Journal of Current Research in Engineering and Science
JCRES
Bi-Annual Online Journal (ISSN: 2581 - 611X)
VOLUME:8, ISSUE:2, AUGUST 2025, PAPER NUMBER:50

Diagnosis of Diabetes Retinopathy using Multimodal Fusion Approach

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Abstract— Diabetic Retinopathy (DR) is a complication arising from Diabetes Mellitus (DM), which can lead to significant vision problems and even blindness due to damage to the retina. In its early stages, DR may not present noticeable symptoms or cause only minor, fluctuating vision issues. However, as the condition progresses, it impacts both eyes and can result in partial or complete vision loss. DR primarily develops when blood sugar levels remain uncontrolled, and if not detected early, it can cause permanent vision impairment. This study introduces an innovative multimodal fusion approach for diagnosing diabetic retinopathy. The proposed method integrates Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Ensemble Learning techniques, each contributing its unique strengths to the overall model. Initially, CNNs are used to extract high-level features from retinal images, leveraging their ability to identify intricate visual details. An SVM classifier then processes these extracted features, which enhances decision-making by defining complex decision boundaries. To further boost diagnostic accuracy, we incorporate Ensemble Learning, which combines the outputs of multiple models to create a more robust and generalized prediction. This approach not only improves the accuracy of diabetic retinopathy detection but also offers a scalable and efficient solution for applying advanced machine-learning techniques in clinical settings.

Keywords— Diabetic Retinopathy, Activation Function (ACAF), Convolutional Neural Network (CNN), Feature Extraction, Classification, Accuracy, Diabetes Mellitus, Support Vector Machines(SVM), Ensemble Learning, Multiple Models.

1. INTRODUCTION:

Diabetic Retinopathy (DR) is a situation that stems from Diabetes Mellitus (DM), which itself results from various microvascular and macrovascular abnormalities, alongside impaired glucose metabolism, leading to a continual disorder. Statistics indicate that approximately 80% of people with diabetes who have had the situation for 15 to 20 years broaden DR [1]. Currently, over 171 million people international are suffering from diabetes and the World Health Organization (WHO) initiatives that this range will upward push to 366 million by 2030. The commonplace signs and symptoms of DR encompass the appearance of spots or darkish strings in a single's vision (floaters), blurred vision, darkish or empty areas inside the visual field, new times of shade blindness or diminished color notion, negative night vision, and issue reading or seeing distant gadgets. DR usually progresses through stages: non-proliferative DR (NPDR) and proliferative DR (PDR). NPDR, the initial stage, may be similarly categorized into moderate, mild, and excessive paperwork. In slight NPDR, small balloon-like swellings within the retinal blood vessels, known as microaneurysms (MAs), may form, that could leak fluid into the retina. If these swellings burst, they can cause small blood spots, referred to as hemorrhages (HEMs).

As the situation advances, fluid and proteins leak from the damaged blood vessels, forming exudates (EXs). Exudates are classified into two kinds: The hard exudates are shiny yellow and waxy in appearance, while soft exudates have a white and fuzzy appearance and aren't properly described at the edges. Thus, MN, the earliest level of NPDR, may be described by the arrival of one or extra MA lesions and might, or might not, contain the presence of EX or HEMs. About forty percent of diabetic sufferers manifest moderate NPDR. There are, however, 2 entities that are more common and approximately 16% of patients with intermediate NPDR develop PDR within a year) respective. High-risk NPDR includes three or more severe signs and is the most likely to progress to PDR (50% within a year). Proliferative diabetic retinopathy – The most advanced stage of DR, PDR is characterized by the presence of new, fragile blood vessels in the retina and vitreous (gel-like substance filling the back of the eye). To avoid these risks and concerns, we must adopt a new solution that works with an artificial intelligence approach to analyzing an acceptably large volume of data (more the samples, the better the chances) and optimally selected images from different sources for early detection of Diabetic Retinopathy (DR). The possibility of this making a significant difference to people who have had long-term diabetes with the knock-on effect of helping to save their sight and quality of life. Consequently, multiple intelligent and technology-assisted means have been developed to detect DR using machine learning (ML) algorithms such as Support Vector Machines (SVM). Conventional machine learning methods encounter challenges when confronted with real-time analysis of extensive, intricate, and high-dimensional data, such as images.

These approaches lack the necessary domain knowledge and data representation capabilities, resulting in significant computational demands and limited adaptability in terms of performance. Conversely, Deep Learning (DL), an advanced subset of machine learning, excels in automating intricate tasks, unveiling concealed patterns, and effectively accommodating high-dimensional data. DL models, such as Convolutional Neural Networks (CNN), present enhanced domain awareness, dependable decision making, and overall superior performance in comparison to traditional machine learning approaches. Traditional machine learning methods can achieve remarkable success in knowledge discovery, but they generally have limited or even poor performance for complex data types like imbalanced, high-dimensional, and/or noisy datasets.

This problem emerges, chiefly because these techniques struggle in capturing the various features and components of such data across varying levels. This is where ensemble learning, a prominent research area in the field of data mining, brings together three disciplines focusing on different aspects of large-scale heterogeneous and fragmented data: data fusion, data modeling, and model clearing. In general, Ensemble learning starts with feature extraction involving multiple transformations.

A vanilla ensemble classification model works in two fundamental steps: Firstly, it yields labels of classes using various weak classifiers. It processes these outputs by consistent function (i.e., specific voting schemes) and then combines them to get the final output. Some of the ensemble classification techniques used in practice like Bagging, AdaBoost, and Random forests are better steps towards improving model accuracy than a single estimator(Random subspaces), Gradient boosting, etc. For example, the Bagging method where involves multiple subsets from the training dataset created by selecting samples with replacements. These training sets feed single models that will then be combined. A distinctive thing about the Bagging method is that the models are trained parallel which makes it compute faster and maintain consistency before submitting final results.

2. LITERATURE SURVEY:

There have been several approaches earlier on in DR detection; VM emphasized classifying NPDR to levels through Support Vector Machines (SVM) which differentially deployed saliency features with Street View data [38]. Carrera et al. This form has been done previously by the work of(2017) which categorized blood vessel density, number of microaneurysms, and hard exudate density as the most important features. This consisted of a two-class classification process: first identifying whether there is and then the presence or absence of NPDR. We compare this methodology with Decision Trees (DT), which achieved on average an accuracy of 85% and a maximum sensitivity of 95%. In the field of research, there have been some advancements in detecting microaneurysms from fundus images along with almost stage-based classification to determine the exact phase in which Diabetic Retinopathy (DR) has settled.

For instance, Yun et al. The designed methodology is to separate the retina fundus images into normal and different degrees of DR severity (moderate, severe, and proliferative DR). They pre-processed the images using morphological operations with disc and diamond structuring elements. Next, six features of pixel perimeter and area in the RGB channel were obtained. The classification was performed using a one-layered feed forward neural network of 8(6 input units corresponding to the extracted features, 4 output units representing different severity levels of DR) hidden units. They do so in their research by J. Calleja et al. We have DR detection: [6] conducted a two-step methodology to detect diabetic retinopathy (DR). It used Local Binary Patterns (LBP) for feature extraction and Machine Learning Techniques such as Support Vector Machines (SVM) and Random Forests to classify them. The Random Forest classifier had a better Accuracy of 97.46% as compared to the SVM. It is worth pointing out however that this is a small dataset with only 71 images used in the study. There are a myriad of computational methods reported in the literature for diabetic retinopathy (DR) estimation. Most of these techniques are aimed at replicating the experience of human experts and automating the detection of kidney lesions in retinal images for DR screening and grading.

In particular, this dataset challenges submissions to identify neovascularization and lesions (Messidor). Based on the revolutionary achievements of deep learning models in various image processing fields, researchers also turned to apply these models for detecting diabetic retinopathy (DR) recently. Critically, a lesion detector, i.e., the region-based fully convolution neural networks (R-FCN), which was designed to detect abnormal lesions automatically for DR diagnosis in four stages as well. Instance-learning methods help in the quest to predict lesions in fundus images, especially on the Messidor dataset. Detection and diagnosis of diabetic retinopathy (DR) have become potential applications for deep learning models as they can learn important features from input images, not rely on manually extracted features. This powerful representation of data has made deep models, especially Convolutional Neural Networks(CNNs), highly successful in understanding the complexities of retinal images. The recent studies concentrated on developing automated computer-aided diagnosis systems that utilize Deep Learning (DL) mechanisms to detect and classify the DR from digital fundus images. Baleen and Peto (2019) also began to consider the wider implications of AI, ML, and DL in ophthalmology and Cheung et al. In recent research, Mahendran et al.(2019) emphasized the use of the DL model to detect DR and Diabetic Macular Edema (DME) using Optical coherence tomography and digital fundus images. The fact that these studies indicate a rising tendency to incorporate Deep Learning methodologies into DR detection is confirmed. K. Anant et al. In the image mining and processing of DR, sharper / LANrobm's DIARETDB1 database used texture and wavelet features for early diagnosis with an accuracy of 97.95% [8].

M. Gandhi et al. Reference proposed an automated DR detection through a method with an SVM classifier and detection of exudates in fundus images. Moreover, some work applies deep learning and traditional manual features for the assessment of DR detection together. For example, J. Orlando et al. Chudzik, Bielecki & Pazlar in Ref [10] detected red lesions in the retina by using a CNN with additional handcrafted features. Pragathi P. [39] developed an ML algorithm named SVM PCA-MFO which is a combination of support vector machines (SVMs), PCA, and moth-flame optimization for the integrated approach. We evaluate an ensemble of ML algorithms of Gradient Boosting Trees (GBT), Decision Trees (DT), Support Vector Machines (SVM), Random Forest (RF), and Naïve Bayes to DR dataset, the results achieved indicate that SVM is the best model with mean accuracy equal to 76.96%. The performance was evaluated in an eight-class classification after the moth-flame optimization technique was integrated with SVM and PCA, and better performance compared to previous ML algorithms, and obtained an average value of 85.61%, efficiently classifying the DR severity levels. In the context of diabetic retinopathy (DR) detection, Wei Zhang discussed DeepDR, a system that applies transfer learning and ensemble learning for detecting DR in fundus images. To achieve accurate DR detection, DeepDR uses state-of-the-art deep neural networks including common Convolutional Neural Networks and novel customized autoencoder-inspired deep neural networks.

The system was developed with a caliber dataset of DR medical images in subdivisions such as NO-DR and MILD, MODERATE, and PROLIFERATIVE DR (level 1, 2) meticulously labeled by clinical ophthalmologists. We aim to build a strong model to identify DR from large datasets on high-end computational machines. To this end, we plan to apply transfer learning by using various pre-trained ConvNets to extract deep features from fundus images. We intend to leverage the information internalized in these models, to find the most important features for DR detection. In the next step, we build a stacked deep neural network to detect and classify the level of severity of diabetic retinopathy while using early-layer dropouts to prevent overfitting.

3. MATERIALS AND METHODS:

A. Image Preprocessing

Images in the collection, which uses the official diagnostic standard for diabetic retinopathy from the Indian Diabetic Retinopathy Image Collection (IDRID), are first acquired during image preparation. This is a multi-faceted step around comprehensively augmenting the dataset. This technique, which exists in the preprocessing phase and serves as the first step, is called Histogram Equalisation; meaning that we make changes to the intensity levels to achieve a desired histogram of images. Histogram equalization is applied using histograms learned from each image in the dataset for red, green, and blue channels individually while preserving color details to the extent in their original color space across all further processing steps. The pixel intensity values are first histo-equated to spread them across the full 8-bit color space. This enhances the image contrast and reveals smaller details. It's focused on improving mid-range contrast, containing over-contrast, and boosting high-contrast areas. Those modifications help increase the accuracy of later analysis stages. For example, the white patches on either side of colored segments in both the LuminalFundus are exaggerated to highlight differences when contrasted against normal fundi (right) versus a continuous color space range (left).

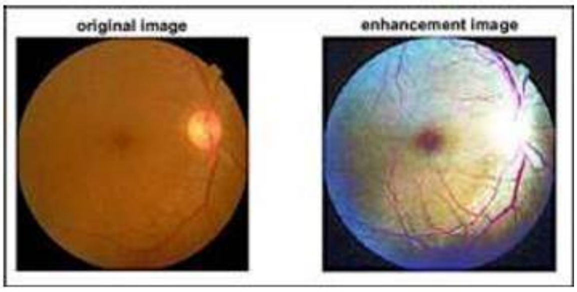

Fig.1. Histogram equalized Image

B. Noise Reduction procedure

Since we are categorizing the samples as they are, apparently uniform distribution will do well, and after getting them a HeLa_Less is used to enhance the color contrast between tissues so that it can be differentiated. Median Filtering: Median filtering is a nonlinear method for reducing “salt and pepper” noise very effectively [29], widely used in image processing because of its efficiency. This works better than convolutional filters for noise reduction as it preserves important pixel values and in turn image details. As seen in Fig. Binary Surreal autoregressive model with all of the atoms in layer 1, for \(D=12\).5Metric (CLL) Method Image a.median filtering improvements are clearer and demonstrate effectively this method does at removing noise without loss of significant features.

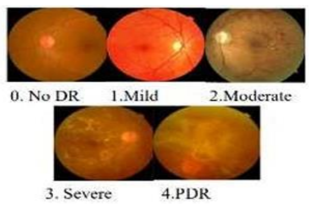

Fig .2. Each DR Stage image with histogram equalized.

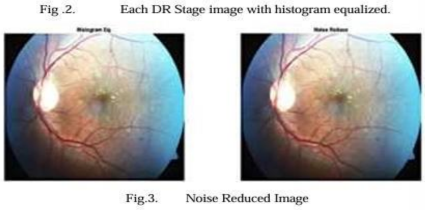

Fig.3. Noise Reduced Image

C. Image Re-sizing

A resized image means an image has different dimensions, than the original picture without cropping and either increased or decreased in size. This process entails changing the dimensions of the image, which can make a difference in both size and quality. Resizing large photos to the same small height or width is mainly for feature extraction. It is especially helpful in 200x200 pixels, which was demonstrated to obtain great precision and real-time performance.

D. Feature Extraction

Feature selection is the process of selecting informative features, i.e. those characteristics (often variables) of training examples that are used in making predictions… from unprocessed raw data. This method greatly reduces the data that needs to be analyzed but at the same time retains crucial information and speeds up overall processing. In this study, four crucial features supposing the early discovery of DR are pre-planned and analyzed. A microaneurysm is a tiny balloon (or bulge) in the wall of a small blood vessel, and they are among the earliest signs of diabetic retinopathy or damage to the retina that can result from diabetes. The optic disc (OD) (also known as the blind spot) is another critical part of an eye and it is where the optic nerve enters and exits on the retina. Therefore, the OD serves as an essential retinal landmark for the scrutiny of different retinal conditions.

Hemorrhages (HEs) which are the most frequent type of retinal bleeding usually associated with diseases like DR, hypertension, and age-related macular degeneration. Various diseases of the retina are diagnosed and managed based on the fovea, which is a small pit in the retinal area that is responsible for high visual acuity. Following the initial feature extraction process, the features obtained are then reviewed by an ensemble classifier. DR, which is damage to blood vessels in the retina due to diabetes can cause blindness if complications are not treated. Accordingly, early diagnosing of the deformity is essential to enable early interventions that can be administered before loss of vision.

E. VisualSimultaneous Localisation and Mapping (vSLM)

VSLM (Visual Simultaneous Localization and Mapping), is a method that allows you to determine the spatial coordinates of the device, together with the derived from camera data representation on this piece of the map. Deployed in robotics and computer vision, VSLM plays a key role in real-time map generation and object localization. This research utilizes the concept of visual SLAM to analyze and predict visual features from retinal fundus images for identifying diabetic retinopathy (DR). The scenes that VSLM intelligently recognizes and follows – using its adaptive vision algorithms – are constantly changing visual elements in the environment. It is essential for identifying primary symptoms in retinal images, including microaneurysms, hemorrhages, and exudates– critical predictors of DR — as well as the detailed description of anatomical structures within the retinal tissue to improve localization methods of lesions and anomalies.

F. Wavelet Convolutional NeuralNetwork (Wavelet CNN)

The Wavelet CNN represents a deep learning architecture that integrates wavelet transforms with CNN to conduct spatial and spectral analysis of images. This model is employed in conjunction with vSLM-extracted features to enhance the detection of diabetic retinopathy (DR). The Wavelet CNN method utilizes wavelet transforms to acquire spectral features from retinal images, thereby complementing the spatial data derived from the vSLM map.

G. Hierarchical feature learning

Wavelet CNN conv layers perform an implied operation on input images to extract various levels of details in depth. These features include basic properties such as edges and textures, together with some pathological properties like certain types of lesions and appearances that are crucial for the diagnosis of DR.

H. Classification

We propose to predict the severity of DR with a modified CNN classifier (MCNN) that uses features obtained from analysis by both vSLM and Wavelet CNN algorithms, as having an MCNN classifier is ideal in managing the dimensionality of large datasets while performing classification tasks efficiently. In this proposed model, as the vSLM and Wavelet CNN are not homogenized in the extraction of distinct features from retinal images the novel algorithm uses them in conjunction. Combining spatial and spectral features with the Transformation power of Wavelet CNNs enhances its scaleable accuracy as well as reliability for DR detection. Moreover, the mapping and localization capabilities of vSLM enhance diagnostic accuracy through visualization of detected lesions in their anatomically appropriate location.

I. Modified CNN

Convolutional Neural Networks (CNNs) have seen unprecedented success in the domains of computer vision tasks e.g., image classification, localization, and segmentation. Their architecture is designed to operate on grid-like data structures (for example, images) through layers that specialize in detecting and optimizing local spatial feature hierarchies: Convolutional Layers. CNNs are particularly important because the classification of diabetic retinopathy (DR) requiring detailed information from fundus images is an essential part of diagnosis. The choice of activation functions is one of the key factors affecting performance in a CNN. Those functions make the model non-linear and have a significant impact on how some learning optimization functions work.

4. RESULTS AND DISCUSSION:

Datasets such as Messidor, IDRiD, Kaggle EyePACS, and APTOS contain photographs taken under standardized conditions. Including a variety of non-standard situations. Although the uniformity of some datasets raises concerns about the suitability of trained algorithms for real-world situations, however, the heterogeneity across diverse datasets poses challenges for Algorithms Especially because of the noise generated. Therefore, it is an obstacle to efficient and effective analysis. Datasets such as Messidor, IDRiD, Kaggle EyePACS, and APTOS contain photographs taken under standardized conditions. Including a variety of non-standard situations. Although the uniformity of some datasets raises concerns about the suitability of trained algorithms for real world situations, however, the heterogeneity across diverse datasets poses challenges for Algorithms Especially because of the noise generated. Therefore, it is an obstacle to efficient and effective analysis. The retinal images used in this study were obtained from the EyePACS dataset, which was generously provided by Kaggle. There are 3,662 images in total. These images were taken with varying levels of noise and quality. It presents a variety of real-world situations. The dataset is divided into 550 images for testing and 3,112 images for training. Each image is associated with an intensity value from 0 to 4, which indicates the DR level. An intensity level of 0 indicates a normal image with no DR indication.

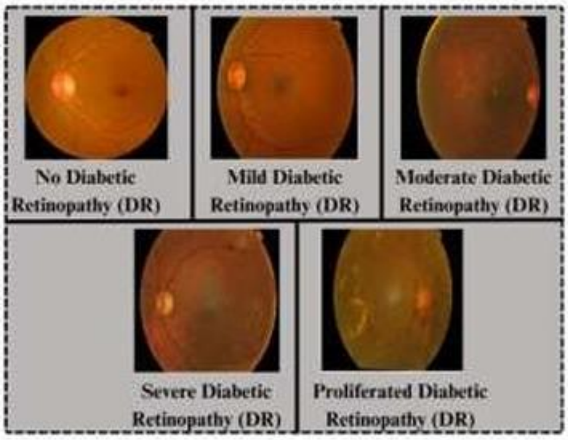

Fig.4. Various Types Of DR

The various features were extracted using the vSLM and wavelet CNN techniques. The results emphasize the gradual progression of DR by demonstrating the growing complexity and quantity of extracted features at each stage. In Stage 0, there were no pathological characteristics such as microaneurysms or hemorrhages observed. Only optic disc and basic retinal structure mapping were found to be significant. As the disease advances to mild and moderate stages, there is a clear rise in the number of microaneurysms, hemorrhages, and exudates, indicating the worsening severity of DR. The spectral features also become more noticeable, offering a more detailed depiction of retinal defects. During severe and proliferative stages, extracted features reach their maximum level, exhibiting a significant concentration of all disease markers, which highlights the critical state of the retina. The detailed retinal structure maps and improved spectral features in these advanced stages are essential for accurate diagnosis and treatment planning, highlighting the efficacy of feature extraction methods employed in this study.

The ensemble learning model was compared with other advanced ensemble techniques, such as Bagging, Boosting, and Random Forest, using the EyePACS dataset for diabetic retinopathy detection. Key parameters for the experiments included 200 epochs, a learning rate of 0.01, a batch size of 64, and the Adam optimizer. The performance of the proposed ensemble method was evaluated across different epochs, learning rates, and batch sizes, utilizing the Scikit learn and Keras frameworks. The proposed ensemble approach consistently achieved higher accuracy than other ensemble methods, particularly as the number of epochs increased.

Several ensemble learning techniques, including Bagging, Boosting, Random Forest, Stacking, and Gradient Boosting, were applied to classify DR images into five categories based on severity. A comparative analysis was performed to assess the performance of the proposed ensemble model on various benchmark datasets, including DiaretDB0, DRIVE, CHASE, and EyePACS Kaggle. The proposed ensemble method consistently outperformed other models in terms of accuracy, precision, F1 score, and AUC, while maintaining the lowest model loss. Significant improvements in accuracy and model loss were observed, particularly on the Kaggle and DRIVE datasets, demonstrating the robustness and effectiveness of the ensemble method in detecting and classifying DR.

When the model was retrained using the ensemble learning approach, all evaluated datasets showed improved performance. The model achieved a higher accuracy of 97.12% on the DiaretDB0 dataset, outperforming other models such as

ResNet-152 and VGG-19. The proposed ensemble method reached a high accuracy of 99% incorrect classifications. On the EyePACS Kaggle dataset, the model achieved an accuracy of 99.02%, proving its strong capability in handling diverse image attributes. Similarly, the accuracy for the DRIVE dataset was 99.15%, while for the CHASE dataset, it was 98.12%. These results confirm the effectiveness of the ensemble method and its ability to consistently deliver high accuracy across varied datasets. This highlights its applicability in diagnosing and classifying DR.

5. CONCLUSION:

The paper gives a comprehensive review of the method developed for the detection and classification of DR. Features used in this evaluation are vSLM, Wavelet CNN for feature extraction, and a new CNN model which is accompanied by ACAF for detection and classification. Feature extraction procedure which used vSLM to produce precise retinal maps succeeded in the accurate identification of microaneurysms, hemorrhages, and exudates that define the signs of DR. This method improved the spatial context of retinal images to a large extent, which was advantageous in accurate detection of DR. vSLM was incorporated and complete Wavelet CNN for extracting spatial and spectral features from the retinal images was performed. The combination of wavelet transforms with CNNs enhanced and developed the model to capture fine details linked with several phases of DR and further investigation of retinal anatomy. The analysis of the multiple benchmark datasets showed that the proposed CNN model with the inclusion of ACAF would recommend the best method for the classification of DR stages. It outperformed other models consisting of ResNet-152 and VGG-19 with an accuracy of 97.12 % for use on the DiaretDB0 dataset. The EyePACS Kaggle demonstrated an even degree of the model as it got an accuracy of 99.02%. Additionally, it achieved 99.15 % on the DRIVE dataset. The results of accuracy on the CHASE dataset show only 98.12 % accuracy. These results demonstrate the ability of the proposed integrated model to achieve DR detection and of the proposed feature extraction and classification methods in detecting DR.

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