A NOVEL 3D-CNN BASED FEATURE EXTRACTION BASED CLASSIFICATION FOR DIABETIC RETINOPTHY (DR) DETECTION

Shaik Akbar¹, Divya Midhunchakkaravarthy²

¹Department of Computer Science & Engineering, PDF Scholar, Lincoln University College, Malaysia
²Professor, Department of Computer Science & Engineering, Head - Academic and Student Affairs, Centre of Post Graduate Studies, Lincoln University College, Malaysia
¹dr.shaikakbar@gmail.com@gmail.com, ²divya@lincoln.edu.my

Corresponding Author: Dr. Shaik Akbar

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Abstract

Diabetic retinopathy (DR) is one of the eye diseases that results in vision loss if not diagnosed earlier. The automated computer aided models on the DR images help in accurate treatment disease prevention. Microaneurysms (MA) and red spots are the indicators of DR for disease diagnosis. Many DR classification approaches have been proposed in the literature with deep learning framework and non-linear functionality. Also, these models are not applicable to large feature space due to high true negative rate. To optimize these problems, a hybrid feature selection based deep learning classifier is used to detect the MA and red spots disease severity on the large image dataset. In this paper, a new feature extraction approach is implemented to find the essential positive bag features to the deep learning framework. A hybrid SVM classification model is used to classify the disease patterns with high true positive rate. Experimental results are simulated on different DR image class labels; results show that the hybrid deep learning classification model is better than the traditional models under various statistical metrics on large dataset.

Keywords: Diabetic Retinopathy, Deep learning, Feature Extraction, Classification

I. Introduction

Diabetic retinopathy (DR) in the past 50 years has been identified as the most common cause of blindness. Diabetic retinopathy usually presents blurred vision, floats and flashes and sudden vision loss. In general, diabetes constitutes one of the most widespread diseases, which leads to multiple complications in the human body [VIII]. According to 2014 statistics, this disease has increased to 478 million patients, from a hundred million patients in 1980; its global prevalence has increased
from 4.7% to 8.5% [XV]. Diabetic retinopathy (DR) is more prone to diabetes history in patients [X]. DR has small blood vessels across the retina, through which blood circulates, blocked due to the high blood sugar levels. Damaged vessels cause a blood shortage in the retinal region that can lead to permanent vision loss. Early warning signs are not present until the vision is affected. Exudates (EXs), micro aneurysms (MAs) and hemorrhages (HMs) are the main signs of DR. MAs are the primary indication of thin vessel dilations in non-proliferative diabetic retinopathy (NPDR). MAs appear round, red and small. The severity of the damage depends on the NPDR phases.

**Fig. 1:** Image with NPDR Features

In recent years, large data sets and the computing power offered by GPUs have been motivated by research into deep-learning algorithms that have shown excellent performance in various computer vision tasks and achieved a decisive action over traditional methods. First, by multilevel wavelet decomposition and recurrent development, the authors use the optical disk. Then the blood vessels were extracted from the median filtered images using the histogram analysis. The three-stage frequency transformation of micro aneurysms and hemorrhages were used to identify exudates while multilevel histogram analyses. Finally, the lesions extracted were aggregated to determine whether or not the image was DR-infected. The template delivered 80 percent responsiveness and 50 percent specificity.

Diabetic Retinopathy (DR) is one of the main causes of eye vision and there are valuable behaviors that hold back the disease's development as long as it is identified at an early stage. In its initial stage, however, DR is usually asymptomatic and so the diabetic patients do not undergo any eye exams waiting for the best possible treatment and severe retinal damage to be done before it is too late. Normal diabetic patient retinal examination guarantees early DR detection, which significantly reduces the risk of blindness. Mass screening is time consuming due to the incidence of diabetes and requires many qualified graders to screen the fundus photographs examining the retinal lesions.

DR is composed of a distinctive community of lesions that have been observed for several years in the retinal of people with diabetes mellitus. The anomalies that define DR arise with small variations in the order of their presentation in predictable progression. Vascular occlusion and dilation occur in the early stages. With the growth of new blood vessels, it progresses into a proliferative retinopathy [XV].
The reason for the removal and detection of blood vessels is varied, ranging from the need to identify vessel locations to help reduce false detection of other lesions to the detection of vessel networks. In a normal human eye, the optic nerve head carries from the eye to the brain from 1 to 1.2 million neurons. The optic disc is also the point of entry for the major blood vessels supplying the retina. Pattening of these blood vessels near the optic disk region plays a major role in eye disease diagnosis. An ophthalmologist checks for normal and abnormal vessels in this region. During this operation, retina images (also called Fundus Images (FIs)) are carefully processed using medical picture camera and are actively searched for the presence of DR artifacts by screeners and ophthalmologists. Various eye-related disorders can be identified and diagnosed with the aid of retinal images and humans play a pivotal role in them. Many disorders, such as glaucoma diabetic retinopathy and macular degeneration, are very dangerous because they can lead to blindness if they are not diagnosed in a timely and correct manner. Automatic identification of retinal objects is therefore very important and, among them, the most important to be considered is the detection of retinal vessels. But the vessels of the retina are anomalous [VI]. As a consequence, it does not provide even and proper blood flow to the retina. As a consequence, there is a certain amount of scar tissue in the newly formed retina vessel which results in the retina wrinkle. Some of the retinal vessel knowledge involves the pattern of size, width, and branching. Such research not only updates the information related to the physiological changes, but also helps to accurately detect diseases at an earlier stage.

II. Related Works

Various neural networks are used, namely Multilayer Perceptron (MLP), Modular Neural Network (MNN), Generalized Feed Forward Neural Network (GFFNN) and CNN. These neural networks are carefully qualified by varying number of hidden layers, varying number of hidden layers of processing elements (PEs), percentage of data tagging used for cross validation and training data, transfer functions, learning rules, step size, number of epochs[XIII]. In order to explore the finest configuration among all configurations, comprehensive and organized computer simulations are carried out. Finally, all configured neural networks are tested on data from training and cross validation and/or data from testing. Different performance parameters, i.e., Mean Square Error (MSE), training time spent per epoch per specimen per run, ratio of total number of specimens (N) to number of free parameters (connection weights & biases) i.e. For each neural network, an N / P ratio is observed for neural network complexity, an average percentage of classification accuracy, sensitivity, specificity and accuracy[XIII]. It is recommended to detect diabetic retinopathy in retinal images with the finest neural network with the maximum average percentage of classification accuracy with the best possible performance parameters.

4Different selection parameters of each configuration of the neural network are analytically varied to obtain the maximum average classification accuracy to validate the data sets. In theory, it is well-known that a non-linearly separable classification problem can be solved by a neural network with a single hidden layer. However, to
increase the classification accuracy of the neural network, it is necessary to add more hidden layers when the decision boundaries are more complex. Blood vessel diameter is used as a measure for the detection of DR [IV]. Hemorrhages are detected using mathematical morphology-based techniques [XVII]. Most of the methods discussed above are useful for analyzing the specific features on the retina. While screening a person for DR detection, depending on the severity of the disease, any of the features may appear in the fundus image. Therefore, the screening methods cannot decide that a fundus image is normal until all abnormal features are excluded from the presence. This is time consuming and also prone to inter or intra-observer variability. Location of optic disks is an important issue in retinal image analysis since it is an important landmark feature to locate anatomical components in retinal images, to track vessels and to record changes due to disease and size within the optic disk region. To distinguish the disk from other features of the retina, it is often necessary to locate the disk. Correct location of the optic disk may enhance the extraction of the disk boundary. Vessels direction matched filters have a very high rate of success in diseased images, but they are very expensive computationally because they require retinal vessel segmentation as an initial step in the process of location. Although the method is robust and solves the initialization problem faced by the deformable models, it needs a parameter set tuning that weighs the different energy terms. The results of segmentation show consistency in the handling of different geometric and photometric variations found in the dataset. Deformable models provide high boundary tracing accuracy, but they have a great complexity in computing. Results of segmentation showed good consistency in handling variations in geometry and photometry. They proposed an adaptive thresholding method used by Wellner to locate the fovea center for the early detection of Diabetic Retinopathy. To identify fovea region from other methods, the background is separated from the region. OD and vascular tree are extracted from the fundus using morphological and kisch methods by anatomical position. The drawback of this method is to identify the type of diabetic retinopathy with the cell density of fovea.[XI] presents an algorithm for measuring the incidence of laceration related to diabetic retinopathy (DR) from fundus images.

It was performed using a widespread analytical technique that identifies red and bright lesions effectively.[XIV] introduces a feature extraction technique. They limit the universal distinctive character of the fundus images and distinguish the standard from the images. But a large set of database does not evaluate the performance.

Diabetic Macular Edema (DME) is a higher diabetic retinopathy indication that results in permanent loss of vision. The two methods are discussed using the color fundus images to recognize and categorize the DME [V]. The learning approach that uses the standard fundus images manages DME recognitions. In order to identify the universal uniqueness of the fundus images, an attribute extraction approach was introduced.

Deep Convolutionary Neural Networks (CNN) has been shown to be better suited for classifying images and locating objects. Different CNN networks have been proposed so far and nearly all have achieved impressive results in the task of
classification. CNN's learning, however, depends on the large hand-labeled data that acts as a monitoring signal. Learning in a supervised manner ignores much of the data structure's information [III]. In order to use this information, they proposed an unsupervised learning algorithm that uses the Generative Adversarial Network (GAN) framework to learn features in an adversarial way.

GAN [VII] is a new framework for adversarial learning of generative models. The main purpose of using GAN is to avoid the probabilistic assumption that arises in the estimation of the maximum probability of generative models. In the GAN framework, an adversarial map is learned that transforms the sample from latent (mostly noise) distribution to the required distribution of data (real distribution). Here, two networks, a generator and a discriminator are opposed and adversarial trained. The generator's role is to learn the true distribution of data, while the discriminator learns to distinguish between the samples generated from the true samples. Both networks are multilayer perceptrons (MLP) here and can be easily trained using the back-propagation algorithm.

Reverse mapping is not learned in the existing form of the GAN framework, i.e. projecting data back into latent space (feature space). To overcome this shortcoming in the GAN framework by introducing in the framework a new module called encoder E. The encoder E, maps data to latent space from the distribution of data. This new framework is generally referred to as the Bi-directional Generative Adversarial Network (BiGAN). The BiGAN encoder learns to predict data-driven features, and thus these features serve as a useful data representation for supervised tasks. In general, second to last layer features in CNN are used in classification as they represent the most important features of a given image [XII]. However, we also extracted features from the auxiliary classifier for detection of minute features such as micro aneurysms and concatenated it with the main features of the classifier to form a single feature vector that is then used in SVM training. Note that we use SVM as a classifier in our approach for both classifications, i.e. binary and multiclass. SVM therefore classifies the samples into DR and No DR for binary classification and into 5 classes, i.e. No DR, Mild DR, Moderate DR, Severe DR and Proliferative DR for multiclass classification, once the network is trained on inception network and features are extracted. Growing region combined with edge detection is used to detect OD. Experimental results revealed the superior nature of the proposed approach in terms of sensitivity and specificity for fovea localization and disk boundary detection. But the major drawback of this approach is the need for accurate selection of seed points for growing region. On normal and abnormal images, this technique is implemented. Experimental results concluded that even for blurred images, the proposed algorithm is suitable. Hough transform [II] is used for detection of OD. In order to detect glaucoma in retinal images, the detected optical disk features are provided as inputs to the classifiers. This work emphasized the applicability of OD detection techniques to distinguish between normal and abnormal images. But this experiment does not include images of low quality. The unsupervised color thesholding technique was used for optical disk detection [IX]. In this work, yellow color and small size of the OD are used as important 18 features to identify exudates.

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These features have clearly revealed that for normal and abnormal images the OD's color, size and shape are different. They perform clustering algorithm-based detection of OD. Localization is initially performed using the clustering algorithm and then OD extraction is performed via fuzzy circular transformation of Hough. The results are validated by ophthalmologists. They demonstrate a hybrid parabolism and optic nerve head detection based on the Markov model. The OD extracted is used to distinguish between normal and pathological eyes. Experimental results revealed the superior nature of the approach proposed. The principle of multi-scale extraction of features to segment retinal vessels was implemented on fundus images. The main advantage of this approach is that it can detect the different widths, lengths and orientations of the blood vessels. The demerit of this approach is the inability to detect thin vessels. Another disadvantage of this approach is the lack of a proper performance measure. The wavelet features and the supervised classifier were used to segment the blood vessels [XVI]. The Gaussian model classifier is the classifier used in this work. Also compared to the conventional K-NN classifier are experimental results. But in terms of calculation time and accuracy, the proposed approach outperforms the K-NN classifier. From the vascular network are extracted the structural features used in this work. The structural features are then used to distinguish the different types of blood vessels as input for the SVM classifier. In the case of thin blood vessels, however, the system failed. From these images, the Eigen vectors are extracted and used for segmentation of vessels. The proposed approach to evaluate the segmentation algorithm is tested on the DRIVE database. They used a hybrid method for the extraction of the retinal blood vessel. This work uses the concept of morphology as well as fuzzy clustering algorithms. But to preserve the weak edges, few post-processing procedures are required. But the database used is not sufficiently large to ensure that the proposed technique is robust. The characteristics extracted using morphological operators are then used as the neural classifier input. In this paper, only two-level classification is reported. Diabetic Retinopathy (DR) images have been differentiated. This work uses the Back Propagation Neural Network (BPN) as the classifier. In retinal images, [I] used the reverse segmentation method to detect macular degeneration. In this work, different qualities of retinal images are used and the proposed system has produced superior results for the entire data set. They perform the detection of DR-based mathematical morphology methods. Different morphological operations are used in this work and the effect of these exudates detection operations is analyzed in detail, but it is necessary to accurately detect blood vessels to ensure the high success rate of the proposed system.

The main objectives of the proposed work include:

- Implementing a novel 3D feature extraction approach to find the relevant feature set.
- Implementing a deep learning framework to find essential features on the filtered training image data.
- Implementing a hybrid SVM classifier to detect the severity of the disease patterns on the C3D deep image features.

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III. Proposed Model

Proposed model is designed and implemented in two phases, i.e., image feature extraction and disease severity classification. In the first phase, a novel mathematical filter is applied on the fundus training detect the shape and statistical analysis for disease severity classification. In this phase, a novel filtering approach is used to remove the noise and to smooth dark red dots and bright spot lesions. In the second phase, a deep CNN network is applied on the filtered data to find the essential features for classification problem.

These features are used to find and classify the disease pattern on large number of training samples using deep learning-based classification model. In the deep learning phase, a pre-trained C3D framework is used to filter the essential features in each training image for classification problem. Finally, in the classification phase, a new classifier is implemented to predict the disease classes. In this phase, a hybrid non-linear classifier is used to train the C3D features for disease class prediction.

Fig. 2: Architecture of the Proposed 3D-CNN Model for DR Detection

Features Extraction

Step 1: Input training disease and normal images.

Step 2: Filter the images using disease patterns as.

Step 3: The probability based gabor filter is used to detect the micro aneurysins and red dots in the given image. \(a_x, b_y\) are the major and minor axis of fundus image. \(P(a_x/C)\) is the probability of the red dot patterns available in the major axis with class label \(C\). Similarly, \(P(b_y/C)\) is the probability of the red dot patterns available in the minor axis with class label \(C\).
Minimum curvature patterns of the image is computed as

\[ G_{\text{min}}(r_x, r_y) = \min \left\{ \frac{e^{-\sqrt{r_x^2 + r_y^2} / 2 \sigma}}{r_x \sqrt{2 \pi}}, \frac{e^{-\sqrt{r_x^2 + r_y^2} / 2 \sigma}}{r_y \sqrt{2 \pi}} \right\} \]

(2)

Maximum curvature patterns of the image is computed as

\[ G_{\text{max}}(r_x, r_y) = \max \left\{ \frac{e^{-\sqrt{r_x^2 + r_y^2} / 2 \sigma}}{r_x \sqrt{2 \pi}}, \frac{e^{-\sqrt{r_x^2 + r_y^2} / 2 \sigma}}{r_y \sqrt{2 \pi}} \right\} \]

(3)

Step 4: Each disease intensity feature values of ROI and kernel density estimation are marked for feature extraction.

Each image is partitioned into blocks to find the nearest neighbor features along with its variations. Let Bi and Bj, represents the block partitions with means and covariance matrices of blocks i\textsuperscript{th} and j\textsuperscript{th} blocks of frame. In this step, each block and its adjacent blocks are used to find and mark the disease patterns and its orientations in each image.

Feature Extraction and Classification using C3D Framework

Most of the traditional C3D framework use convolution kernels of 3 × 3 × 3 to filter the features in the disease prediction. Proposed C3D deep learning network is used to find the low-level features and to filter the ranked features obtained in the algorithm 1. Here, different convolution layers, max pooling and filters are used to find the essential features for data classification process. At the end fully connected layer is used to filter the essential disease features in the image using softmax activation function as shown in figure 3. These features are used to classify the disease severity using the proposed classification model.
Deep Learning Based Classification Model

Proposed classification model is used to predict the severity level of disease based on the C3D features. Initially, deep learning features are trained using the feature extraction algorithm and then these features are filtered by C3D model based on class severity. A novel non-linear multi-class classification model is proposed to predict the level of disease severity on the selected features space.

Step 1: Feature space $FS = C3DF(Filter(Images))$;

Step 2: To each C3D feature $f$ in $FS$

Step 3: Find the feature correlation based on the mutual information and chisquare measure as

$$e_i = \frac{1}{2} \text{correlation}(F_i(r)) \sum_r (MI_{c}(r) - O_c(r))^2$$

$$O_{a}(r) = \sum_{i} \text{MI}_{a_i}(r) \psi_{a_0}$$

$$N_{a_i}(r) = \chi(N_{a_i}(r) \psi(N_{a_i}(r))$$

$$N_{a}(r) = \sum_{i} \nu_{a_i} x_i(r) + a_i$$

Step 4: done

Step 5: Apply the non-linear SVM classification on the features using the following objective function and kernel function as

$$\min \ J = \frac{1}{2} \left\| \text{sign} (w \cdot \phi(x) + k) \right\|^2 + \epsilon \nu, \sum_{i=1}^{n} (y_i' + y_i)$$

s.t.

$$\nu_i = \frac{1}{2} \ln \left( \frac{1 - y_i}{y_i} \right)$$

$$\nu = \arg \min \ \nu_i$$

$$w \cdot \phi(x) + k - y_i \leq \epsilon + y_i$$

$$y_i - w \cdot \phi(x) - k + \nu_i \leq \epsilon + y_i$$

$$y_i, \nu, y_i' \geq 0, i = 1, 2, \ldots n$$

Fig. 3: Filter based 3D CNN model

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IV. Experimental Results

Experimental results are simulated in python and java environment with cloud computing environment. In our work, Amazon AWS cloud server with multiple GPU instances are used to simulate the results on the image dataset. The performance of proposed system is measured using specificity (Spec), sensitivity (Sen), accuracy (Acc), and true positive value (PPV).

\[
\text{Sen} = \frac{TP}{TP + FN}
\]

\[
\text{Spec} = \frac{TN}{TN + FP}
\]

\[
\text{PPV} = \frac{TP}{TP + FP}
\]

\[
\text{Acc} = \frac{TP + TN}{TP + TN + FP + FN}
\]

where

TP (True Positive): Predicting disease patterns in MA region.
FP (False Positive): Wrongly predicting patterns in non MA region.
TN (True Negative): Correctly predicting disease patterns in Non-MA regions
FN (False Negative): Wrongly predicting patterns in non-MA regions.

Figure 4, illustrates the performance of traditional C3D with SVM model on training data. From the figure it is observed that the existing model is not optimal as the size of the training data increases with different class labels.
Table 1: Performance Comparison of Present Classification Model to Existing DR Approaches by using Specificity Metric.

| Sample Size | SVM  | ANN  | PNN  | Proposed |
|-------------|------|------|------|----------|
| #10         | 0.861| 0.897| 0.95 | 0.963    |
| #20         | 0.885| 0.89 | 0.938| 0.977    |
| #30         | 0.873| 0.894| 0.944| 0.956    |
| #40         | 0.875| 0.898| 0.948| 0.959    |
| #50         | 0.867| 0.895| 0.948| 0.97     |
| #60         | 0.866| 0.896| 0.938| 0.97     |
| #70         | 0.877| 0.893| 0.942| 0.959    |
| #80         | 0.877| 0.9  | 0.94  | 0.971    |
| #90         | 0.887| 0.899| 0.941| 0.967    |
| #100        | 0.894| 0.913| 0.953| 0.9784   |

Table 1, describes the comparison of present classification model to existing DR approaches by using specificity metric. As shown in the table, it is noted that the current DR model has better specificity than the traditional DR techniques in each sample size.

Table 2: Performance Comparison of Present Classification Model to Existing DR Approaches by using Recall Metric.

| Sample Size | SVM  | ANN  | PNN  | Proposed |
|-------------|------|------|------|----------|
| #10         | 0.871| 0.891| 0.939| 0.966    |
| #20         | 0.884| 0.893| 0.94  | 0.955    |
| #30         | 0.874| 0.89 | 0.942 | 0.971    |
| #40         | 0.864| 0.891| 0.941 | 0.971    |
| #50         | 0.866| 0.892| 0.95  | 0.957    |
| #60         | 0.89  | 0.891| 0.95  | 0.97     |
| #70         | 0.865| 0.894| 0.938 | 0.964    |
| #80         | 0.859| 0.892| 0.941 | 0.966    |
| #90         | 0.87  | 0.898| 0.949 | 0.975    |
| #100        | 0.876| 0.92 | 0.945 | 0.972    |

Table 2, describes the comparison of present classification model to existing DR approaches by using recall metric. As shown in the table, it is noted that the current DR model has better recall than the traditional DR techniques in each sample size.
Figure 5: Performance Comparison of Present Classification Model to Existing DR Approaches by using Accuracy Metric.

Figure 5 describes the comparison of present classification model to existing DR approaches by using accuracy metric. As shown in the table, it is noted that the current DR model has better accuracy than the traditional DR techniques in each sample size. Also, proposed classification model has better efficiency on each selected C3D feature space on large data.

Figure 6: Performance Comparison of Present Classification Model to Existing DR Approaches by using Precision Metric.

Figure 6 describes the comparison of present classification model to existing DR approaches by using precision metric. As shown in the table, it is noted that the current DR model has better precision than the traditional DR techniques in each sample size. Also, proposed classification model has better efficiency on each selected C3D feature space on large data.

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Table 3: Performance comparison of present classification model to existing DR approaches by using runtime (ms)

| Sample Size (%) | SVM+C3D   | ANN+C3D   | PNN+C3D   | Proposed model++C3D |
|-----------------|-----------|-----------|-----------|---------------------|
| #10             | 8871.49   | 7979.7    | 7470.68   | 6333.93             |
| #20             | 8404.66   | 7932.22   | 7201.42   | 6000.39             |
| #30             | 8315.83   | 8121.03   | 7175.51   | 6136.4              |
| #40             | 8490.84   | 8121.92   | 6947.05   | 6291.8              |
| #50             | 7911.21   | 8041.39   | 7437.47   | 5982.53             |
| #60             | 8526.14   | 8146.74   | 6843.83   | 6644.23             |
| #70             | 8253.63   | 7951.54   | 6806.64   | 6279.8              |
| #80             | 8333.58   | 7907.64   | 7616.55   | 6621.84             |
| #90             | 8248.56   | 8049.79   | 7391.48   | 6014.66             |
| #100            | 8510.47   | 7913.21   | 6822.46   | 6635.42             |

Table 3, represents the comparative study of different deep learning models on training dataset in terms of runtime (ms). From the table 3, it is observed that the current model has less runtime (ms) in each sample size and feature space on large training dataset.

Fig. 7: Disease Severity Prediction on the Sample Image using Feature Extraction and Classification Models

Figure 7, illustrates the output of disease prediction using the proposed model on the sample input test image. Figure a, describes the sample input image, b) represents the....
features identified on the sample input image using filtering approach and c) represents the severity region of the input image using C3D and classification model.

V. Conclusion and Future Scope

Diabetic retinopathy disease severity level requires identifying the MA and red spots position of exudates. Specific classification strategies are used to detect the presence and position of various stages of diabetic retinopathy such as microaneurysms, haemorrhages and exudates. Although the classifiers and the methods of extraction of features are very familiar, the novelty of classification model predicts the connected component labeling based on the neighborhood approach. To optimize these problems, a hybrid feature selection based deep learning classifier is used to detect the MA and red spots disease severity on the large image dataset. In this paper, a new feature extraction approach is implemented to find the essential positive bag features to the deep learning framework. A hybrid SVM classification model is used to classify the disease patterns with high true positive rate. Experimental results are simulated on different DR image class labels; results show that the hybrid deep learning classification model is better than the traditional models under various statistical metrics on large dataset.

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