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A Survey on Diabetic Retinopathy Image Classification Features & Techniques

Nand Kishor, Prof. Akrati Shrivastava, Associate Prof. Dr. Jayshree Boaddh
Department Computer of Science and Engineering
Vaishnavi Inst. of Tech. & Science,Bhopal, India

Abstract- The remarkable success of machine learning has prompted interest in its application to medical imaging diagnosis. Even though state-of-the-art deep learning models have achieved human-level accuracy on the classification of different types of medical data, these models are hardly adopted in clinical workflows, mainly due to their lack of interpretability. This paper has done a deep survey on diabetic retinopathy image classification work done by researchers. Paper has list the features used by the researcher for medical image classification. Further techniques involve in diabetic retinopathy image classification was detailed. Finally various methods of image classification models comparison evaluation parameters were mentioned by the paper.

Keywords: Image Classification, Feature Extraction, Diabetic Retinopathy, Image Processing.

I. INTRODUCTION

Diabetic Retinopathy (DR) is one of the most common microvascular complications of diabetes mellitus and affects the blood vessels of the retina. It is characterized by retinal abnormalities such as microaneurysms, hemorrhages, neovascularization, and retinal edema. Diabetic retinopathy is considered one of the major causes of visual impairment and blindness among the working-age population worldwide. Studies indicate that more than 80% of diabetic patients develop some degree of retinopathy after 20 years of diabetes, while more than 90% of vision-threatening cases can be effectively treated if detected at an early stage.

Due to its progressive nature, diabetic retinopathy has become a major public health concern. Clinical screening guidelines recommend that diabetic patients undergo retinal examination every 12 to 24 months for timely identification of retinal abnormalities. Several clinical studies have demonstrated that regular screening enables early diagnosis and appropriate medical intervention, which significantly reduces the risk of severe visual impairment and blindness.

Despite the importance of regular retinal screening, access to specialized ophthalmic examination remains limited in many healthcare settings, particularly in rural and underdeveloped regions. Retinal examination requires specialized equipment and trained ophthalmologists, making screening inaccessible for many patients. As a result, a large number of diabetic individuals fail to undergo timely retinal assessment and are diagnosed only at advanced stages of the disease. Therefore, early detection and intervention remain the most effective approaches for minimizing retinal damage and preventing permanent vision loss.

In diabetic retinopathy patients, several retinal lesions develop as indicators of disease progression. These lesions include microaneurysms, hemorrhages, exudates, and neovascularization, which require early detection for effective clinical management.

Microaneurysms are small localized swellings in retinal capillaries caused by weakening of blood vessel walls. They are considered the earliest clinically visible signs of diabetic retinopathy. These swollen blood vessels may rupture and leak blood into surrounding retinal tissues.

Hemorrhages occur when retinal capillaries rupture, leading to blood leakage within the retina. They appear as dark red irregular patches and indicate progression of retinal vascular damage.

Exudates are lipid or protein deposits that leak from damaged retinal blood vessels. These are generally classified into two categories:

Hard exudates, which appear as yellowish lipid deposits

Soft exudates (cotton wool spots), which appear as whitish-grey patches caused by retinal nerve fiber infarction

Neovascularization refers to the abnormal growth of new blood vessels on the retinal surface. These vessels are fragile and prone to rupture, often causing severe retinal bleeding and vision loss.

Stages of DR

Diabetic retinopathy is a progressive and complex retinal disorder. The severity of diabetes directly increases the risk of retinal damage and visual impairment [6]. Based on disease progression, diabetic retinopathy is broadly classified into two major stages shown in fig. 1:

- Non-proliferative DR is recognized as one of the basic forms of DR. In other words, it is the beginning phase of DR, which comprises hard exudates along with edema.
- Proliferative DR has been categorized as an advanced stage of DR, which occurs when the image retina begins to grow new blood vessels. This might result in severe eyesight loss due to vitreous hemorrhage conditions.

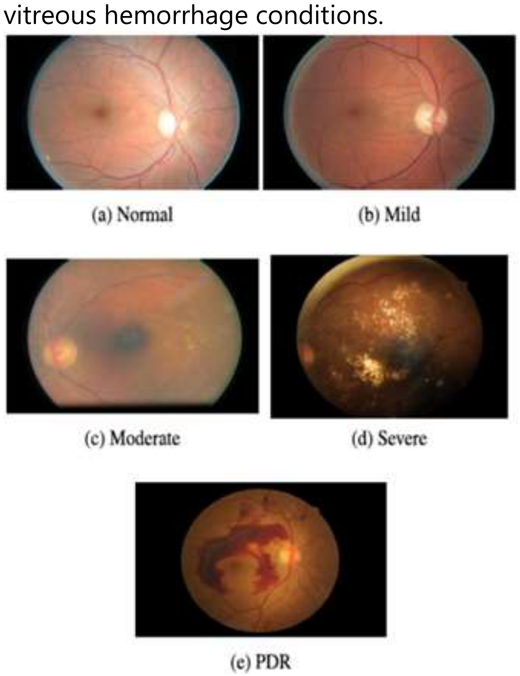

Fig. 1. Diabetic retinopathy retinal image showing lesions.

Types of Diabetes According to Masaki Yamaguchi and related studies, diabetes is broadly classified into three main categories:

Type 1 Diabetes Mellitus (T1DM), often referred to as juvenile diabetes, occurs when the pancreatic beta cells stop producing insulin. It is considered one of the most serious forms of diabetes and is commonly diagnosed in children and adolescents. Individuals with T1DM generally require multiple daily insulin injections to regulate their blood glucose levels effectively.

Type 2 Diabetes Mellitus (T2DM), commonly known as adult-onset diabetes, is the most widespread form of diabetes, accounting for nearly 90% of diabetes cases globally. It can develop at any stage of life and typically begins with insulin resistance, a condition in which the body becomes less responsive to insulin. Over time, this can impair the pancreas' ability to produce sufficient insulin to maintain normal blood glucose levels.

Gestational Diabetes, as discussed by Meri Raffetto, is a temporary form of diabetes that develops during pregnancy and usually resolves after childbirth, though it may increase the future risk of developing Type 2 diabetes.

A study conducted by Masaki Yamaguchi explored the use of machine learning techniques for predicting next-morning fasting blood glucose (FBG) levels. The research involved four insulin-dependent diabetic patients monitored over a three-month period. Participants were provided with three portable commercial devices: a blood glucose monitor, a metabolic rate monitor, and a laptop-based food intake tracking system.

The blood glucose monitor was used to record fasting blood glucose once per day, while the metabolic rate monitor measured calorie expenditure by tracking the body's energy consumption. In addition, custom calorie-calculation software was developed to estimate food intake. This software displayed various meal options on the laptop, enabling patients to select their breakfast, lunch, and dinner choices for nutritional tracking.

After sufficient data collection, machine learning algorithms were applied to estimate blood glucose levels. However, the prediction accuracy declined after the eighth week of observation. The reported error rates for the four participants were 8.9%, 26.1%, 13.5%, and 22.2%, respectively. This limitation was mainly attributed to the restricted amount of glucose data available, as only one blood glucose reading per day was used for model training and prediction.

In recent years, machine learning and particularly deep learning approaches have shown remarkable effectiveness in analyzing complex clinical datasets. These methods have been successfully applied in numerous healthcare domains, including disease diagnosis, patient phenotyping, and prediction of medical events. Furthermore, Electronic Health Records (EHRs) serve as a rich and valuable source of patient information, enabling the development of more accurate and intelligent predictive healthcare models.

II. RELATED WORK

Kobat, S.G. et al. [5] introduced an innovative method for the automated classification of diabetic retinopathy (DR) using fundus photographs. Their approach involves non-fixed-size patch division along horizontal and vertical axes to enhance classification accuracy. A new fundus image dataset was also compiled for experimentation. Deep features were extracted from both the entire image and eight subdivided patches using the DenseNet201 architecture via transfer learning, utilizing its final global average pooling and fully connected layers. The most relevant features were then selected using Neighborhood Component Analysis (NCA).

In [6], T. Palaniswamy et al. proposed an IoT and deep learning-based DR diagnosis model named IoTDL-DRD. This system uses IoT devices to collect retinal fundus images, which are uploaded to a cloud platform for processing. The images undergo preprocessing to enhance contrast and reduce noise. A Mayfly Optimization-based Region Growing (MFORG) algorithm is then used to segment lesion areas. Features are extracted using DenseNet, and classification is performed using a Long Short-Term Memory (LSTM) network. To further optimize performance, the LSTM parameters are tuned using the Honey Bee Optimization (HBO) algorithm.

H. Vohra et al. [7] developed a smart DR detection system aimed at affordability and early diagnosis. Utilizing a low-cost imaging setup with a 28D lens and a camera, high-resolution fundus images are captured and analyzed using Convolutional Neural Networks (CNNs). The system detects not only DR but also other retinal diseases like age-related macular degeneration (AMD) and glaucoma. A cloud-hosted web application on AWS enables users to upload images, receive automated diagnoses, and access reports.

Kusum Yadav et al. [8] proposed a hybrid segmentation method combining Modified Inertia Weight Particle Swarm Optimization (MIWPSO) with Fuzzy C-Means (FCM) clustering. Traditional FCM struggles with noise due to lack of spatial context. Their modified FCM integrates spatial information into the fuzzy membership matrix, improving robustness to noise. The hybrid FCM-MIWPSO approach demonstrated high precision and accuracy in medical image segmentation.

Xuebin Xu et al. [9] presented RT2Net, a multi-view joint learning framework that leverages both global fundus features and local vascular features for more accurate DR diagnosis. Initially, the fundus images are preprocessed using contrast-limited adaptive histogram equalization, followed by segmentation of the vascular structures. These inputs are fed into two separate branches of RT2Net, and a feature fusion module combines the outputs. The final classification model identifies DR across five severity levels.

Roberto Romero-Oraá et al. [10] introduced an attention-based mechanism that differentiates between dark and bright retinal structures through prior image decomposition. This approach improves the model by creating distinct attention maps for red and bright lesions. The overall framework is composed of various components, including image quality evaluation, data augmentation techniques, transfer learning strategies, and model fine-tuning. For feature extraction, it leverages the Xception architecture, while the focal loss function is employed to handle class imbalance issues during the training phase.

III. RETINOPATHY CLASSIFICATION IMAGE FEATURES

Color Features Color-based features are highly significant in retinal image analysis because several pathological indicators of diabetic retinopathy, including hemorrhages, microaneurysms, and exudates, can be differentiated based on their color characteristics and spatial distribution, as highlighted by Michael D. Abràmoff and colleagues. To effectively analyze retinal abnormalities, images are often processed in different color spaces, including:

Corner Feature In order to stabilize the video frames in case of moving camera it require the difference between the two frames which are point out by the corner feature in the image or frame. So by finding the corner position of the two frames one can detect resize the window in original view. This feature is also use to find the angles as well as the distance between the object of the two different frames. As they represent point in the image so it is use to track the target object.

Texture: It is highly desired that semi or fully automatic image inspection can be done which will desired information in from the inserted image. This is possible due to high decrease in the computational cost of the methods. Most of the industries have high desired to make automatic visual inspection of different materials. This reduce the inspection doubts and increase the efficiency of the final product. Some of market applications are paper mills [8], stone industry, wooden factory [9]. As these application have product development work which analyze the texture feature of the material. As it is required that all the stones coming should have even quality of surface. As raw stone are broken down to plates for having even surface. Here image of the stone surface help in identifying the even surface of the image, without any manual involvement. So texture feature of the image help in finding the effective material. One more application is research analysis of new material have particle size in nano meters. As naked eyes or surface touch cannot judge the actual condition of the material.

Shape Picture recovery utilizing shape highlights has been a troublesome and testing issue. In arithmetic 'shape' is characterized as the 'geometric data expected to portray a question when area, scale and rotational impacts are evacuated'. Specialist are occupied with catching state of the pictures so they can be utilized to register likeness between the picture things. In a perfect world, it ought to have the capacity to extricate the ideal arrangement of shape includes that describe the perceptual properties of a picture. Lamentably, there is no formal structure to depict what portrays shape in this area.

This outcomes demonstrate that highlights of noteworthy gatherings are more essential in making closeness judgments. As per the critical highlights are the nearness of straight lines, right edges, parallelism and segments of equivalent size or dispersing. From a computational point of view good shape measure should satisfy several requirements including robustness against noise, occlusion and geometric variations, and stability against small variations of shape. In addition similar shapes should have similar feature vectors which are significantly different from others.

Histogram Feature: In this step image vector obtained after pre-processing is used where histogram of the image is find at one bins. This can be understand as let scale of color is 1 to 10, than count of each pixel value is done in the image. So as per above vector Hi=[0, 0, 0, 4, 3, 5, 2, 1 2, 0] where H represent the color pixel value count and i represent the position in the H matrix with color value.

Corner Feature: In order to stabilize the video frames in case of moving camera it require the difference between the two frames which are point out by the corner feature in the image or frame. So by finding the corner position of the two frames one can detect resize the window in original view. This feature is

also use to find the angles as well as the distance between the object of the two different frames. As they represent point in the image so it is use to track the target object.

IV. TECHNIQUES OF MEDICAL IMAGE CLASSIFICATION

Medical image classification is a fundamental task in computer-aided diagnosis systems that aims to automatically assign medical images to predefined categories based on their visual characteristics. The increasing availability of medical imaging modalities such as X-ray, Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), ultrasound, and histopathological imaging has created a demand for accurate and efficient classification methods. These techniques assist healthcare professionals in disease detection, diagnosis, prognosis, and treatment planning while reducing the possibility of human error [8].

Traditional medical image classification methods rely on feature extraction and machine learning algorithms. In these approaches, image features such as texture, shape, color, and intensity are extracted manually and then supplied to classification algorithms. However, with the advancement of deep learning, automated feature learning has become possible, significantly improving classification accuracy and robustness [9]. The following are six widely adopted techniques used for medical image classification.

Support Vector Machine (SVM) Support Vector Machine (SVM) is one of the most widely used supervised machine learning algorithms for medical image classification. SVM operates by identifying an optimal hyperplane that maximizes the separation between different image classes. The algorithm is particularly effective for high-dimensional datasets and can efficiently handle nonlinear classification problems through kernel functions such as radial basis function (RBF), polynomial, and sigmoid kernels [10].

In medical imaging, SVM has been extensively applied to classify brain tumors from MRI images, breast cancer lesions from mammograms, retinal abnormalities from fundus images, and lung diseases from chest X-rays. The effectiveness of SVM largely depends on the quality of extracted features. Therefore, image preprocessing and feature extraction play crucial roles in achieving high classification performance [11].

K-Nearest Neighbor (KNN) K-Nearest Neighbor (KNN) is a non-parametric classification algorithm that categorizes a new image based on the majority class among its nearest neighboring samples. The similarity between images is typically calculated using distance metrics such as Euclidean distance, Manhattan distance, or cosine similarity [5].

KNN is simple to implement and does not require a training phase, making it suitable for small medical datasets. It has been utilized in the classification of skin lesions, diabetic retinopathy images, and mammographic abnormalities. Although KNN can achieve satisfactory results, its performance decreases when dealing with large datasets due to increased computational complexity and sensitivity to irrelevant features [5].

Random Forest (RF) Random Forest is an ensemble learning technique that combines multiple decision trees to improve classification performance and reduce overfitting. Each decision tree is trained using a random subset of training samples and features. The final classification result is determined through majority voting among the trees [6].

The robustness and stability of Random Forest make it highly suitable for medical image classification tasks. It has been successfully applied in cancer diagnosis, tissue classification, Alzheimer's disease prediction, and cardiovascular disease detection. Furthermore, Random Forest provides feature importance information, enabling researchers to identify the most influential image characteristics contributing to disease classification [6].

Artificial Neural Network (ANN) Artificial Neural Networks (ANNs) are computational models inspired by the structure and functioning of the human brain. ANNs consist of interconnected neurons organized into input, hidden, and output layers. During training, the network learns patterns from image features by adjusting connection weights using optimization algorithms such as backpropagation [7].

ANNs have demonstrated effectiveness in classifying medical images involving tumor detection, organ segmentation, and disease diagnosis. Compared to traditional machine learning approaches, ANNs can model complex nonlinear relationships among image features. However, shallow ANN architectures often require handcrafted feature extraction and may struggle with highly complex image datasets [7].

Convolutional Neural Network (CNN) Convolutional Neural Networks (CNNs) represent one of the most significant advancements in medical image analysis. CNNs automatically learn hierarchical image representations through convolutional, pooling, and fully connected layers. Unlike traditional methods, CNNs eliminate the need for manual feature engineering by directly extracting relevant features from raw image data [8].

CNN-based models have achieved remarkable success in detecting pneumonia from chest X-rays, identifying diabetic retinopathy from retinal images, classifying skin cancer lesions, detecting brain tumors, and diagnosing Alzheimer's disease from MRI scans. Their ability to learn complex spatial patterns makes them highly effective for medical image classification tasks [9]. Furthermore, CNNs have demonstrated superior performance compared to conventional machine learning techniques across numerous benchmark datasets [10].

Transfer Learning-Based Deep Networks Transfer learning has emerged as an effective solution for medical image classification, particularly when limited annotated data are available. In transfer learning, pre-trained deep learning models developed on large-scale image datasets are adapted to specific medical imaging applications [11].

Popular pre-trained architectures such as ResNet, VGG16, DenseNet, Inception, and EfficientNet are commonly employed for transfer learning. These models leverage previously learned visual representations and fine-tune them using medical image datasets. Transfer learning significantly reduces training time, computational requirements, and data dependency while improving classification accuracy [12].

Researchers have successfully applied transfer learning to classify COVID-19 chest X-rays, breast cancer histopathological images, retinal diseases, and neurological disorders. Due to its effectiveness and efficiency, transfer learning has become one of the most preferred approaches in modern medical image analysis [12].

V. EVALUATION PARAMETERS

As various techniques evolve different steps of working for segmenting image into appropriate category. So it is highly required that proposed techniques or existing work need to be compare on same dataset. But image classification which are obtained as output is need to be evaluate on the function or formula. So following are some of the evaluation formula which help to judge the classification techniques ranking.

$$\Pr ecision = \frac{True\_Positive}{True\_Positive + False\_Positive}$$

This recall rate is the ratio of the number true class identified by an algorithm to the number of sources actually class present in the system.

$$\Pr ecision = \frac{True\_Positive}{True\_Positive + False\_Positive}$$

F-measure is an inverse average of precision and recall values.

$$F\_Score = \frac{2 * \Pr ecision * \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call}$$

Accuracy its an ratio of total number of correct prediction for all class set to the total number of prediction sets.

$$Accuracy = \frac{Correct\_Classification}{Correct\_Classification + Incorrect\_Classification}$$

In above true positive value is obtained by the system when the classified pixel is same as in actual case or ground truth pixel. While in case of false positive value it is obtain by the system when the classified pixel is not of same case as in actual in or ground truth pixel.

VI. CONCLUSION

Medical image classification has become an essential component of modern healthcare by assisting clinicians in the accurate diagnosis of diseases from medical images such as MRI, CT, X-ray, and retinal scans. Various classification techniques, including SVM, KNN, Random Forest, ANN, CNN, and transfer learning models, have been successfully applied to improve diagnostic accuracy. This survey reviewed the existing research on diabetic retinopathy image classification and discussed the image features, classification methods, and evaluation metrics commonly used by researchers. Although deep learning models have achieved outstanding classification performance, their limited interpretability remains a challenge for clinical adoption. Future research should focus on developing explainable and reliable classification models that can enhance physician trust and support effective clinical decision-making in healthcare environments.

REFERENCES

1. Ikram, A. et al. A systematic review on fundus image-based diabetic retinopathy detection and grading: Current status and future directions. IEEE Access 12, 96273–96303 (2024).
2. Wang, X. et al. UD-MIL: Uncertainty-driven deep multiple instance learning for OCT image classification. IEEE J. Biomed. Health Inform. 24, 3431–3442 (2020).
3. Raman, R., Ramasamy, K., Rajalakshmi, R., Sivaprasad, S. & Natarajan, S. Diabetic retinopathy screening guidelines in India: All India Ophthalmological Society diabetic retinopathy task force and Vitreoretinal Society of India Consensus Statement. Indian J. Ophthalmol. 69(3), 678–688.
4. Rajalakshmi, R. et al. Tele-ophthalmology versus face-to-face retinal consultation for assessment of diabetic retinopathy in diabetes care centers in India: a multicenter cross-sectional study. Diabetes Technol. Ther. 24(8), 556–563.
5. Kobat, S.G.; Baygin, N.; Yusufoglu, E.; Baygin, M.; Barua, P.D.; Dogan, S.; Yaman, O.; Celiker, U.; Yildirim, H.; Tan, R.-S.; et al. Automated Diabetic Retinopathy Detection Using Horizontal and Vertical Patch Division-Based Pre-Trained DenseNET with Digital Fundus Images. Diagnostics 2022.
6. T. Palaniswamy and M. Vellingiri, "Internet of Things and Deep Learning Enabled Diabetic Retinopathy Diagnosis Using Retinal Fundus Images," in IEEE Access, vol. 11, pp. 27590-27601, 2023.
7. H. Vohra et al., "A Low-Cost AI-Powered System for Early Detection of Diabetic Retinopathy and Ocular Diseases in Resource Limited Settings," in IEEE Access, vol. 13, pp. 97322-97336, 2025.
8. Kusum Yadav, Yasser Alharbi, Eissa Jaber Alreshidi, Abdulrahman Alreshidi, Anuj Kumar Jain, Anurag Jain, Kamal Kumar, Sachin Sharma, Brij B. Gupta. "A Comprehensive Image Processing Framework for Early Diagnosis of Diabetic Retinopathy", Computers, Materials and Continua, Volume 81, Issue 2, 2024, Pages 2665-2683.
9. Xuebin Xu, Dehua Liu, Guohua Huang, Muyu Wang, Meng Lei, Yang Jia. "Computer aided diagnosis of diabetic retinopathy based on multi-view joint learning" Computers in Biology and Medicine, Volume 174, 2024, 108428.
10. Roberto Romero-Oraá, María Herrero-Tudela, María I. López, Roberto Hornero, María García. "Attention-based deep learning framework for automatic fundus image processing to aid in diabetic retinopathy grading". Computer Methods and Programs in Biomedicine, Volume 249, 2024, 108160.
11. Litjens, G., Kooi, T., Bejnordi, B. E., et al. "A Survey on Deep Learning in Medical Image Analysis." Medical Image Analysis, vol. 42, 2017, pp. 60–88.
12. Shen, D., Wu, G., and Suk, H. I. "Deep Learning in Medical Image Analysis." Annual Review of Biomedical Engineering, vol. 19, 2017, pp. 221–248.

13. Vapnik, V. N. The Nature of Statistical Learning Theory. Springer, New York, 1995.

14. Noble, W. S. "What Is a Support Vector Machine?" Nature Biotechnology, vol. 24, no. 12, 2006, pp. 1565–1567.
15. Cover, T., and Hart, P. "Nearest Neighbor Pattern Classification." IEEE Transactions on Information Theory, vol. 13, no. 1, 1967, pp. 21–27.
16. Breiman, L. "Random Forests." Machine Learning, vol. 45, no. 1, 2001, pp. 5–32.
17. Haykin, S. Neural Networks and Learning Machines. 3rd Edition, Pearson Education, 2009.
18. Krizhevsky, A., Sutskever, I., and Hinton, G. E. "ImageNet Classification with Deep Convolutional Neural Networks." Advances in Neural Information Processing Systems, 2012, pp. 1097–1105.
19. Esteva, A., Kuprel, B., Novoa, R. A., et al. "Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks." Nature, vol. 542, no. 7639, 2017, pp. 115–118.
20. LeCun, Y., Bengio, Y., and Hinton, G. "Deep Learning." Nature, vol. 521, no. 7553, 2015, pp. 436–444.
21. Pan, S. J., and Yang, Q. "A Survey on Transfer Learning." IEEE Transactions on Knowledge and Data Engineering, vol. 22, no. 10, 2010, pp. 1345–1359.
22. Shin, H. C., Roth, H. R., Gao, M., et al. "Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning." IEEE Transactions on Medical Imaging, vol. 35, no. 5, 2016, pp. 1285–1298.