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Diabetic Retinopathy Detection Using Machine Learning and Texture Features

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Abstract - Diabetic retinopathy (DR) is a medical condition due to diabetes mellitus that can damage the patient retina and cause blood leaks. This condition can cause different symptoms from mild vision problems to complete blindness if it is not timely treated. *Hemorrhages*, *hard Exudates*, and *Micro-aneurysms* (HEM) that appear in the retina are the early signs of DR. Early diagnosis of HEM is crucial to prevent blindness. Textures features such as *LBP* have been widely used in the past as a technique for DR detection. In this work, we introduce the use of different texture features for DR, mainly Local Ternary Pattern (LTP) and Local Energy-based Shape Histogram (LESH). We show that they outperform LBP extracted features. *Support Vector Machines* (SVM) are used for the classification of the extracted histogram. A histogram binning scheme for features representation is proposed. The experimental results show that LESH is the best performing technique with an obtained accuracy of 0.904 using SVM with a Radial Basis Function kernel (SVM-RBF). Similarly, the analysis of the ROC curve shows that LESH with SVM-RBF gives the best AUC (Area Under Curve) performance with 0.931.

keywords— *Diabetic retinopathy, LESH, LTP, machine learning, SVM.*

Introduction-

Diabetic retinopathy is the leading cause of blindness in the working-age population of the developed world. It is estimated to affect over 93 million people. The US Center for Disease Control and Prevention estimates that 29.1 million people in the US have diabetes and the World Health Organization estimates that 347 million people have the disease worldwide. Diabetic Retinopathy (DR) is an eye disease associated with long-standing diabetes. Around 40% to 45% of Americans with diabetes have some stage of the disease. Progression to vision impairment can be slowed or averted if DR is detected in time, however this can be difficult as the disease often shows few symptoms until it is too late to provide effective treatment.

Currently, detecting DR is a time-consuming and manual process that requires a trained clinician to examine and evaluate digital color fundus photographs of the retina. By the time human readers submit their reviews, often a day or two later, the delayed results lead to lost follow up, miscommunication, and delayed treatment.

Clinicians can identify DR by the presence of lesions associated with the vascular abnormalities caused by the disease. While this approach is e ective, its resource demands are high. The expertise and equipment required are often lacking in areas where the rate of diabetes in local populations is high and DR detection is most needed.

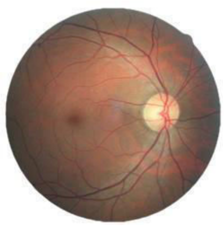


Figure 1.1: Eye data sample with attention spot

The need for a comprehensive and automated method of DR screening has long bee and previousefforts have made good progress using image classification, pattern recognition, and machine learning. With color fundus photography as input, the goal of this competition is to push an automated detection system to the limit of what is possible ideally resulting in models with realistic clinical potential. The winning models will be open sourced to maximize the impact such a model can have on improving DR detection.

Literature Survey The two-step (i.e., feature extraction and prediction) automated DR detection approaches dominated the eld of DR detection for many years. Given color fundus photography, this type of approaches often extracted visual features from the images on the parts of blood vessels, fovea and optic disc. The generic feature extraction methods developed in computer vision area were widely used here, e.g, hough transform, gabor lters and intensity variations. With the extracted features, an object detection or object registration algorithm like support vector machines and k-NN were used to identify and localize exudates and hemorrhages [15, 16]. As mentioned before, this type of approaches are not as e ffective as the recent deep learning approaches, such as Bengio (2009). All these deep learning approaches adopted the standard architecture like AlexNet and GoogLeNet to build their CNN, and based on the experimental results these deep learning approaches significantly outperform the traditional two-step approaches. Moreover, the recent DR detection competition held in Kaggle witnessed that all top solutions adopted CNN as the key algorithm. However, all these CNN approaches require complex neural network structures, and it is hard for practitioners to understand the insight of CNN and clearly explain that which region of the color fund us photography is the main cause of the disease.

Understanding the insights of CNN has always been a pain point, though CNN yields excellent predictive performance.Wang and Yang (2017) It is well-known that deriving theoretical results is quite challenging due to the non liner and non-convex nature of CNN. To mitigate this issue, considerable e orts have been put on visu-alizing the CNN. A deconvolutional networks approach was proposed to visualize activated pattern in each hidden unit. This method is limited as it is hard to sum-marize all hidden units's patterns into one pattern, and also only the hidden neurons in the hidden layers are analyzed though the networks considered also contain the fully-connected layers. The work and the reference therein include the objection location task besides the conventional object classification problem, so their CNN can predict the label of an image and also identify the region of the object related to the class label. Though this type of CNNs can predict the location of the object of interest, it still cannot reveal the insight of CNN. Recently, have presented the methods to invert the representation of images in each layer of the CNN. However, these approaches can only indicate what information is preserved in each layer of the CNN.

II.PROPOSED APPROACH AND DATABASE

The most work most related to our method is [24] in which class activation map is proposed to characterize the weighted activation maps after global average pooling or global maximum pooling layer. This idea has recently been generalized to time series analysis to localize the signi cant regions in the raw data. In this paper, we extend the method from a classi cation to a regression setting and shed light on DR detection problem.

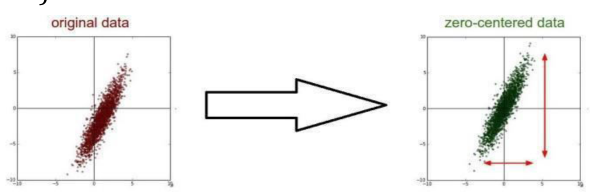
III. FEATURE EXTRACTION

The proposed approach extracts texture features for learning and classification, more specifically: Local Ternary Pattern (LTP) and Local Energy-based Shape Histogram (LESH].

III.1 Image Data Prepossessing

The importance of data pre-processing can only be emphasized by the fact that your neural network is only as good as the input data used to train it. If important data inputs are missing, neural network may not be able to achieve desired level of accuracy. On the other side, if data is not processed beforehand, it could e ect the accuracy as well as performance of the network down the lane.

Figure 3.1: Mean subtraction (Zero centering the data)



It's the process of subtracting mean from each of the data point to make it zero-centered. Consider a case where inputs to neuron (unit) are all positive or all negative. In that case the gradient calculated during back propagation will either be positive or negative (same as sign of inputs).

One of the most common problem in training deep neural network is over- tting. You'll realize over- tting in play when your network performed exceptionally well on the training data but poorly on test data.

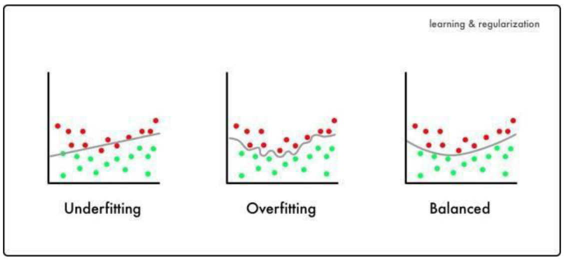


Figure 3.2: Need of Regularization

IV. Neural Network Model Architecture

ImageNet is a common academic data set in machine learning for training an image recognition system. Code in this directory demonstrates how to use TensorFlow to train and evaluate a type of convolutional neural network (CNN) on this academic data set.

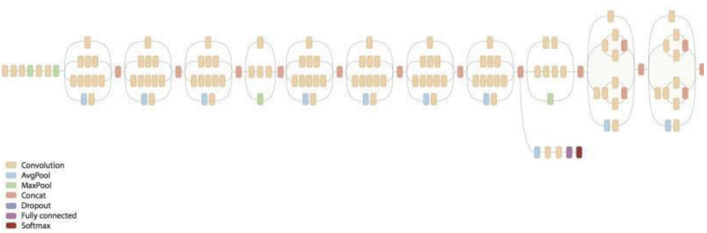


Figure 4.1: Model architecture

The training procedure employs synchronous stochastic gradient descent across multiple GPUs. The user may specify the number of GPUs they wish to harness. The synchronous training performs batch-splitting by dividing a given batch across multiple GPUs

IV.A. Attention in Neural Networks

Informally, a neural attention mechanism equips a neural network with the ability to focus on a subset of its inputs (or features): it selects speci c inputs. Let x R_d be an input vector,z R_k a feature vector, a $[0; 1]_k$ an attention vector, g R_k an attention glimpse and f (x) an attention network with parameters . Typically, attention is implemented as

$$a = f\varphi(x)$$

$$g = a \odot z$$

Its ability to approximate different classes of function depends on its architecture.

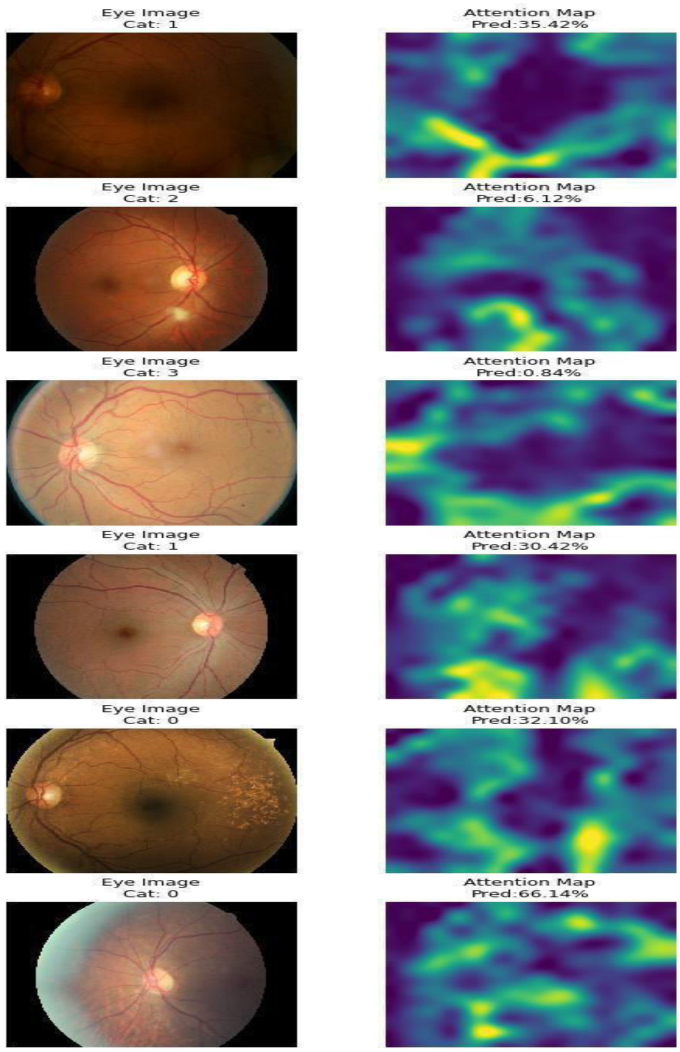


Fig 4.2:Attention Model Output

Attention mechanisms expand capabilities of neural networks: they allow approxi-mating more complicated functions, or in more intuitive terms, they enable focusing on specific parts of the input. They have led to performance improvements in natural language benchmarks, as well as to entirely new capabilities such as image captioning, addressing in memory networks and neural programmers.

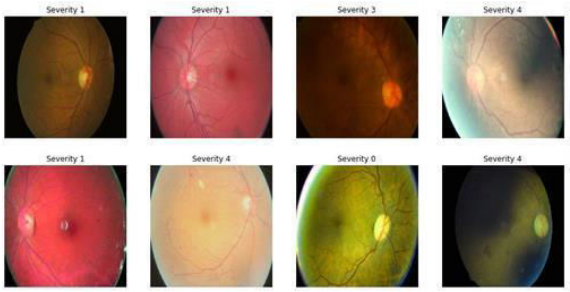


Fig 4.3: Training data set output

V. Evaluation and Results

We have total 1151 data of different individual in our dataset. There are 1151 rows and 20 columns in the dataset. After splitting the data into two parts now we have 920 rows for train data and for test data we have 231 rows. When we trained our train data for analysis performance of different algorithms, this is the result we got- For NNET algorithm our training accuracy is 72.61. NNET stands for neural net-works which is one of the most efficient algorithms among all of them. It gives us 72.61% accuracy for the training set which is highest among all the previous algorithms we used.

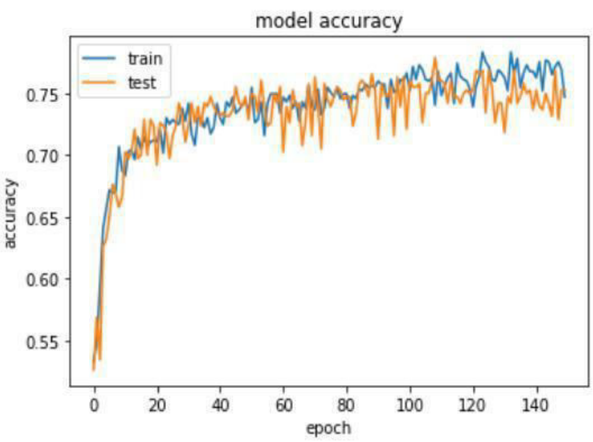


Figure 5.1: Train-Test model accuracy

From the plot of accuracy we can see that the model could probably be trained a little more as the trend for accuracy on both datasets is still rising for the last few epochs

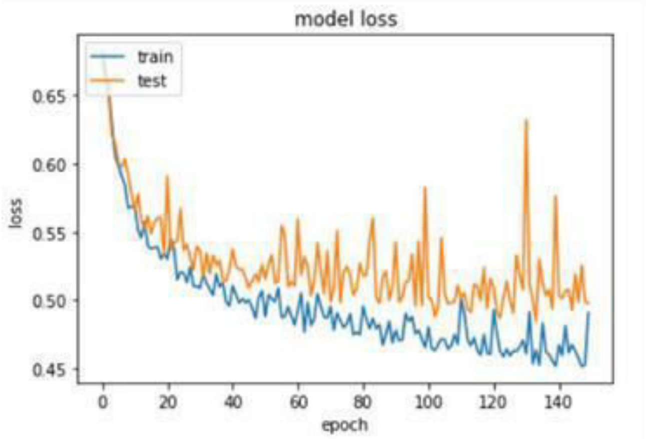


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Fig :5.2 Train-Test model loss

From the plot of loss, we can see that the model has comparable performance on both train and test datasets. If these parallel plots start to depart consistently, it might be a sign to stop training at an earlier epoch. If the lines of train -test loss seem to converge to the same value and are close at the end, then the classifier has high bias. If on the other hand the lines are quite far apart, and then we have a low training set error but high validation error, then your classifier has too high variance.

Finally a clinician has rated the presence of diabetic retinopathy in each image on a scale of 0 to 4, according to the following scale:0-No DR,1-Mild, 2-Moderate, 3-Severe,4- Proliferate DR

V.I.ROC Curve for healthy vs sick

Here we make an ROC curve for healthy (severity == 0) and sick (severity>0) to see how well the model works at just identifying the disease.

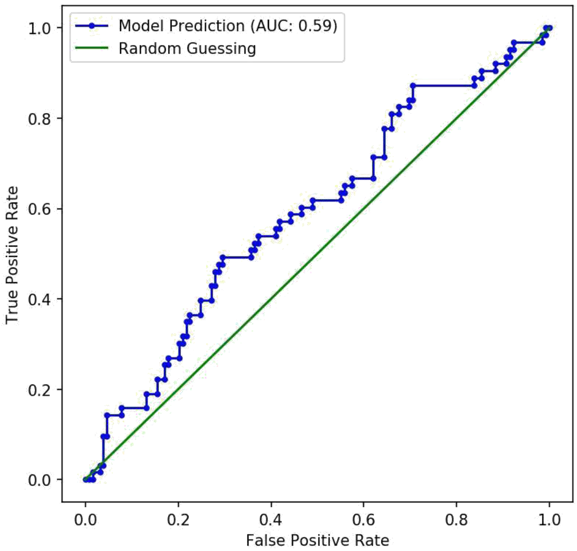

Figure 5.3: ROC Curve

VI. Conclusion

The increase in diabetes cases limits the ability of current manual testing. New algorithms for assisted diagnosis are becoming very important today. Early detection of diabetes can help the patients and limits the bad health consequences such as blindness.

Using retinal fundus images can help automate the diagnosis. Micro hemorrhages and aneurysms, known as HEM, are the early signs of diabetic retinopathy (DR) and are difficult to identify because of their similarities with normal parts of a healthy human. Other problems such as non-uniform lighting, low contrast, etc. can lead to a bad diagnosis.

Texture based techniques for DR detection were proposed in the past. Most of these techniques use LBP and wavelets for feature extraction from retinal images. In this work, we propose the use of new texture features, mainly LTP and LESH. These techniques capture the local relationship between neighboring pixels and features and are less sensitive to variation in illumination, color, noise, etc. These features extracted from the retinal fundus images are used to learn signs of HEM and differentiate between DR and non-DR. SVM is used to classify these features. Polynomial and RBF kernels were the best performing in the detection of DR.

The proposed approach is suitable even for small datasets. New techniques based on deep learning are data hungry but show impressive performances in different classification tasks including DR. Future work include works on different areas, different algorithms, hardware implantation, software implementation.

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