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RETINAL LESIONS DETECTION USING TRANSFER LEARNING FOR DIABETIC RETINOPATHY

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ABSTRACT: Diabetes' serious complication, diabetic retinopathy (DR), which can potentially be lifethreatening, might result in vision loss in certain situations. Although it has no symptoms in the early stages, this illness is regarded as one of the "silent diseases" that go unnoticed. It can occur if person have type one or type two diabetics. Also it occur due to high sugar levels in blood. At starting there is only mild vision problems eventually lose sight. It is an ordinary eye disease found in people with diabetes. This analysis automatically and efficiently detect and classify the severity of DR. The extracted features are fed to CNN for classification purpose. This method reducing the workload of an ophthalmologist with an higher accuracy of around.

KEYWORDS*:* Diabetic Retinopathy (DR), Micro Aneurysms (MA), recursive region growing segmentation (RRGS), Hemorrhages (HEM)

I. INTRODUCTION

Diabetes is a severe (can be long-lasting) condition where the body cannot generate enough insulin or utilize the insulin it produces. The longer a patient has diabetes and has poor blood sugar management, the greater the chance of complications, some of which could be fatal. Numerous illnesses, including kidney damage, nerve damage, eye damage, cardiovascular disease, hearing loss, Alzheimer's, skin issues, infections, foot damage, and numerous other complications, can be brought on by diabetes. Globally, 1.5 million deaths were recorded from diabetes in 2019, according to the World Health Organization (WHO). The organization approved five worldwide coverage and treatment goals for diabetes in May 2022, which are to be met by 2030. Diabetes affected 536.6 million people aged 20 to 79 worldwide in 2021, with a forecast rise to 783.2 million by 2045. Diabetes affected men and women at almost the same proportions, while people aged 75 to 79 had the highest prevalence. Estimates show that high-income countries had a greater frequency than low-income ones (11.1% vs. 5.5%) and in urban regions (12.1%) than in rural ones (8.3%) in 2021. Over a billion people globally, or more than 10.5% of all adults, now have diabetes, which affects a little over half a billion people [1].

To avoid complications from DR, the WHO and the American Academy of Ophthalmology advise patients with diabetes to have eye exams at least once a year. This early evaluation would prevent progression caused by any examination delay. However, for two critical reasons, this advice is inappropriate in many countries. First, several patients, particularly in developing countries, cannot afford routine eye tests. Secondly, not enough medical professionals to meet the demand for ophthalmologists and not enough screening equipment due to the rise in diabetes patients [2]. Additionally, patients with early-stage DR do not show explicit symptoms or have vision problems.

Due to excessive blood sugar levels, DR is a secondary illness or consequence of

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diabetes that damages a diabetic person's eyes. Identification of diabetic patients with retinopathy helps to avoid vision loss. Retinopathy can be avoided with early identification and a healthy lifestyle. Through techniques like image processing and deep learning models, artificial intelligence detects DR. Proliferative (PrDR) and non-proliferative (NPrDR) retinopathy are the two stages of DR grading. The retina is healthy without DR, and there are three levels of NPrDR: mild, moderate, and severe [10].

The main cause of DR is due to damages in the retinal blood vessels. Too much sugar level in blood may cause blocks in blood vessels that nourishes the retina, there stop its blood supply. As a result, the eye try to grow new blood vessels. But these newly developing blood vessels don't develop well and properly so it leak fastly and easily. At initial states there is no symptoms or there is only mild vision problems, finally it may cause blindness. The stage can occur in anyone in any age who have type I or type II diabetes. The symptoms of DR may include blurred vision, fluctuating vision, Spots or dark strings floating in vision, bleary-eyed colored vision, empty or dark areas in eye vision and the important one is vision loss. DR usually affects both eyes [7].

Early DR**:** It is also known as non - proliferative DR (NPDR).Here new blood vessels are not developing or proliferating during NPDR the blood vessels walls become weaker. Micro aneurysms bulges from the walls of the blood vessel and some case leaking blood and fluids into the retinal. Larger retinal vessels begin to dilate and the vessels become irregular, and the NPDR may progress from mild to severe that is more blood vessels become begin to swell and may blocked. In Some case macula that is the central part of the retina begins to swell is known as macular edema, and this condition requires treatment [6].

Advanced DR**:** DR, it may lead to severe, this condition is known as proliferative DR. Here damaged blood vessels become blocked and will cause unconditional growth of new and unusual blood vessels growth in the retinal layer, and may leak a clear, gelatin like substance known as vitreous. Finally the growth of this new blood vessels cause the retina to isolate from the back of the eye. This recently created vessels interfere with the normal flow of fluid and leads to pressure on the eyeball. It damages the nerve that carries signal from eye to optic nerve, is known as glaucoma.

DR is described by different lesions such as dark lesion/red lesions and bright lesions. Dark lesion includes hemorrhages (HEMs) and micro aneurysms (MAs). And the bright lesions include exudates (EXs). MAs, is the initial stage of DR, it appears as smaller reddish and smaller circular dots. Hemorrhages are due to retinal ischemia. They appear as bright red spots with variable size and shapes. EXs which appears as a bright, yellowish patches of different sizes and shapes. A CAD which accurately identify these lesions for screening DR.

In this work first perform green channel extraction, it provide maximum contrast combines the use of green channel filter extraction, it helps to distinguish MAs and Has from the other retinal features. Then the Matched filter (MF) along with Laplacian of Gaussian (LoG) improve the diabetic lesion detection performance. Matched Filter will produce a strong and good responses to vessels, MAs and HEMs detection. To segment EXs and HEMs LoG filter together with MF is used. Contrast enhancement based on Differential Evolution (DE) automatically set the bandwidth and gain for bright lesions for making the system more

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flexible for different image depending on their attributes. Retinal blood vessel extraction can be detected using MF and LoG filtering combination. For detecting exudates and boundaries of similar pixel within the region Recursive region growing segmentation (RRGS) algorithm is used. In RRGS, only consider the nearest pixels in the a like region to maintain homogeneous grey scale properties. Then feature extraction and classification is based on convolutional neural network. It is a feed forward NN, extract large number of features. The feature vectors are created by using PCA

Transfer learning applies knowledge from one problem to a similar one. It allows a pre-trained model to apply information from a massive quantity of labeled data to a similar task and then fine-tune it to the target task using relatively small amounts of labeled data. Collecting labeled data is both time-consuming and expensive in various practical applications. Transfer learning can solve this problem by starting with a pretrained model that is already familiar with the core patterns and features of the data. It enables satisfactory results with a substantially smaller amount of labeled data than traditional methods require.

II. LITERATURE SURVEY

Qomariah, D.U.N.; Tjandrasa, H.; Fatichah, C , et.al [3], explained the input dataset, features were extracted using a CNN model, and the classification was performed using a support vector machine model. Compared to classifying using the CNN model, this strategy offered faster execution. Medical imaging is crucial at all fundamental health difficulty levels and various medical diseases. DR grading from fundus photos has been the subject of much research using a variety of transfer learning approaches using publicly available datasets.

Hussain, M.A.; Islam, S.O.B.; Tiwana, M.; Qureshi, W et al. [4] described accessible predictor and classifier for hard exudates using artificial neural networks (ANN). Feature extraction and detection were performed using the Speed Up Robust Features technique. For classification, however, Feed-Forward Backpropagation ANN was employed. The work's major flaw is that it only used a dataset containing 48 photos. Ahmad et al., compare multiple designs, including Inception-ResNetV2, ResNet50, NASNet, InceptionV3, VGG16, DenseNet121, Xception, and VGG19. The models carried out classification and localization tasks, which were trained on a proprietary dataset and tested on the Messidor-2 dataset. The CNN and Contrast Limiting Adaptive Histogram Equalization (CLAHE) approaches increased the area under the curve and the fundus images' quality.

Fayyaz, A.M.; Sharif, M.I.; Azam, S.; Karim, A.; El-Den, J, et.al [8] described the SVM kernels with Ant Colony System (ACS) feature selection method. It evaluates a technique for detecting DR using 250, 550, and 750 features. The cubic SVM classifier significantly outperformed all other kernels, with an accuracy of 92.6%, 91.8%, and 93%, respectively, for 250, 550, and 750 attributes.

Jena, P.K.; Khuntia, B.; Palai, C.; Nayak, M.; Mishra, T.K.; Mohanty, S.N [9] described the segmentation which was performed utilizing an asymmetric deep learning architecture for DR screening using U-Net networks. CLAHE is used to analyze and improve the green channel images. For APTOS and MESSIDOR, the non-DR detection accuracy was 98.6% and 91.9%, while the PrDR detection accuracy was 96.8% and 95.76.

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Kothare, K.S.; Malpe, K. et.al [5] constructed a support vector machine and Naive Bayes model with a binary pattern approach. The algorithm was applied to choose pertinent features. As opposed to this, the models were used to categorize patients as having the condition. Concerning accuracy, execution time, and memory use, the support vector machine performs better than the naive Bayes.

III. Retinal Lesions Detection Using Transfer Learning For Diabetic Retinopathy

Based on the size images are classified into two sets. First resize the input images into 600* 800 pixels. From the RGB components the maximum contrast for the pixel is provided by the green channel component. The green image which contains 256 pixel levels. This will reduce the storage space and computational time. retinallesion detection because the OD and blood vessels are the major sources of false positives in bright and dark lesion detection. The vessels which appears as dark lengthened structures in the retinal images, so the faulty removal of vessels restrict dark retinallesion detection. And this faulty removal cause OD to suppress some bright lesions.

So the evacuation of OD and vein extraction assumes an essential job in sore identification. Here use a kernel fuzzy c-means to extract the vessels because it provides high blood vessel extraction accuracy. OD which is occupied in the Center third of the retina. For removing optic disc first focused on the center third of the green intensity images. Next, median filter is used to process the image of pixel size 11 × 11 for locate the narrow blood vessel inside OD. To detect OD location morphological closing and opening operations are performed. Morphological opening eliminates the small objects in the retina. The exudates appears as yellow colored lesions of different sizes and shapes. RRGS identify similar pixels to determine the boundary in a region. RRGS, consider to nearest pixel to have enough properties of homogeneous grey scale. Here each image pixels are arranged in raster form. A pixel p, located at (x, y) co-ordinates has 4 neighboring pixel co-ordinates of (x, y+1), (x, y-1), (x-1, y) and (x+1, y).

Where pi is the adjacent pixel, where i represents the horizontal or vertical co-ordinate related to the pixel p. At first the difference in intensity between p and pi are calculated. pi get added to the region and it's top if it's difference is less than or equal to the threshold value. This process is repeated till the point when all pixels are blended and the first pixel is included in that. Then replace the merged pixels by median intensity of the region. This is repeated until the whole image was segmented. The background median intensity was set as the threshold value for classification of the image. Segmented regions above and below this threshold were classified as exudate and nonexudate regions respectively. As the OD and exudates are similar with in a defined boundary, then extract this region using OD recognition algorithm to avoid the classification with the exudates.

Matched Filtering and Laplacian of Gaussian Filtering**:** along with a Gaussian kernel obtains a high responses for both the dark lesion and the bright lesions. At sharp intensity transition the LoG response gives a zero crossing at its center. This filter along with MF, detects the bright and dark lesions with an intensity profile. Mutual Information Maximization using DE**:** I(X; Y) represents the mutual information of two Independent Random Variables X and Y with probability distribution p(x) and p(y), respectively.

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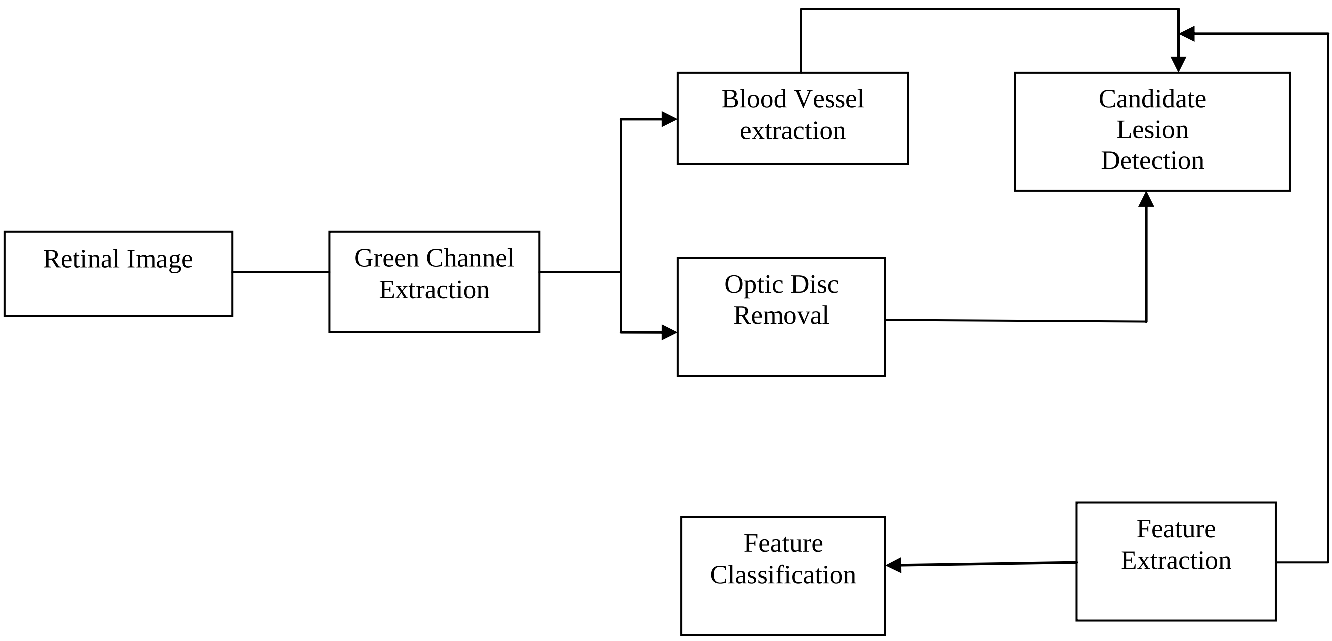

Fig .1: Block Diagram

In MA detection, for a local window if the neighboring pixels count is less than a particular threshold, at that point the pixel is discarded. In HEM discovery, the region whose area is not exactly a specific edge is then removed. HEMs are look like a dark lesions, then at that point the pixel is just for HEM if its corresponding intensity in the original image is less than a particular certain value. Perform closing operation for EXs, if the candidate regions areas are above a particular threshold using a structuring element (SE) having disc shaped. This will fills up the gaps between the background pixel and EXs.

To take out these background pixels (whose intensity levels are significantly smaller than EXs), pixels with intensity (in the initial image) less than the average intensity in a localized window (inside EX area) are rejected. HEMs, MAs and EXs appears with different properties like size, shape and color. MAs are smaller in size but they appears as a dark red color with circular shape; HEMs appears as dark red dots of medium size; and EXs appears in whitish and yellow colors. Then form a feature set for lesion using color, intensity, shape and statistical features. Also use Gabor features for enhancement and candidate lesion detection regions.

Principal Component Analysis (PCA) is used to select discriminative features which are used to detect DR, there by reduces the no of samples. The selected features include the area, microneurysms counts, perimeter and counts of the exudate and the area and perimeter of blood vessels. These discriminative features are given to the CNN for classifications. The CNN network architecture having multiple hidden layers of small neurons. Convolutional layers consist of neurons, and having grids in each and every convolutional layer. After convolution layer next is the pooling layer subsampled the previous convolutional layer information. This pooling done in different way, such as the normal, extreme most extreme etc. Outputs from previous layers are used to form a fully connected layer. It is used as a dense feature to portray the entire input image. Then the network optimization is obtained by back propagation and stochastic gradient descent.

Depending on the type of the layer the forward &backward propagations may alter. The first layer which learns deep layer characteristics of the network, then the last layer convolutional layer, learns theDR classification features like hard exudate. The convolution blocks and the batch normalization layer after each convolution layer starts the network. Pooling is performed at a kernel size of 2x2 and 3x3 strides. The network flattened to 1D after the final convolutional block. Then avoid over fitting we by weighted class. Also perform withdrawn on dense layers, to reduce over fitting, until reaches dense five node classification layer uses a softmax activation to predict the classification outcome. Similarly, in convolution layers, L2 regularization were used for biases and weight. Gaussian initialization is used to reduce training time.

IV. PERFORMANCE ANALYSIS

In this section performance of retinal lesions detection using transfer learning for diabetic retinopathy is discussed. The data sets used for testing and training are entirely different. So there is no collision between these two sets. The performance is judged based on sensitivity, specificity and Accuracy.

Table.1: Performance Analysis

Parameters	Accuracy	Sensitivity	Specificity
ACS	94.52	81.3	86.7
SVM	96.8	89.7	85.4
CNN	99.1	97.4	95.8

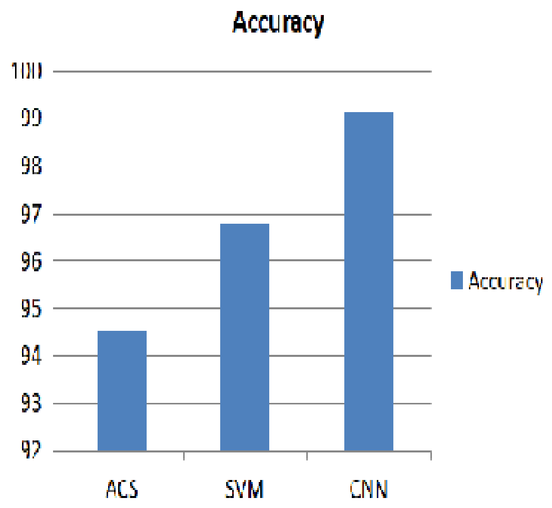

Fig.2: Accuracy Comparision Graph

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In fig.2 accuracy comparision is observed between ACS, SVM and CNN. The accuracy of CNN shows higher.

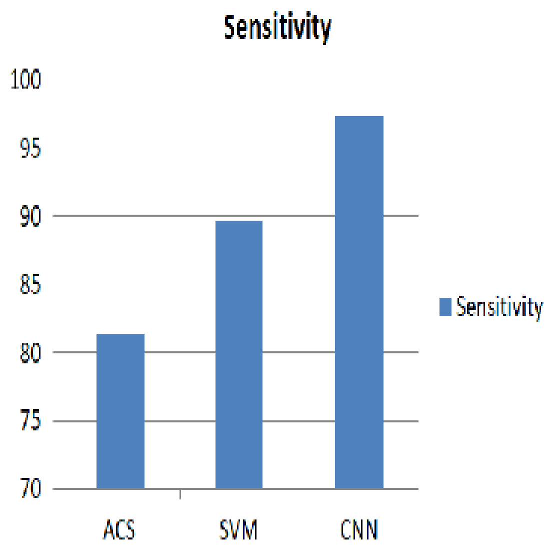

Fig.3: Sensitivity Comparision Graph

Sensitivity comparision graph is observed in fig.3. The sensitivity of CNN shows higher.

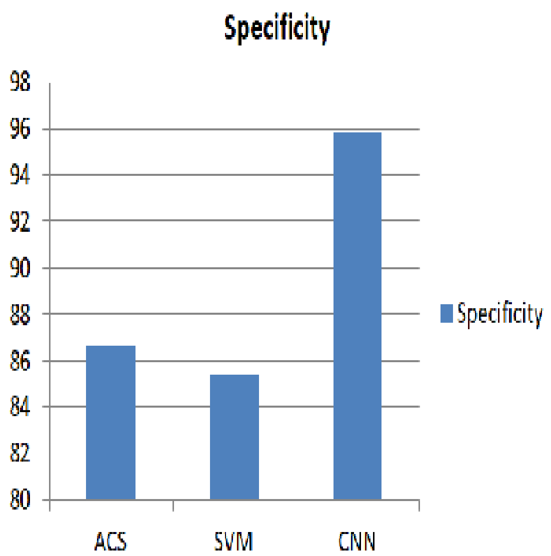

Fig.4: Specificity Comparision Graph

The comparision between ACS, SVM and CNN of specificity is observed. The specificity of CNN is higher when compared with others.

V. CONCLUSION

Retinal Lesion detection includes matched and LoG filters pursued by post-processing step. These approaches are combined in an intelligent and subsequent manner to achieve accurate and efficient methods to detect distinct lesions independent of their shape, size, text etc. MFRmax and LoGRmax are used for lesion detection. And perform hard exudates detection, candidate detection. After that feature extrsaaction is performed then it is followed by PCA for creating feature vector. And the final classification is based convolutional neural network .This method provides higher detection accuracy.

VI. REFERENCES

[1] Rajini, H.N. A Novel Approachfor the Diagnosis of Diabetic Retinopathy Using Convolutional Neural Network. In Proceedings of the 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS), Coimbatore, India, 15–16 March 2019; pp. 1102–1107.

[2] Pires, R.; Avila, S.; Wainer, J.; Valle, E.; Abramoff, M.D.; Rocha, A. A data-driven approach to referable diabetic retinopathy detection. Artif. Intell. Med. 2019, 96, 93–106.

[3] Qomariah, D.U.N.; Tjandrasa, H.; Fatichah, C. Classification of Diabetic Retinopathy and Normal Retinal Images Using CNN and SVM. In Proceedings of the 2019 12th International Conference on Information & Communication Technology and System (ICTS), Surabaya, Indonesia, 18 July 2019; pp. 152–157.

[4] Hussain, M.A.; Islam, S.O.B.; Tiwana, M.; Qureshi, W. Detection and Classification of Hard Exudates with Fundus Images Complements and Neural Networks. In Proceedings of the 2019 5th International Conference on Control, Automation and Robotics (ICCAR), Beijing, China, 19–22 April 2019; pp. 206–211.

[5] Kothare, K.S.; Malpe, K. Design and Implementation of Inspection Model for knowledge Patterns Classification in Diabetic Retinal Images. In Proceedings of the 2019 3rd International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 27–29 March 2019; pp. 1220–1223.

[6] Sudeshna Sil Kar, Santi P, Maity. "Blood vessel extraction and optic disc removal using curvelet transform and kernel fuzzy c-means", Computers in Biology and Medicine, 2016

[7] Darshit Doshi, Aniket Shenoy, Deep Sidhpura, Prachi Gharpure. "Diabetic retinopathy detection using deep convolutional neural networks", 2016 International Conference on Computing, Analytics and Security Trends (CAST), 2016

[8] Fayyaz, A.M.; Sharif, M.I.; Azam, S.; Karim, A.; El-Den, J. Analysis of Diabetic Retinopathy (DR) Based on the Deep Learning. Information 2013, 14, 30

[9] Jena, P.K.; Khuntia, B.; Palai, C.; Nayak, M.; Mishra, T.K.; Mohanty, S.N. A Novel Approach for Diabetic Retinopathy Screening Using Asymmetric Deep Learning Features. Big Data Cogn. Comput. 2013, 7, 25.

[10] Pan, S.J.; Yang, Q. A survey on transfer learning. IEEE Trans. Knowl. Data Eng. 2010, 22, 1345–1359.