## IBM-EPBL/IBM-Project-31325-1660199088

## LITERATURE REVIEWS: Deep Learning Fundus Image

## Analysis for Early Detection of Diabetic Retinopathy.

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**TITLE:** A Deep Learning Ensemble Approach for Diabetic Retinopathy Detection

**AUTHOR: S**ehrish Qamar, Fiaz Gul Khan, Sajid Shah, Ahmad Khan, Shahaboddin Shamshir band, Zia Ur Rehman, Iftikhar Ahmed Khan, and Waqas Jadoon.

**YEAR:** 2019

The different **preprocessing** steps that we perform on the input dataset before giving it to the model. This paper uses the Kaggle2 dataset which contains 35126 color fundus images, each is of size 3888 × 2951. It contains the images from five different classes based on the severity of diabetic retinopathy (DR). The distribution of different classes is shown in the first row of Table 1, which is perfectly imbalanced. Training of deep networks with imbalance data leads to classification biasness. In the first preprocessing step, we resize each input image shown in to 786 × 512 shown in by maintaining the aspect ratio to reduce the training over head of deep networks. Moreover, for balancing the dataset they performed up-sampling and down-sampling. The up-sampling is performed with augmentation of minority classes by randomly cropping patches, of size 512 × 512 as shown in, followed by flipping and 90 degrees rotation to balance the samples of different classes, enrich the dataset and avoid overfilling as shown in. In down-sampling extra instances of majority classes are removed to meet the cardinality of the smallest class. In the resultant distributions, before flipping and rotation, each image is normalized to avoid features biasness and speed-up training time. The dataset is divided into three parts: training, testing, and validation sets with ratio 64% and 20% and 16% respectively. During training, the validation set is used to check and reduce the over-fitting.

**Ensemble method** is a meta-algorithm that combines several machine learning techniques into one predictive model. It can be used for different objectives such as to decrease variance (Bagging), bias (boosting), or improve predictions (stacking). Stacking is a model used to combine information from multiple predictive models to generate a new model. The stacked approach often outperforms individual models due to its soothing nature. Stacking highlights each base model where it performs best and discredits each base model where it performs poorly. For this reason, stacking is most effective when the base models are significantly different.

**TITLE:** Automated Detection of Diabetic Retinopathy using Deep Learning

**AUTHOR:** Carson Lam, MD, Darvin Yi, Margaret Guo, Tony Lindsey, PhD Biomedical Informatics Department, Stanford University

**YEAR:** 2017

Automated techniques for diabetic retinopathy diagnoses are essential to solving these problems. While deep learning for binary classification in general has achieved high validation accuracies, multi-stage classification results are less impressive, particularly for early-stage disease. In this paper an automatic DR grading system capable of classifying images is introduced based on disease pathologies from four severity levels. A convolutional neural network (CNN) convolves an input image with a defined weight matrix to extract specific image features without losing spatial arrangement information. We initially evaluate different architectures to determine the best performing CNN for the binary classification task and aim to achieve literature reported performance levels. We then seek to train multi-class models that enhance sensitivities for the mild or early stage classes, including various methods of data preprocessing and data augmentation to both improve test accuracy as well as increase our effective dataset sample size. We address concerns of data fidelity and quality by collating a set of ophthalmologists verified images. Finally, we address the issue of insufficient sample size using a deep layered CNN with transfer learning on discriminant color space for the recognition task. Then trained and tested two CNN architectures, AlexNet and GoogLeNet, as 2-ary, 3-ary and 4-ary classification models. They are tuned to perform optimally on a training dataset using several techniques including batch normalization, L2 regularization, dropout, learning rate policies and gradient descent update rules3. Experimental studies were conducted using two primary data sources, the publicly available Kaggle dataset of 35,000 retinal images with 5-class labels (normal, mild, moderate, severe, end stage) and a physician-verified Messidor-1 dataset of 1,200 color fundus images with 4-class labels. Throughout this study we aim to elucidate a more effective means of classifying early stage diabetic retinopathy for potential clinical benefits.

**TITLE:** Classification of Diabetic Retinopathy Images Using Deep Learning Models. **AUTHOR:** Suvajit Dutta, Bonthla CS Mandeep, Syed Muzamil Basha IEEE Network. **YEAR:** 2018

The paper focuses on getting an optimal model through machine learning, which will include the classical Neural Networks (NN), Deep Neural Networks (DNNs) and the Convolution Neural Networks (CNNs). The neural networks inherit the concept of a biological brain. The outcomes are often hard to achieve as the biological neurons are more complex than these artificial ones, then also researchers have succeeded to some levels. The neural networks performed well but with increased complexity and data size the need for advanced techniques produced, bringing the concepts of deep learning to existence. Prior to deep learning, the hierarchical attribute learning approaches came to light, but due to the problems such as vanishing gradient, started losing their aura as while tracing back to the features it often becomes difficult to get the desired results. Deep learning models, like DNNs and CNNs, delivered solutions to overcome this problem of gradient descent. Fuzzy C-Means clustering also comes to picture here, as if the data have any missing labels when the Image Classification will be done at the later stages. So, in order to predict the labels, Fuzzy C – Means is applied so as to find the clusters.

Extracted the statistical features from unprocessed RGB images. (average, median, standard deviation, skewness, root mean square error, mean absolute deviation, quartiles, minimum, maximum & threshold level). RGB image taken and converted into grayscale for image filtering (Median filter, Morphological processing), applied edge detection for feature extraction from images and binary conversion of image to highlight all features. First Statistical data taken into consideration for image classification with Feed Forward Neural Network (FNN) for classification, after that Deep Neural Network (DNN) performed and compared the result with FNN. Secondly image classification done on processed images with Feed forward Neural Network (FNN) model and Deep Neural Network (DNN) model. Performed Convolutional Neural Network (CNN) on processed images (VGG16 model). Both the result has been compared as per performance and accuracy measurements with testing image set.

**TITLE:** Machine Learning Identification of Diabetic Retinopathy from Fundus Image

**AUTHOR:** Nikita Gurudath, Mehmet Celenk and H.Bryan Riley

**YEAR:** 2019

In this paper, the number of NPDR images are higher in order to train the system to identify a class that has similarities to the other two classes. The primary research approach involves three major steps.

Matched filter techniques are used to approximate the gray-level profile of a blood vessel by a Gaussian distribution. The resulting image Ig (n1, n2) is subjected to

a local thresholding scheme based on entropy. Feature extraction is performed on the image after thresholding, It (n1, n2). The nature of the fundus images is such that classification requires surface inspection. Texture of images provide information about the spatial distribution of gray levels that is integral to defining the regions in fundus images that have abnormalities. A three-layer, feed-forward artificial neural network is selected to implement classification using the backpropagation training algorithm. This research showed an automatic detection of the three classes by considering all the anomalies which are critical for classification as the disease progresses. A major outcome, this research aims to check for consistency in classification accuracy when presented with a larger sample set. Considerations for future work include developing an e-health digital computer based-system that reliably implements the processing steps.