi(t) = \frac{1}{\sqrt{2\pi}} exp\left(-\frac{t^2}{2} + j2\pi t\right) \tag{7}$$

Where, $\frac{1}{\sqrt{2\pi}}$ represents wavelet amplitude parameter. The Morlet wavelet is then transformed by expansion and translation techniques which is mathematically expressed by the Eq. (8).

$$\varphi_{d_f,\tau}(t) = \frac{|d_f|}{\sqrt{2\pi}} exp\left[-\frac{{d_f}^2(t-\tau)^2}{2} + j2\pi d_f(t-\tau)\right] \tag{8}$$

Where, t and τ indicates time parameters were variable unit of s; d_f stands for wavelet dominant frequency. The MWT is a double–window function used for extracting multi-scale features which is crucial to identify subtle differences between various lesions corresponding to severity levels of DR. The real part in MWT is formulated as given in Eq. (9).

$$\varphi(t) = \left(\frac{\beta}{\sqrt{2\pi}}\ e^{-\beta^2 t^2/2}\right) cos(\omega_0 t) \tag{9}$$

Where, β represents bandwidth parameter that leverages the rate and frequency bandwidth of Gaussian filter which determines the resolution in the frequency domain. Thus, adjusting the frequency resolutions of wavelet transform leads to extracting significant features from the segmented image. These features are further fed as input to the ResNet for the detection process.

3.4.2. ResNet

The ResNet is a kind of deep neural network consists of convolutional, pooling and fully connected layers and mainly skip connections. The convolutional layers are presented at first which obtain input as extracted features by MWT and end with several pooling and fully connected layers. After completing the convolutional and pooling operations, the extracted features are processed using 3×3 convolutional kernels with 64 channels. Then the features map obtained by combining all features is down-sampled by a convolutional operation with a step size of 2. The residual learning unit in ResNet is expressed in Eqs. (10) and (11).

$$Y_l = h(x_l) + F(X_l, W_l) \tag{10}$$

$$X_{l+1} = f(y_l) \tag{11}$$

Where, F represents residual function; X_l and X_{l+1} denotes input and output vectors of lth residual unit which consists of multiple layers; $f(y_l)$ stands for activation function; $h(x_l)$ represents identity mapping.

The step size of two is applied in 1×1 convolution operation on a Feature Map (FM) with the size of $56 \times 56 \times 4$ during the skip connection that results in a $28 \times 28 \times 128$ FM. This FM is then added to another $28 \times 28 \times 128$ FM matrix that was generated earlier, producing a combined $28 \times 28 \times 128$ FM after the application of a loss function.

Next, a convolution operation is performed with a 3×3 convolution kernel on an FM with dimensions $14 \times 14 \times 256$. Following this, data normalization is applied, and the FM is produced using the loss function. The output FM of this step is used as the input for the next operation. Data normalization is again applied, resulting in a new $14 \times 14 \times 256$ FM. This newly obtained feature map is then added to another FM from the previous step through a skip connection, then, a loss function is applied to obtain a final feature map as output. At last, the ResNet detection model detects the DR effectively by the fully connected layer which utilizes the information that obtained from lesion features. The hierarchical structure of ResNet can learn a rich set of features that are provided by the MWT method and distinguish the similarities between severity classes effectively. The skip connections in the ResNet model preserve essential information while learning high-level features that improve the DR detection process.

4. Results and discussion

The performance of the proposed MWT-ResNet model for DR detection is evaluated by four different performance metrics. The proposed MWT-ResNet method is simulated using Python 3.9 with a system configuration of i7 processor, 16 GB RAM and Windows 10 OS. Performance measures used for evaluation are Accuracy, Precision, Sensitivity (Recall), Specificity, F1-Score, Area Under the Curve (AUC), Kappa and Elapsed time. The mathematical expression of performance metrics is represented in Eqs. (12) to (22).

$$Accuracy = \frac{TP+TN}{TN+TP+FN+FP} \times 100 \tag{12}$$

$$Precision = \frac{TP}{TP+FP} \tag{13}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{14}$$

$$Specificity = \frac{TN}{TN+FN} \quad (15)$$

$$F1 - Score = \frac{2 \times Precision * Sensitivity}{Precision + Sensitivity} \quad (16)$$

$$AUC = \int_0^1 TPR\ (FPR)\ d\ (FPR) \quad (17)$$

$$Kappa\ = \frac{p_0 - p_c}{1 - p_c} \quad (18)$$

Where, $$p_o = \frac{\sum_{k=1}^{N}(TP(k)+TN(k))}{N} \quad (19)$$

$$P_c = \frac{p_{c1}+p_{c2}}{N^2} \quad (20)$$

$$P_{c1} = \sum_{k=1}^{N}\big(TP(k) + Fp(k)\big) \times \sum_{k=1}^{N}\big(TP(k) + FN(k)\big) \quad (21)$$

$$P_{c2} = \sum_{k=1}^{N}\big(FN(k) + TN(k)\big) \times \sum_{k=1}^{N}\big(FP(k) + TN(k)\big) \quad (22)$$

Where, TN is True Negative, FN is False Negative, TP is True Positive, and FP is False Positive, FPR – False Positive Rate, TPR true Positive Rate, k represent patients.

4.1 Quantitative and qualitative analysis

The performance analysis of the proposed MWT-ResNet for DR detection using IDRiD and Messidor datasets is illustrated in Table 1. The proposed MWT-ResNet algorithm is evaluated and compared with existing detection approaches such as Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), DenseNet-121, and Resnet utilized in DR detection. The proposed MWT-ResNet achieved an accuracy of 98.36%, precision of 97.91%, sensitivity of 97.86%, F1-score of 97.88% and Specificity of 97.84%. The IDRiD dataset consists of retinal fundus images with annotations for lesions that related to DR. The proposed MWT-ResNet helps in detecting small-scale lesions, such as micro aneurysms and hemorrhages, which are often hard to spot in raw images enhancing the detection of DR.

The performance analysis using the Messidor dataset is illustrated in Table 2. The proposed MWT-ResNet algorithm is evaluated and compared with existing approaches such as CNN, LSTM, DenseNet-121, and ResNet utilized in DR detection. The proposed MWT-ResNet achieved accuracy of 0.993, precision of 0.988, sensitivity of 0.985, F1-score of 0.986 and Specificity of 0.986. The utilization of MWT improved the ResNet model's detection performance by providing good features that make it easier for the network to learn discriminative patterns for DR detection.

The performance analysis of the proposed MWT-ResNet using IDRiD dataset is illustrated in Table 3. The proposed MWT-ResNet algorithm is evaluated and compared with other transform approaches such as Wavelet Transform (WT), Adaptive Wavelet Transform (AWT) and Discrete Wavelet Transform (DWT). In DR detection, this enables a precise extraction of localized features such as microaneurysms, haemorrhages, and exudates, which are key indicators of DR. The MWT's ability to handle non-stationary signals (like retinal images) that helps to identify small but critical variations in textures and patterns.

Table 1. Performance analysis of proposed MWT-ResNet in IDRiD dataset

Methods	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
CNN	94.59	94.24	93.68	93.33	93.95
LSTM	95.47	94.88	94.62	93.81	94.74
DenseNet-121	96.92	95.79	95.74	94.81	95.76
ResNet	97.45	96.87	96.83	95.79	96.85
Proposed MWT-ResNet	98.36	97.91	97.86	97.84	97.88

Table 2. Performance analysis of proposed MWT-ResNet in Messidor dataset

Methods	Accuracy	Precision	Sensitivity	Specificity	F1-Score
CNN	0.932	0.932	0.928	0.923	0.930
LSTM	0.949	0.947	0.942	0.937	0.945
DenseNet-121	0.963	0.958	0.952	0.947	0.955
ResNet	0.976	0.969	0.978	0.974	0.973
Proposed MWT-ResNet	0.993	0.988	0.985	0.986	0.986

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Table 3. Performance analysis of MWT-ResNet in IDRiD dataset

Methods	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
WT-ResNet	92.66	91.90	91.55	91.38	91.72
AWT-ResNet	95.73	94.61	94.27	93.96	94.43
DWT-ResNet	96.48	95.85	95.49	94.82	95.66
Proposed MWT-ResNet	98.36	97.91	97.86	97.84	97.88

Table 4. Performance analysis of proposed MWT-ResNet

Methods	Accuracy	Precision	Sensitivity	Specificity	F1-Score
WT-ResNet	0.947	0.936	0.932	0.927	0.934
AWT-ResNet	0.959	0.948	0.944	0.939	0.946
DWT-ResNet	0.975	0.966	0.963	0.958	0.964
Proposed MWT-ResNet	0.993	0.988	0.985	0.986	0.986

The performance analysis of the proposed MWT-ResNet using Messidor dataset is illustrated in Table 4. The proposed MWT-ResNet algorithm is evaluated and compared with other transform approaches such as WT, AWT and DWT.

The performance analysis of the proposed MWT-ResNet using the IDRiD dataset is illustrated in Fig. 2. The proposed MWT-ResNet algorithm is evaluated and compared with other classifiers and transform-based feature extraction approaches such as CNN, LSTM, DenseNet-121, ResNet, WT, AWT and DWT respectively.

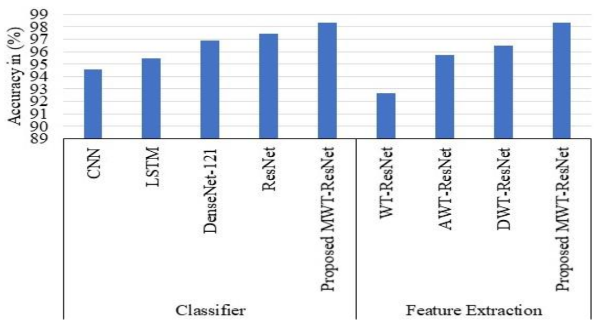

Figure. 2 Performance analysis of the proposed method in IDRiD dataset

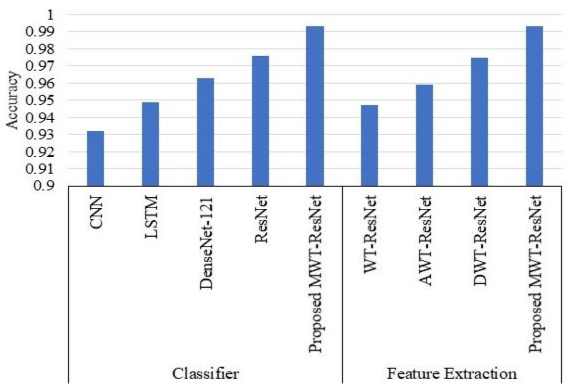

Figure. 3 Performance analysis of the proposed method in Messidor dataset

The performance analysis of the proposed MWT-ResNet using Messidor dataset is illustrated in Fig. 3. The proposed MWT-ResNet algorithm is evaluated and compared with other classifiers and transform based feature extraction approaches such as CNN, LSTM, DenseNet-121, ResNet, WT, AWT and DWT respectively.

The performance of proposed MWT-ResNet in ROC curve for IDRiD and Messidor datasets is represented in Figure 3 and 4. The proposed method achieved AUC of 98.50% and AUC 99.5% which is greater than existing detection methods due to the advantages of multi-scale features extracted by MWT with information of size, texture, shape of lesions. This helps the ResNet model to easily detect both small and big lesions efficiently. The performance of DR detection using MWT-ResNet using confusion matrix for IDRiD and Messidor dataset is illustrates in Figure 6 and Figure 7. The proposed method achieved better results for IDRiD and Messidor datasets. The MCW segmentation method segments the lesions correctly by markers that lead the MWT feature extraction method to extract DR features with subtle differences of lesions between the severity stages. The features with in-depth information enhanced the performance of DR detection by ResNet approach.

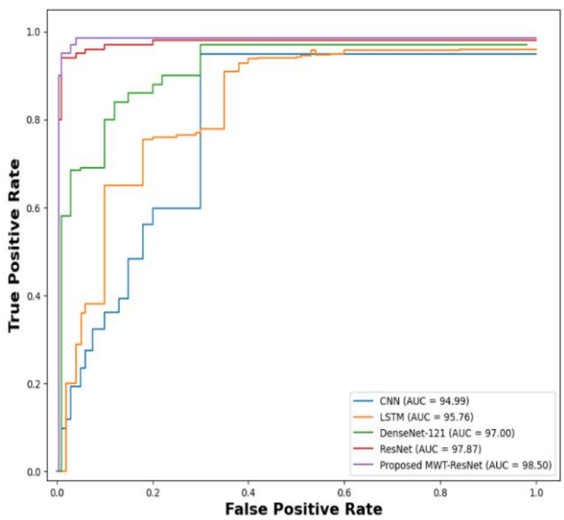

Figure. 4 ROC curve for IDRiD dataset

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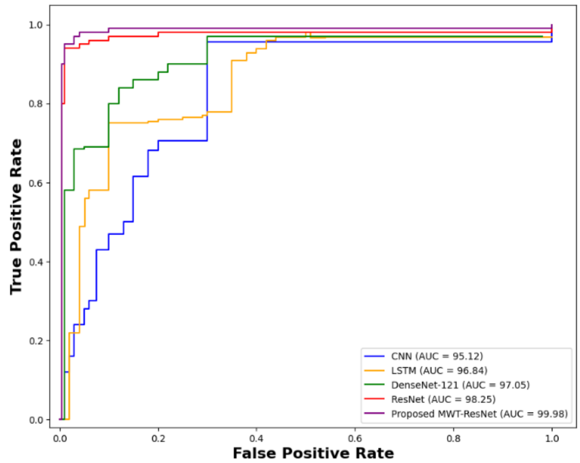

Figure. 5 ROC curve for Messidor dataset

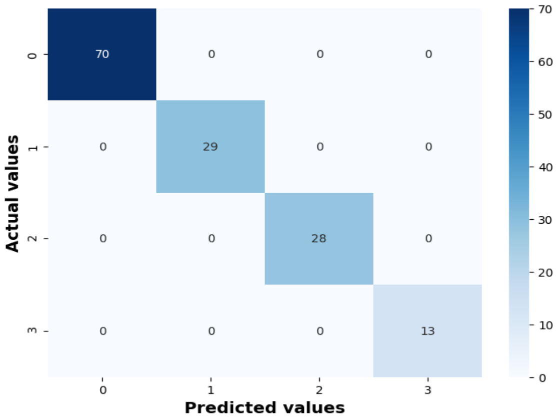

Figure. 6 Confusion Matrix for IDRiD dataset

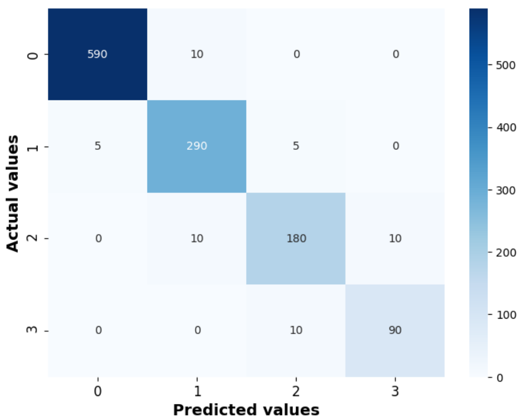

Figure. 7 Confusion Matrix for Messidor dataset

4.2 Comparative analysis

The comparative analysis of the proposed MWT-ResNet model with the existing DR detection model with two different datasets is depicted in this section. The comparative analysis with existing methods for two datasets is illustrated in Tables 5 and 6 using various performance metrics of accuracy, precision, sensitivity and specificity. The Comparative analysis using the IDRiD dataset is illustrated in Table 5. The proposed MWT-ResNet algorithm is evaluated and compared with existing approaches such as E-Effgaz [16] and GB-ResNet [17].

The Comparative analysis using Messidor dataset is illustrated in Table 6. The proposed MWT-ResNet algorithm is evaluated and compared with existing approaches such DCNN [16] and DNN-BOA [17]. The integration of MWT and ResNet achieved high accuracy of 98.36% and 0.993 for IDRiD and Messidor datasets. The MWT focused on multiscale and multi-frequency analysis of retinal images to extract relevant features. ResNet learns these features effectively and differentiates the severity levels of DR effectively which enhances the detection of DR.

4.3 Discussion

The proposed MWT-ResNet achieved better results in DR detection using IDRiD and Messidor datasets effectively. The advantages of the proposed method and the drawbacks of existing approaches are discussed in this section. E-Effgaz [16] model failed to improve the accurate detection performance of DR severity levels due to similar features for mild and moderate classes. GB-ResNet [17] model struggles to distinguish differentiation between severity grades due to subtle differences that decrease the classification accuracy of ResNet. DCNN [19] model faced challenges in precise detection due to inadequate quality and imbalanced datasets. DNN-BOA [20] model has limitations of difficulties in differentiating similarities between the severity levels of DR, due to inadequate data in severity classes.

Table 5. Comparative analysis of MWT-ResNet in IDRiD dataset.

Methods	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)	AUC
E-Effgaz [16]	97.52	96	94	93.5	93	0.93
GB-ResNet [17]	94.40	94.52	94.40	N/A	94.42	N/A
Proposed MWT-ResNet	98.36	97.91	97.86	97.84	97.88	0.95

Table 6. Comparative analysis of MWT-ResNet in Messidor dataset.

Methods	Accuracy	Precision	Sensitivity	Specificity	Kappa	Elapsed Time	F1-Score	AUC
DCNN [19]	0.935	N/A	0.936	0.935	0.838	12.035	N/A	0.967
DNN-BOA [20]	0.989	0.973	0.983	0.987	N/A	N/A	0.978	N/A
Proposed MWT-ResNet	0.993	0.988	0.985	0.986	0.877	8.36	0.986	0.978

To overcome these limitations, an MWT-ResNet is proposed for efficient DR detection using retinal images. The quality of retinal images is enhanced by the CLAHE technique and the MCW is employed to segment blood vessels, and exudates effectively using markers. MWT extracts features from multiscale regions of retinal images to identify the subtle differences between lesions. ResNet learns the information from extracted lesion features effectively by residual learning which enhances the detection of DR precisely.

5. Conclusion

The MWT-ResNet is proposed for accurate DR detection using retinal images to prevent vision loss by early diagnosis. MWT focused on multiscale and multi-frequency analysis of retinal images to extract relevant features. ResNet learns these features effectively and differentiates the severity levels of DR effectively which enhances the detection of DR. The CLAHE technique utilized in preprocessing enhances the contrast of retinal images to ensure that small pathological features are more prominent for DR detection. An MCW segmentation method is employed for segmenting the various sizes of lesions based on severity levels of DR. The enhanced boundary delineation in MCW helps to segment the small lesions associated with DR accurately. Finally, the proposed MWT-ResNet model detects the DR accurately with the help of extracted multi-scale features. The experimental results of the proposed MWT-ResNet method achieved high accuracy of 98.36 % and 0.983 for IDRiD and Messidor datasets which is compared to existing methods like GB-ResNet and DCNN. In future, advanced DL methods will be implemented to enhance detection and classification of severity levels of DR.

preparation, writing—review and editing, visualization, have been done by 1st author. The supervision and project administration, have been done by 2nd author.

Notation

Notations	Descriptions
C_k	Cumulative histogram
k	Intensity level
$\sum_{k=0}^{L-1} n_k$	Total number of clipped pixels n
L	Total number of intensity levels
I_N	A morphological reconstruction of the retinal image
N	Morphological operations
f	Marker
D	A flat structuring element
$m(t)$	Morlet wavelet which is a Fourier transform.
$\frac{1}{\sqrt{2\pi}}$	Wavelet amplitude parameter
t and τ	Time parameters were variable unit
s	Seconds
d_f	Stands for wavelet dominant frequency.
β	Bandwidth parameter
F	Residual function
X_l and X_{l+1}	Input and output vectors of l th residual unit which consists of multiple layers
$f(y_l)$	Activation function for residual learning y_l
$h(x_l)$	Identity mapping for input x_l

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft

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