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A REVIEW TO DETECT DIABETIC RETINOPATHY THROUGH ENHANCE CLASSIFICATION ACCURACY OF DEEP LEARNING

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ABSTRACT

Data mining and image mining provides mechanism to extract useful information out of the big data provided for extraction. Medical field analysis and classification plays critical impact on providing useful information regarding diseases. The segments or parts associated with overall operation includes. Pre-processing: It is the mechanism of handling missing information from within the image dataset provided for evaluation. Processing of pre-processed data: Pre processed data is passed through the layers of deep learning for processing. Feature extraction: After passing through the layers, features are extracted from the image dataset for classification. Segmentation: After feature extraction, basic segment of the image is extricated and pointless parts are dispensed with from the image. Classification: Result is given in terms of disease prediction from the image dataset presented for evaluation.

The result is given in terms of accuracy and precession. Accuracy is a difference between the actual value and approximate value. This value is decreased through the proposed mechanism.

Keywords: Diabetic Retinopathy (DR), Retina, Fundus Images, Classification, Deep Learning (DL), Deep Neural Network (DNN), Macula, Optic Disc.

1. INTRODUCTION

Deep Learning: Deep learning is a type of machine learning in which a model learns to perform classification tasks directly from images, text, or sound. Deep learning is usually implemented using a neural network architecture. The term “deep” refers to the number of layers in the network—the more layers, the deeper the network. Traditional neural networks contain only 2 or 3 layers, while deep networks can have hundreds. In deep learning, a computer model learns to perform classification tasks directly from images, text, or sound. Deep learning models can achieve state-of-the-art accuracy, sometimes exceeding human-level performance. Models are trained by using a large set of labeled data and neural network architectures that contain many layers.

Most deep learning methods use neural network architectures, which is why deep learning models are often referred to as deep neural networks. Deep learning models are trained by using large sets of labeled data and neural network architectures that learn features directly from the data without the need for manual feature extraction.

Deep Learning Applications:

Here are just a few examples of deep learning at work:

• A self-driving vehicle slows down as it approaches a pedestrian crosswalk.

• An ATM rejects a counterfeit bank note.

• A smart phone app gives an instant translation of a foreign street sign.

Deep learning is especially well-suited to identification applications such as face recognition, text translation, voice recognition, and advanced driver assistance systems, including, lane classification and traffic sign recognition.

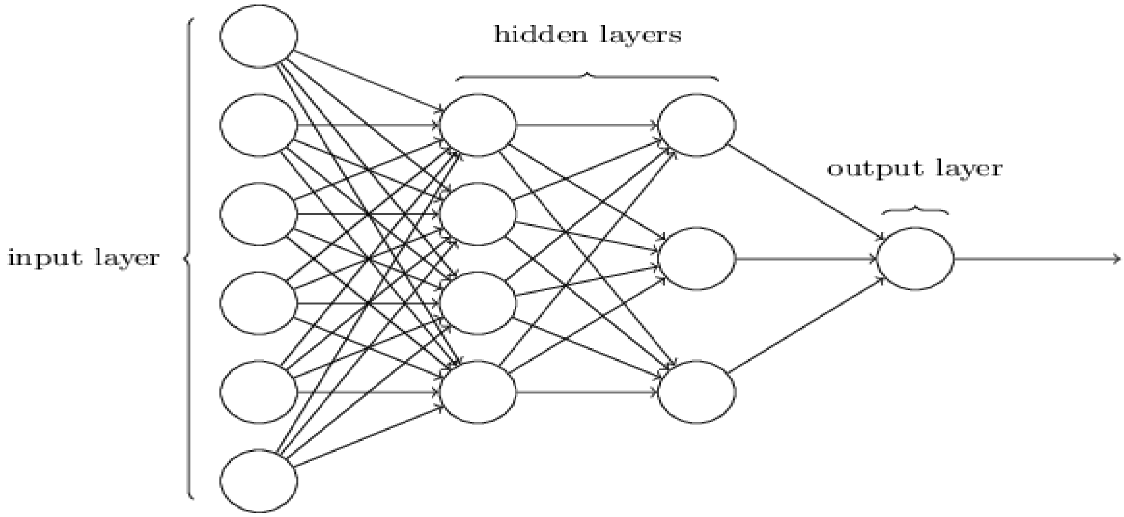

Fig 1. Deep Learning

Diabetic retinopathy (DR) is a chronic disease related with the eye retina which presently comprises of one of the most common causes of blindness and loss of vision. The incidental statistics indicate that DR is the primary cause of blindness in people of working age of the present era. DR is an outcome of diabetes-mellitus, illness which elevates the concentration of glucose in blood. This unusually high glucose levels damage the eye vessel endothelium infuriating set of damages related to the illness. Although having diabetes does not necessarily entail vision mutilation, about 2% of the patients affected by this disease are blind and 10% undergo vision deprivation after 15 years of diabetes as a result of DR complications. Vision-threatening retinopathy is rare in type 1 diabetic patients in the first 3–5 years of diabetes or before puberty. During the next two decades, nearly all type 1 diabetic patients develop retinopathy. Up to 21% of patients with type 2 diabetes have retinopathy at the time of first diagnosis of diabetes, and most develop some degree of retinopathy over time. The estimated prevalence of diabetes for all age groups worldwide was 2.8% in 2000 and will be 4.4% in 2030.

Despite DR being an incurable disease, if the illness is detected and treated in its early stages visual impairment can be avoided in 98% of cases. In this respect, though laser photocoagulation has established to be a successful treatment for preventing major loss of vision produced by DR yet the early detection of the illness is still a difficult task since people affected by it do not recognize symptoms until visual loss develops which usually happens in the later disease stages, when treatment loses its effectiveness.

General step in the analysis of image artifacts are listed as under

a. **Pre- Processing:** This phase is used in order to filter the noisy part of the image and enhance the image set presented for examination. Noise handling mechanism that could be incorporated includes median filtering, Gaussian smoothening, adaptive median filter etc. after the pre-processing phase, feature extraction mechanism is performed.
b. **Feature Extraction:** This mechanism is utilized as a part of request to extricate the basic features out of the picture. These features are utilized to separate valuable data about the disease introduce inside the image. Feature extracted could include Mean, Median, Mode, Kurtosis, Std Deviation, mean deviation etc.
c. **Segmentation:** Features are extracted from enhancement image are examined. Basic segment of the image is extricated and pointless parts are dispensed with from the image. The basic parts are represented with white area and superfluous parts are represented with dark segment. After the image is sectioned the features are removed once more. These features are compared against the training set features in order to identify the lesion if any.
d. **Classification:** The features (Mean, Median, Mode, Kurtosis, Std Deviation, mean deviation etc.) values so extracted are compared against the disease characteristics. These characteristics are examined for fitting in classes of disease. If disease falls into the category of any disease then disease is predicted. For classification, algorithms like K-means, Decision Tree, and SVM etc. can be used.

Technology is enhancing and is widely used in monitoring health. Health related issues occur more frequently due to late discovery of disease. Technology however helps in predicting diseases at the early stages and hence preventing disease. (Mohammed et al. 2014)proposes Internet of Things to create android application for health care. (Dimitrov 2016)Internet of things(IoT) is widely used for collecting information regarding different parameters from the users and then techniques are applied to predict the disease. Techniques used for prediction purposes considered in this paper include (Rao and Kumar 2012)KNN, (Abawajy et al. 2015)Random Forest, (Sinwar and Kaushik 2014)Euclidean distance and (Banerjee 2014)ARIMA. The prediction generated varies depending upon the accuracy of data presented. Accuracy of data presented depends upon the sensors. Sensors if malfunction may produce inaccurate data. Fault tolerance hence is critical in such situations. This paper explore the applications of IoT for collection of data, techniques used to process data presented by sensors and then fault tolerance capabilities possessed by different techniques used to analyse data presented by sensors. Information generated from sensors is stored within dataset. as more and more information in terms of attributes are collected, size of dataset increases. The collected information is then analysed for accuracy and future prediction. The demonstration associated with analysis process is listed as under.

Example 1: Consider sensors attached to human body and collecting information about person heart rate(X), blood pressure(Y) and Temperature(Z). Collected information forms a dataset of following structure in the form of time series

ID	Time	X	Y	Z
1	9:00 AM	120	150	100
1	9:15 AM	123	144	99
1	9:30 AM	122	146	101
1	9:45 AM	124	145	100
1	10:00 AM	123	146	99
2	9:00 AM	121	150	102
2	9:15 AM	125	141	101
2	9:30 AM	126	142	105
2	9:45 AM	121	149	99
2	10:00 AM	120	156	98

Table 1: Dataset of persons records with ID, Time, X,Y and Z.

2. LITRATURE REVIEW

The existing studies and various researchers have investigated the domain of automated diagnosis of Diabetic Retinopathy. This review, therefore, is an attempt to critically explore the literature in the area of machine learning and deep learning techniques used for DR detection culminating the process with derivation of a comparison between the two.**Doshi et al**, **2016 [4]**, Diabetic Retinopathy Detection using Deep Convolutional Neural Networks This paper aims at automatic diagnosis of DR into different stages using deep learning. The design and implementation of GPU accelerated deep Convolutional neural networks to automatically diagnose has been presented hence classifying high-resolution retinal images into 5 stages of the disease based on severity. Three major CNN models were designed their architectures constructed and the corresponding quadratic kappa was found. The single model achieved an accuracy of 0.386 on a quadratic weighted kappa metric and ensemble of three such similar models resulted in a score of 0.3996. [4].

Abbas et al, **2017 [3]**, Automatic recognition of severity level for diagnosis of diabetic retinopathy using deep visual features. In this article, a novel automatic recognition system for classifying diabetic retinopathy (SLDR) in five severity levels is developed through learning of deep visual features (DVFs).However, no pre- or post processing steps were performed. Extraction of DVF features was done from each image by using color dense in scale-invariant and gradient location-orientation histogram techniques. Learning involved a semi-supervised multilayer deep-learning algorithm along with a new compressed layer and fine-tuning steps. This SLDR system was evaluated and compared with state-of-the-art techniques using the measures of sensitivity (SE), specificity (SP) and area under the receiving operating curves (AUC). Around 750 fundus images were analyzed and highly satisfying results were obtained which demonstrated that the proposed SLDR system is appropriate for early detection of DR and provide an effective treatment for prediction type of diabetes.[3]

Gulshan et al, **2016 [13]**, Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs. The given paper applied deep learning to construct an algorithm for automated detection of diabetic retinopathy along with diabetic macular edema in retinal fundus photographs. Deep Convolutional neural network was used for image classification trained using a dataset of 128175 retinal images graded 3 to 7 times for diabetic retinopathy and diabetic macular edema by a panel of 54 US licensed ophthalmologists and ophthalmology senior residents between May and December 2015.The algorithm was also validated in January and February 2016 using 2 separate datasets. The algorithm so developed had high sensitivity and specificity for detecting referable diabetic retinopathy. Further research is necessary to determine the feasibility of applying this setup in the clinical environment. [13]

Jen Hong Tan et al, **2017[1]**, Automated Segmentation of Exudates, Hemorrhages, Microaneurysms using Single Convolutional Neural Network) The paper proposes to use a 10-layer Convolutional neural network to automatically concurrently segment and differentiate exudates, hemorrhages and micro-aneurysms. Input images were normalized before segmentation. The net is trained in two stages to improve performance. 30,275,903 effective points in the CLEOPATRA database achieving satisfactory results although a drop in sensitivity is observed for hemorrhages and micro-aneurysms. This study shows that it is possible to get a single Convolutional neural network to segment such pathological features on a wide range of fundus images with reasonable accuracy. [1]

Gargeya et al, 2016 [7], Automated Identification of Diabetic Retinopathy Using Deep Learning. This paper presents the development followed by an evaluation of a data-driven deep learning algorithm as a diagnostic tool for automated DR detection. The algorithm processed color fundus images and besides classifying them as healthy (no retinopathy) or having DR, identification of cases relevant for medical referral is also done. A total of 75 137 publicly available fundus images from diabetic patients were used to train and test this model to differentiate healthy fundi from those with DR. A panel of retinal specialists determined the ground truth for the given data set before experimentation. The model was also tested using the public MESSIDOR 2 and E-Ophtha databases for validation purpose. Visualization of the information learned was done using an automatically generated abnormality heat map. The model achieved adequate and accurate results. [7]

Grinsven, 2016 [2], Fast Convolutional neural network training using selective data sampling: Application to hemorrhage detection in color fundus images. The proposed method provides an improvement and speed-up of the CNN trained for medical image analysis tasks by dynamically selecting misclassified negative samples. Heuristic sampling of training samples is done based on classification by the current status of the CNN. Weights are then assigned to the training samples. A comparison has also been performed between the two i.e., CNN with (SeS) and without (NSeS) the selective sampling method. Focus is on the detection of hemorrhages in color fundus images. Performance was improved and satisfactory and a comparable area under curve characteristic was achieved on two data sets. However, the SeS CNN statistically outperformed the NSeS CNN on an independent test set. [2]

Quellec et al, 2017 [5], Deep Image Mining for Diabetic Retinopathy Screening) Here, a generalization of the back propagation method is proposed in order to train ConvNets that produce high-quality heat maps. The proposed solution is applied to diabetic retinopathy (DR) screening in a dataset of almost 90,000 fundus photographs from the 2015 Kaggle Diabetic Retinopathy competition and a private dataset of almost 110,000 photographs (e-ophtha). For the task of detecting referable DR, very good detection performance was achieved. Performance was also evaluated at the image level and at the lesion level in the DiaretDB1 dataset, where the proposed detector trained to detect referable DR outperforms recent algorithms trained to detect those lesions particularly, with pixel-level supervision. At the lesion level, the proposed detector outperforms heat map generation algorithms for ConvNets. [5]

Pratt et al, 2016 [6], Convolutional Neural Networks for Diabetic Retinopathy) In this paper, CNN approach is proposed to diagnosing DR from digital fundus images along with accurate classification of its severity. A network with CNN architecture and data augmentation is developed which identifies features such as micro-aneurysms, exudates and haemorrhages on the retina involved in the classification task and as an outcome provide a diagnosis automatically without user input. To train this network, a high-end graphics processor unit (GPU) is used on the publicly available Kaggle dataset with 80,000 images which demonstrated impressive results, particularly for a high-level classification task. Moreover, 5000 images were used for validation which also presented suitable results.[6]

3. PROPOSED WORK

The thought behind this theme is to recognize the diabetic retinopathy in the eye among the diabetic patients. The condition can cause finish visual deficiency to the patients so the analysis is required to recognize it in its beginning period. By taking the picture of the retina we can recognize the infected retina and typical retina. Swelling of the veins in the eye and cracking causes obscured vision at that point on the off chance that it is not treated it causes visual deficiency.

1. To study the existing techniques of detecting Diabetic Retinopathy;
2. To reduce noise within of retina image by using adaptive median filter ;
3. To increase accuracy of segmentation by using Support Vector Machine ;
4. To compare the new technique with existing technique;

4. METHODOLOGY

1. Obtain the training image from the dataset.
2. Apply the pre-processing phase to eliminate the noise.
3. Apply the SVM segmentation portion to extract critical portions from non critical images.
4. Check the attributes for classification
5. Obtain the parametric result.

5. CONCLUSION

Deep Learning mechanism can handle large dataset. However slight change in the present dataset could lead to drastic change in result due to ambiguity problem present within existing literature.

In order to tackle the issue, stable data presentation by handling noise within the image is considered in considered approach. The decision tree classification is complex and could lead to indifferent results and to tackle the issue Support vector machine can be used since it is resilient in case noisy data is presented to the model. Overall classification accuracy could improve by the application SVM.

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