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DETECTION OF DIABETIC RETINOPATHY USING DEEP LEARNING METHODOLOGY

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Abstract: The escalating prevalence of diabetes globally has positioned it as a significant contributor to mortality rates. Elevated blood glucose levels and insulin resistance are implicated in a spectrum of health complications, encompassing cardiovascular diseases, renal dysfunction, neuropathies, and diabetic retinopathy—a debilitating condition marked by vision impairment. Early detection serves as a pivotal determinant in mitigating the progression of diabetic retinopathy and averting irreversible visual impairment. Consequently, the imperative for a robust screening methodology becomes apparent. To this end, a comprehensive investigation into deep learning strategies has been undertaken. Leveraging publicly available datasets, our research ends have focused on the acquisition and reprocessing of data pertaining to diabetic individuals. Furthermore, the development of sophisticated machine learning algorithms, including deep neural networks such as Convolutional Neural Networks (CNNs), has been instrumental in refining our screening approach. The culmination of these efforts has yielded promising outcomes, as evidenced by the system's proficiency in accurately discerning normal retinal images from those indicative of aberrant pathology with a remarkable degree of certainty. In conclusion, the integration of advanced technologies, such as deep learning and machine learning, holds considerable promise in revolutionizing diabetic retinopathy screening protocols. By harnessing the power of these methodologies, we can enhance early detection, facilitate timely intervention, and ultimately ameliorate the burden of diabetic retinopathy on global visual health outcomes

Keywords: Diabetic Retinopathy, DeepLearning, KNN, CNN

INTRODUCTION:

Diabetes has emerged as a significant global health challenge in recent decades, marked by the prevalence of complications stemming from elevated blood sugar levels and aberrant responses to insulin. These complications encompass a spectrum of ailments, including cardiovascular disease, renal impairment, neurological disorders, and diabetic retinopathy—a condition characterized by irreversible vision loss if left untreated.

Age and familial predisposition are key determinants of an individual's susceptibility to diabetes, whether of type 1 or type 2. Notably, the risk escalates with advancing age, particularly in those with a family history of the disease. The World Health Organization underscores the urgency of addressing diabetic retinopathy as a severe ocular ailment requiring global attention.

In India alone, a staggering 60 million individuals grapple with diabetic eye disease, yet the scarcity of ophthalmologists, with only around 12,000 practitioners, poses a significant challenge in providing adequate care. Compounding this issue is the widespread lack of awareness among affected individuals regarding their diabetic status, exacerbating the prevalence of diabetic retinopathy.

Alarming is the apparent indifference among many individuals towards the propagation of this disease, despite its profound impact on public health. Approximately 18% of diabetics are afflicted with diabetic retinopathy, with diabetic individuals facing a 25-fold increased risk compared to their healthier counterparts.

The insidious nature of diabetic retinopathy underscores the imperative for early diagnosis to forestall the onset of irreversible consequences. However, the condition is notorious for being misdiagnosed due to the absence or mildness of early symptoms, necessitating heightened vigilance and proactive screening protocols.

In conclusion, prioritizing early detection and intervention strategies is paramount in mitigating the burden of diabetic retinopathy and its associated complications. By fostering awareness, enhancing access to specialized care, and implementing comprehensive screening initiatives, we can address this pressing public health challenge and safeguard the visual health of millions worldwide.

1.1 OBJECTIVES

The main objective of our project is,

- To predict or to classify the diabetic retinopathy is normal or abnormal effectively
- To predict the type of or level ofdiabetic retinopathy
- To enhance the overall performance for classification algorithms.

2. LIRERATURE REVIEW:

Deepika Vallabha Ramprasath Dorairaj, Kamesh Namuduri, and Hilary Thompson have elucidated that the progressive damage inflicted upon the retina due to diabetes escalates over time [1]. The spectrum of non-proliferative diabetic retinopathy (NPDR) severity spans from moderate to severe, prompting the exploration of techniques aimed at automating the identification and classification of vascular anomalies associated with diabetic retinopathy.Their research proposes a method leveraging Gabor filter banks, renowned for their selective responsiveness to size and orientation, to discern vascular anomalies within retinal imagery.

By harnessing the outputs generated by Gabor filters, the proposed approach facilitates the categorization of retinal images into distinct gradations of severity, ranging from mild to severe manifestations of diabetic retinopathy. moderate, or severe cases. In this study, we examine the use of automated methods for detecting the vascular alterations characteristic of DR's more advanced phases. In the suggested technique, theretinal pictures are processed using scale andorientation selective Gabor filters, which allow for the detection of these aberrations. With the finer granularities of Gabor filter outputs, the difference between moderate and severe NPDR becomes more apparent. The scale-angle representation of the output from the smaller scales is used to make a presence/absence estimation of the anomalies.

Jonathan Long, Evan Shelhamer, Trevor Darrell states that it is possible to get hierarchies of features using convolutional networks, which are strong visual models. In this paper, we demonstrate that state-of- the-art semantic segmentation can beachieved using just convolutional networks that are trained from beginning to finish, pixel-by-pixel.

The essential breakthrough of our work is to construct "totally convolutional" networks, which are able

to efficiently train and infer on data of unlimited sizes.
Here, we provide acomprehensive framework for completely convolutional networks, describe how they may be used to spatially dense prediction problems, and establish links to related models from the past. Fine-tuning allows us to transfer the learned representations from state-of-the-art classification networks (AlexNet, the VGG net, and GoogLeNet) to the segmentation challenge.
Anupam Ghosh and Amlan Chakrabarti states that Diabetic retinopathy, an eye disorder caused by diabetes, may be detected by the process of retinal vascular segmentation [3].
As no other portion of the human circulatory system can be imaged or digitally analyzed without risking damage tothe tissue, the retinal microvasculature stands apart. In this research, we analyzed various popular image segmentation techniques that aid in the detection of retinalabnormalities and investigate a novelmethod for identifying retinal pictureanomalies. Also, we have created an automated diagnosis method for diabetic retinopathy, with a primary emphasis on vessel extraction from retina pictures.
The methods presented in this research include the use of a snake model for automatic extraction of retinal blood vessels, as well aswavelet decomposition and a back propagation neural network for feature extraction and data analysis. Lastly, the wavelet analysis and vessel segmentation algorithm's performance on benchmarkimage databases has been analyzed. As ameans of verifying this outcome, we used the F-score.

3. PROPOSED SYSTEM:

The diabetes dataset is retrieved from a central data warehouse. Next, we'll put into action the picture pre-processing stage. It is now possible to resize images and transform them to grayscale. When the picture has been preprocessed, we may extract features such as GLCM and mean variance median. Ratio (4:1) is used to determine how to divide the image. Much of the information you need is included in the training. Less information will be available during testing. Both the model and its performance are assessed during the training and testing phases. Then we may activate KNN and CNN and other machine learning and deep learning algorithms. In conclusion, the results of the experiments show that the performance measures, such as accuracy andforecast the diabetic retinopathy normal or abnormal and also predict what kind of diabetes, are effective. The experimental results show how dependable.

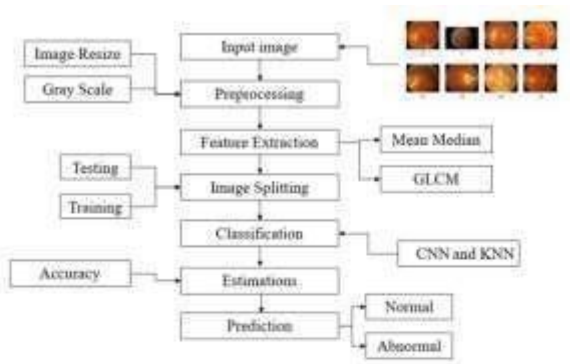
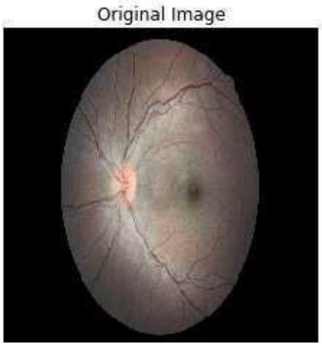


Fig1:System Architecture

4. RESULT:




```
FEATURE EXTRACTION --> MEAN, VARIANCE, MEDIAN

1. Mean Value     = 0.19163652

2. Median Value   = 0.0

1. Variance Value = 0.051075265
```

```
FEATURE EXTRACTION -->GRAY LEVEL CO-OCCURENCE MATRIX
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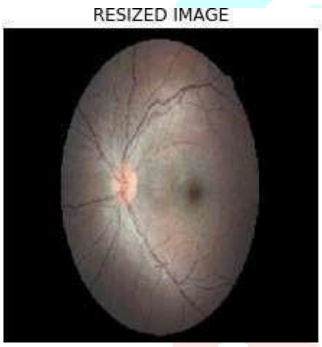
```
GLCM FEATURES =

[0.0, 0.0, 0.06687999, 0.5112593]
```

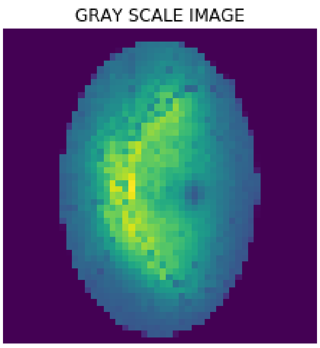



```
     IMAGE SPLITTING

Total no of data        : 250
Total no of test data   : 200
Total no of train data  : 50
Model: "sequential_1"
```

```
CONVOLUTIONAL NEURAL NETWORK (CNN)

Epoch 1/5
200/200 [==============================] - 6s 32ms/step - loss: 0.4490 - accuracy: 0.8333
Epoch 2/5
200/200 [==============================] - 6s 30ms/step - loss: 0.4457 - accuracy: 0.8333
Epoch 3/5
200/200 [==============================] - 7s 35ms/step - loss: 0.4430 - accuracy: 0.8333
Epoch 4/5
200/200 [==============================] - 6s 30ms/step - loss: 0.4406 - accuracy: 0.8333
Epoch 5/5
200/200 [==============================] - 6s 30ms/step - loss: 0.4385 - accuracy: 0.8333
200/200 [==============================] - 0s 2ms/step
```




```
PERFORMANCE ---------> (CNN)

1. Accuracy   = 83.33333432674408 %

2. Error Rate = 16.666656732559204
```

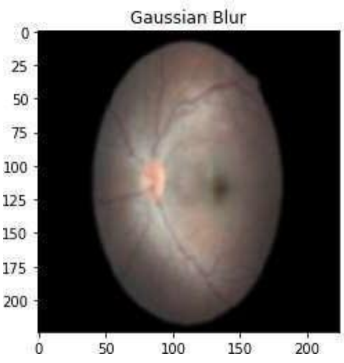
```
PERFORMANCE ---------> (KNN)

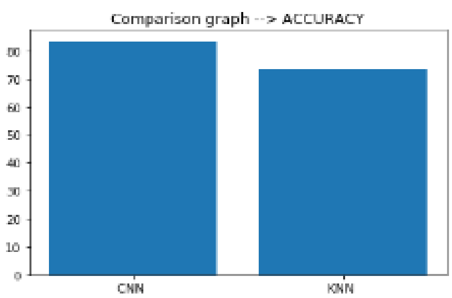
1. Accuracy    = 73.5 %

2. Error Rate = 26.5
```

```
     PREDICTION

DIABETIC ---> MILD
```





5. CONCLUSION&FUTURE SCOPE:

The data was obtained from a source Kaggleas input. Algorithms for machine and deep learning, including KNN and CNN, were created by us. Using an already processed picture, we retrieved the characteristics. In the end, the findings demonstrate the reliability of the method and its ability to accurately anticipate whether or not a given condition would be normal or abnormal. Also, it is possible to foretell the specific kind of diabetes.

FUTURE SCOPE

In the future, we want to expand our deep learning beyond diagnosis of diabeticretinopathy and early detection of exudates to address further critical challenges in ophthalmology. Using the intricate network of blood arteries and their constantly shiftingpatterns.

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