Diabetic Retinopathy Detection using Machine Learning (Image Processing): A Review

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***Abstract*— Diabetic retinopathy (DR) is a serious complication of diabetes mellitus and a leading cause of vision impairment worldwide. Early detection and intervention are crucial in preventing vision loss among diabetic patients. In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown remarkable success in various medical image analysis tasks, including the detection of diabetic retinopathy. This paper presents a novel approach for the automated detection of diabetic retinopathy using CNN's. Our proposed method involves preprocessing retinal fundus images to enhance contrast and remove noise, followed by feature extraction using a pre-trained CNN architecture. The extracted features are then fed into a classification model for the detection of diabetic retinopathy. We utilize a large dataset of annotated retinal images to train and validate our CNN-based detection system, ensuring robust performance across diverse clinical scenarios. Experimental results demonstrate the effectiveness of our approach in accurately detecting diabetic retinopathy, achieving state-of-the-art performance in terms of sensitivity, specificity, and overall accuracy. Moreover, the proposed method exhibits robustness to variations in image quality and pathological characteristics, making it suitable for real-world clinical applications. In conclusion, our study highlights the potential of deep learning, specifically CNNs, as a valuable tool for the early detection and management of diabetic retinopathy. The proposed framework holds promise for integration into existing healthcare systems, facilitating timely diagnosis and intervention to prevent vision loss among diabetic patients.**

***Index Terms*— Diabetic retinopathy (DR), Convolutional Neural Networks (CNNs), CNN-based Detection System, Deep Learning, etc.**

I. INTRODUCTION

Diabetic retinopathy is a significant public health concern, especially in diabetic patients. The retina, a delicate tissue at the back of the eye, is particularly vulnerable to the effects of high blood sugar levels. Prolonged exposure to hyperglycemia leads to microvascular changes, including retinal hemorrhages, micro aneurysms, and neovascularization. These alterations can ultimately result in vision loss if left untreated. Manual assessment of retinal images by ophthalmologists is time-consuming and subject to inter-observer variability. Therefore, there is a growing need for automated methods that can accurately identify DR and classify its severity. Convolutional neural networks (CNNs), a subset of deep learning models, have emerged as powerful tools for image recognition tasks. Their ability to learn hierarchical features directly from raw pixel data makes them well-suited for medical image analysis. In this study, we propose an automated system for diabetic retinopathy detection using CNNs. Our primary objectives are as follows:

- Classification of Retinal Images: We aim to classify retinal fundus images into two primary categories: normal and abnormal. Abnormal images will further be categorized based on the severity of DR.
- Early Intervention: By automating the diagnosis process, we can facilitate early intervention. Detecting DR at an early stage allows for timely treatment, preventing irreversible vision loss.
- Reducing Ophthalmologist Workload: Our system will assist ophthalmologists by providing preliminary assessments, allowing them to focus on complex cases and personalized patient care.

Diabetic Retinopathy (DR) has been considered to be the most menacing eye related disease which causes blindness or vision loss in a long run. Till September 2021, it is estimated that approximately one-third of people with diabetes are affected by diabetic retinopathy (DR) to some extent. This translates to millions of individuals worldwide. In this project, a DR detection technique, involving digital image processing, has been developed by utilizing retinal image, where fundus image has been obtained from patient's retina. Here, certain software has been utilized for analysing the fundus image that are captured via Peek retina attached on smartphone camera lens.

Diabetic Retinopathy (DR) typically progresses through several stages, ranging from mild to severe. The stages of DR, in order of increasing severity, are as follows:

- Mild Non-Proliferative Diabetic Retinopathy (NPDR): In this early stage, microaneurysms (small bulges in blood vessels) may appear in the retina. Some blood vessels may leak, causing minor hemorrhages or fluid buildup.
- Moderate Non-Proliferative Diabetic Retinopathy (NPDR): As the disease progresses, more significant changes occur in the retina. Blood vessels become blocked, leading to reduced blood supply to some areas.
- Severe Non-Proliferative Diabetic Retinopathy (NPDR): In this stage, a significant number of blood vessels become blocked or damaged. This results in a lack of blood supply to large areas of the retina, leading to ischemia (lack of oxygen).
- Proliferative Diabetic Retinopathy (PDR): PDR is the most advanced stage of diabetic retinopathy.

New, fragile blood vessels grow on the surface of the retina and into the vitreous humor (the gel like substance that fills the eye). The most common stages of DR that occur in people are the early stages, including Mild NPDR and Moderate NPDR. These stages often have mild or no noticeable symptoms, making regular eye exams crucial for early detection and intervention. It's important to manage diabetes effectively and monitor eye health regularly to prevent the progression of DR to more advanced stages, which can result in severe vision loss or blindness.

II. LITERATURE REVIEW

Literature survey is the most important step in any kind of research. Before start developing we need to study the previous papers of our domain which we are working and on the basis of study we can predict or generate the drawback and start working with the reference of previous papers. In this section, we briefly review the related work on diabetic retinopathy detection and their different techniques.

[Farrikh Alzami, 2019] described a system for diabetic retinopathy grade classification based on fractal analysis and random forest using MESSIDOR dataset. Their system segmented the images, then computed the fractal dimensions as features. They failed to distinguish mild diabetic retinopathy to severe diabetic retinopathy. [2]

[Qomariah 2019] proffered an automated system for classification of Diabetic Retinopathy and normal retinal images using concurrent neural network (CNN) and support vector machine (SVM). Features comprised of exudates, haemorrhage and microaneurysms. The author partitioned the proposed system into 2 parts: the first part composed with feature extraction based on neural networks and the second part performed classification using SVM. [3]

[Kumar, 2018] proposed a system for improved diabetic retinopathy detection by extracting area and number of microaneurysms using colour fundus images from DIARETDB1 dataset. Pre-processing of fundus images were performed using green channel extraction, histogram equalization and morphological process. Principal component analysis (PCA), contrast limited adaptive histogram equalization (CLAHE), morphological process, averaging filtering were applied for microaneurysms detection and classification is done by linear support vector machine (SVM). [4]

[Mohamed Chetoui, 2018] proffered a system which detect diabetic retinopathy using different texture feature and machine learning classification model. Two features haemorrhage and exudates are extracted using local ternary pattern (LTP) and local energy- based shape histogram (LESH). SVM is used for leaning and classification of extracted histogram using feature vectors of LTP and LESH. [5]

[S Choudhury, 2016] proposed a system which deals with fuzzy C means based feature extraction and classification of diabetic retinopathy using SVM. Blood vessels extraction is performed using top hat filter and mathematical morphology. Retinal vessel density and exudates are chosen as the features. Exudate extraction is done by fuzzy C means segmentation. Gaussian Radial Basis function is used to map the training data into SVM kernel space. [6]

[Sangwan, 2015] described a system that identifies different stages of diabetic retinopathy based on blood vessels, haemorrhage and exudates. The features are extracted using image pre-processing and they are fed into the neural network. SVM based training provided into the data and classify the images into three categories as mild, moderate non proliferative diabetic retinopathy and proliferative diabetic retinopathy. But the system could not give expected results if the exudate areas in the fundus images exceeds that of an optical disc size. [7]

[Morium Akter, 2014] described a system for morphology based exudates detection from colour fundus images. The model uses grayscale conversion, histogram equalisation, thresholding, erosion, dilation, logical AND operation and watershed transformation. The system produces an output with ranges of exudates affected in diabetic retinopathy. [8]

III. SYSTEM DESIGN

The proposed work for diabetic retinopathy detection through image processing involves collecting and pre-processing a diverse dataset of retinal images, developing image processing algorithms and a deep learning model for retinopathy detection, training and validating the model, designing a user-friendly software interface, integrating the software with healthcare systems, rigorous real-world testing and validation, regulatory compliance, healthcare professional training, user support, and a commitment to continuous improvement through ongoing model updates and enhancements. This comprehensive approach aims to create an effective and accessible tool for the early detection of diabetic retinopathy, enhancing patient care and outcomes while complying with healthcare regulations.

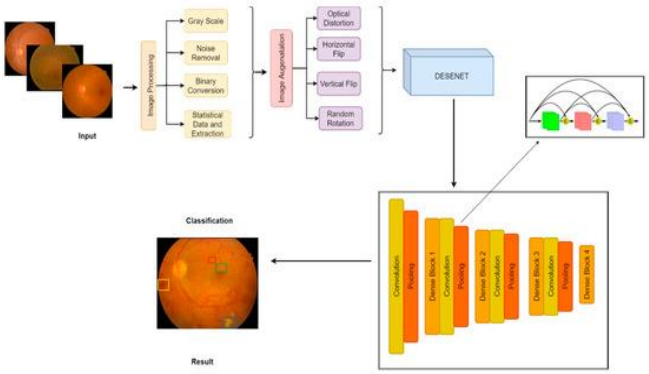

Figure-1: System Architecture Diagram

- Dataset Curation: Curate a diverse dataset of retinal images encompassing different DR severity levels, sourced from publicly available repositories and collaborating healthcare institutions. Annotate the dataset with ground truth labels indicating the presence and severity of DR lesions, ensuring reliable training and evaluation of the CNN model.
- CNN Architecture Design: Explore and evaluate different CNN architectures, including variants of popular models such as Res-Net, VGG, and Inception, to identify the optimal architecture for DR detection. Customize the selected architecture by adjusting hyper-parameters, including network depth, filter sizes, and activation functions, to optimize model performance.
- Training and Validation: Divide the annotated dataset into training, validation, and test sets, ensuring balanced distribution across DR severity levels. Train the CNN model using the training set, employing techniques such as transfer learning and data augmentation to improve generalization performance. Validate the trained model using the validation set and fine-tune hyper-parameters based on performance metrics such as accuracy, sensitivity, and specificity.
- Performance Evaluation: Evaluate the performance of the trained CNN model using the test set, quantifying performance metrics including accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). Compare the performance of the CNN model with existing DR detection methods, including manual grading by ophthalmologists and traditional machine

learning algorithms, to assess its efficacy and robustness.

- Deployment: Once the model has been trained and evaluated, it is deployed into a production environment where it can be used to analyze new input images in real-time.
- Inference: In the inference phase, the deployed model analyzes new blood cell images to detect the presence of ALL cells. The model outputs predictions indicating whether each cell is normal or indicative of leukemia.
- Result Visualization: The final step involves visualizing the results of the ALL detection process. This may include generating heatmaps or overlaying bounding boxes on the original images to highlight regions identified as ALL cells.

Overall, the system architecture for detecting Acute Lymphoblastic Leukemia using deep learning encompasses data acquisition, preprocessing, model training, evaluation, deployment, inference, and result visualization stages, providing a comprehensive framework for automating the leukemia detection process.

IV. MATHEMATICAL MODEL

A mathematical model for image processing and machine learning in diabetic retinopathy (DR) typically involves multiple stages, including image acquisition, preprocessing, feature extraction, classification, and prediction. Below is an overview of the mathematical models used at each stage:

1. Image Processing Stage
   a. Preprocessing
   - Histogram Equalization to enhance contrast.

$$s_k = (L-1)\sum_{j=0}^{k}\frac{n_j}{N}$$

Where,
s_k is the new intensity level,
L is the total number of gray levels,
n_j is the number of pixels with intensity j, and
N is the total number of pixels.

   - Gaussian Filtering for noise reduction:

$$G(x,y) = \frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Where,
σ is the standard deviation of the Gaussian distribution.

   - Adaptive Thresholding using Otsu's method:

$$\sigma_B^2 = w_1 w_2(\mu_1 - \mu_2)^2$$

2. Feature Extraction
   a. Texture Features (Haralick Features)
   - Gray-Level Co-occurrence Matrix (GLCM)

$$P(i,j) = \frac{N_{ij}}{N}$$

Where,
P(i,j) is the probability of gray-level i transitioning to j,
Nij is the number of occurrences, and N is the total number of transitions.

   - Entropy (measures randomness in pixel intensities.

$$H = -\sum_{i=1}^{N} P(i)\log P(i)$$

   b. Edge and Vessel Detection
   - Hessian Matrix (for vessel enhancement)

$$\boldsymbol{H} = \begin{bmatrix} \frac{\partial^2 I}{\partial x^2} & \frac{\partial^2 I}{\partial x \partial y} \\ \frac{\partial^2 I}{\partial y \partial x} & \frac{\partial^2 I}{\partial y^2} \end{bmatrix}$$

3. Machine Learning Model
   a. Classification
   - Logistic Regression (for binary classification: DR vs. Non-DR)

$$P(Y=1|X) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\ldots+\beta_n X_n)}}$$

   - Support Vector Machine (SVM)

$$f(X) = w^T X + b$$

with decision boundary:

$$y = \text{sign}(w^T X + b)$$

   b. Deep Learning for DR Detection
   - Convolutional Neural Network (CNN) Layers
Convolution operation:

$$S(i,j) = \sum_m \sum_n I(m,n)K(i-m, j-n)$$

where $I(m,n)$ is the input image, and $K(i,j)$ is the convolution kernel.

   - Activation function (ReLU):

$$f(x) = \max(0,x)$$

   - Fully connected layer:

$$y = WX + b$$

   - Loss Function (Binary Cross Entropy)

$$L = -\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)]$$

4. Prediction & Evaluation
   - Accuracy, Precision, Recall, and F1-Score

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

- **AUC-ROC Curve** (for model performance evaluation):

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

where TPR (True Positive Rate) and FPR (False Positive Rate) are plotted.

This mathematical framework integrates image processing techniques for noise reduction, feature extraction for vessel and lesion detection, and machine learning/deep learning models to classify and predict diabetic retinopathy. It forms the basis for automated DR screening systems used in healthcare.

V. CNN ALGORITHM

- The main technique of the proposed model is to detect diabetic retinopathy.
- The proposed framework is implemented using a convolutional neural network, a type of deep learning technique that convolves input images using kernels or filters to extract features.
- When a fXf filter is applied to a NxN image, the convolution process learns the same feature over the whole image. After each operation, the window slides, and the feature maps learn the features.
- Convolution is the initial layer used to extract features from an input image. Convolution learns visual features from small squares of input data, preserving the link between pixels.

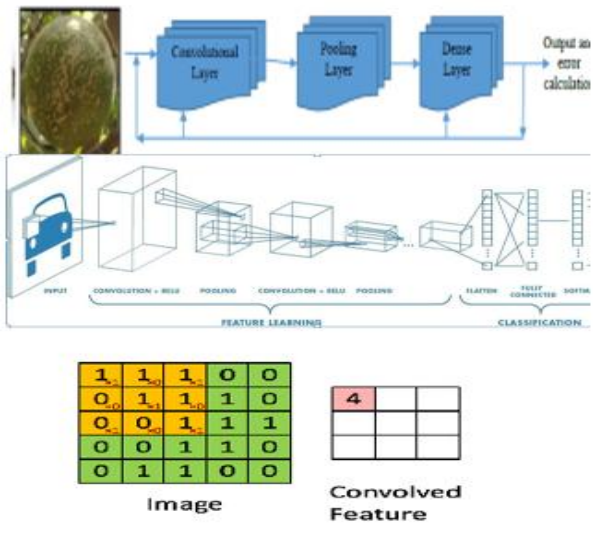

Figure-3: CNN Architecture

- Pooling Layer
  - Pooling layer section reduces the number of parameters for large images.
    - Max Pooling
    - Average Pooling
    - Some Pooling
- Fully Connected Layer
  - In the layer we refer to as the FC layer, we converted our matrix into a vector and fed it into a neural network or other fully connected layer.

VI. CONCLUSION AND FUTURE SCOPE

Conclusion:

Image segmentation techniques perform well comparable to the methods used in practice. Result of image segmentation method is dependent on many factors such as intensity, texture and image content. In our project a fast and efficient method for extracting blood vessels, hard exudates in colour eye fundus image has been presented. The simulation results on retinal dataset illustrates that the proposed methodology can work with retinal images and improves blood vessels and hard exudates detection to reduce human errors or to provide service in remote areas. Our project work demonstrates an important screening tool for early detection of a Diabetic Retinopathy. The proposed method exhibits less computational time to detect automatically the important clinical features of retinal images such as blood vessels, hard exudates and optic disc.

Future Scope:

The future work can be concentrated on extraction of exudates by combining unsupervised and supervised detection methods in order to have better results.

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