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Dianet: A Deep Learning Based Architecture to Diagnose Diabetes Using Retinal Images Only

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ABSTRACT

Diabetes is one of the most common causes of death worldwide, putting a signifigant strain on the global healthcare system. As a result, early detection of diabetes is critical and could save many lives. Current methods for determining whether a person has diabetes or is at risk of acquiring diabetes, on the other hand, rely heavily on clinical biomarkers. They propose an unique deep learning architecture in this paper to predict whether or not a person has diabetes based on an image of his or her retina. Using a small dataset, the authors develop DiaNet. multi-stage convolutional neural network (CNN)-based model that can achieve an accuracy level of over 84 percent on this task and successfully identifies the regions on the retina images that contribute to the decision making process, as confirmed by medical experts in the field To the best of our knowledge, this is the first study to show the differentiating ability of retinal pictures for diabets patients in the Qatari community. After comparing DiaNet's performance to that of other clinical data-based maching learning models, the researchers came to the conclusion that retinal scans contain enough information to identify the Qatari diabetic cohort from the control group. Furthermore, our research demonstrates that retinal pictures may contain prognostic signals for diabetes as well as other comorbidities such as hypertension and ischemic heart disease. The findings led to assume that retinal scans should be included in the clinical setting for diabetes diagnosis in the near future.

Keywords: Convolutional Neural Network, Deep Learning, Diabetes, Machine Learning.

INTRODUCTION

Diabetic eye disease (DED) is a group of eye problems that can affect diabetic people. Such disorders include diabetic retinopathy, diabetic macular edema, cataracts, and glaucoma. Diabetes can damage your eyes over time, which can lead to poor vision or even permanent blindness. Early detection of DED symptoms is therefore essential to prevent escalation of the disease and timely treatment. Diabetes-related long-term damage and collapse of the heart, kidneys, and microvascular circulation of the retina arell related to long-term hyperglycemia [1]. Because changes in retinal vascular anatomy can provide visual cues for diabetes, most clinical guidelines advocate an annual retinal screen for diabetic patients using retinal fundus pictures or dilated eye exams [2, 3]. If we could automate retinal image-based diabetes diagnosis in clinical settings, we could avoigh human-oriented subjective judgement. The ophthalmologist's burden may be reduced, and a large number of patients could be objectively screened in a short period of time [4]. Early on, the disease exhibits little symptoms, making disease detection challenging. As a result, a fully augnated system is necessary to assist in the carly identification and screening process. The inputs image were processed by the convolutional neural network (CNN) through the ginal fundus photos and the entropy images. For the deep learning-based system, transformed entropy imaging of fundus photos can improve the machinery detection accuracy, sensitivity, and specificity of referable DR [7].The research were evaluated in terms of the datasets used, the image pre-processing techniques used, and the classification approach used. Using 237 clinical measurements from a Qatar Biobank (QBB) diabetic cohort, a machine learning (ML) model was able to identify diabetes groups with over 78 percent accuracy. A new deep convoltional neural network based algorithm (DCNN). Unlike the usual DC technique, we use fractional max-pooling instead of the typically used mu pooling layers. It is beneficial for home care, remote medical care, and self-examination [9]. Median filtering and morphological operations for blood vessel detection. They use multilevel throgholding to extract bright regions assumed to be the optic disc or exudates. The methods for thresholding and region expansion are simple, but picking threshold values, region seed locations, and stopping conditions are difficult .

LITERATURE REVIEW

Tahira Nazir [1]Diabetic patients are at the risk of developing different eye diseases i.e., diabetic retinopathy (DR), diabetic macular edema (DME) and glaucoma. DR is an eye disease that harms the retina and DME is developed by the accumulation of fluid in the macula, while glaucoma damages the optic disk and causes vision loss in advanced stages. However, due to slow progression, the disease shows few signs in early stages, hence making disease detection a difficult task. Therefore, a fully automated system is required to support the detection and screening process at early stages.

Gen-Min Lin[2]Entropy images, representing the complexity of original fundus photographs, may strengthen the contrast between diabetic retinopathy (DR) lesions and unaffected areas. The aim of this study is to compare the detection performance for severe DR between original fundus photographs and entropy images by deep learning.

II METHODOLOGY AND IMPLEMENTATION

Automated DED detection systems can be assembled through joint image processing techniques using either Machine Learning (ML) or Deep Learning techniques (DL).The idea is to reduce the computational complexity while training Neural Network architecture (resource intensive).Training images using the DL model can be costly, challenging in terms of *annotated* data collection, and time and power consuming. The pre-processed images are input to DL architecture for the automatic extraction of features and their associated weights to learn the classification rules.The feature to calculate value and compare database. The features weights are optimized recursively to ensure the best classification results. Finally, the optimized weights are tested on an unseen set of images to show result diabetes or not.Since Diabetic Retinopathy is a silent disease that may cause no symptoms or only mild vision problems, annual eye exams are crucial for early detection to improve the chances of effective treatment where fundus cameras are used to capture the retinal images. In order to address the above limitations and maximize the clinical utility of automated detection, in this study the deep transfer learning method using the Inception-v3 network was explored for automatically categorizing any DR present in retinal fundus photographs as no apparent DR, mild/moderate/severe non-proliferative DR (NPDR), and proliferative DR (PDR) to assign the level of DR progression. The proposed approach, with its high accuracy, high sensitivity, and high specificity, could assist in making automated screening for early DR based on retinal fundus photographs and potentially alleviate the demand for the resource-intensive manual analysis of retinal fundus photographs from diverse clinical circumstances so that high-risk patients could be effectively referred for further evaluation and treatment.

i) Convolutional layers

The convolutional layer is the core of a CNN. The Conv layer is another name for it. It uses filters with a set of automatically leamable parameters to extract relevant information from an input image (weights). Filters are constructed using a small matrix with a dimension of one (MxMx3). The output of the convolution layer in CNNs can be represented as.

$X_j^p=\sum_{iNj} Xi^{p-1}{}_{xkij}{}^{p}{}_{Bj}{}^{p}$

Where N_j denotes the number of filters, P represents the p^{th} layer, X_i^{p-1} denotes feature map, k_{ij} denotes convolutional kemel, and B_j, denotes bias term.

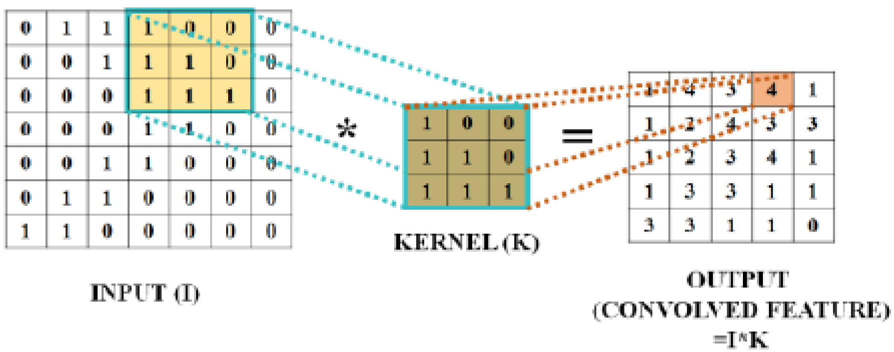

Figure 3 Convolutional layer

III RESULTS AND DISCUSSION

The results of our experiments are presented and analysed in this section. We quantitatively evaluate the performance of our proposed strategy to that of other alternative methods and show that it outperforms them in predicting the concept of diabetes in test participants. We used mean accuracy, sensitivity, specificity, and precision for quantitative performance reporting. Because the data set is well-balanced, the mean accuracy can be used as a model evaluation metric. In this paper we proposed Dianet, a deep learning-based approach for assessing the existence of diabetes in a test subject based on retinal pictures. We used a CNN based architecture that takes a retinal image as input, and outputs a probability distribution over the possible labels; that is control and diabetes. To avoid data leaking, layered cross-validation was used to perform model selection, generalization, and performance estimates on the QBB dataset during the fine-tuning stage. The data was pre-processed and augmented using the same approach in multistage tuning for DiaNet and single-stage tuning. DiaNet to diagnose diabetes using retinal images using CNN

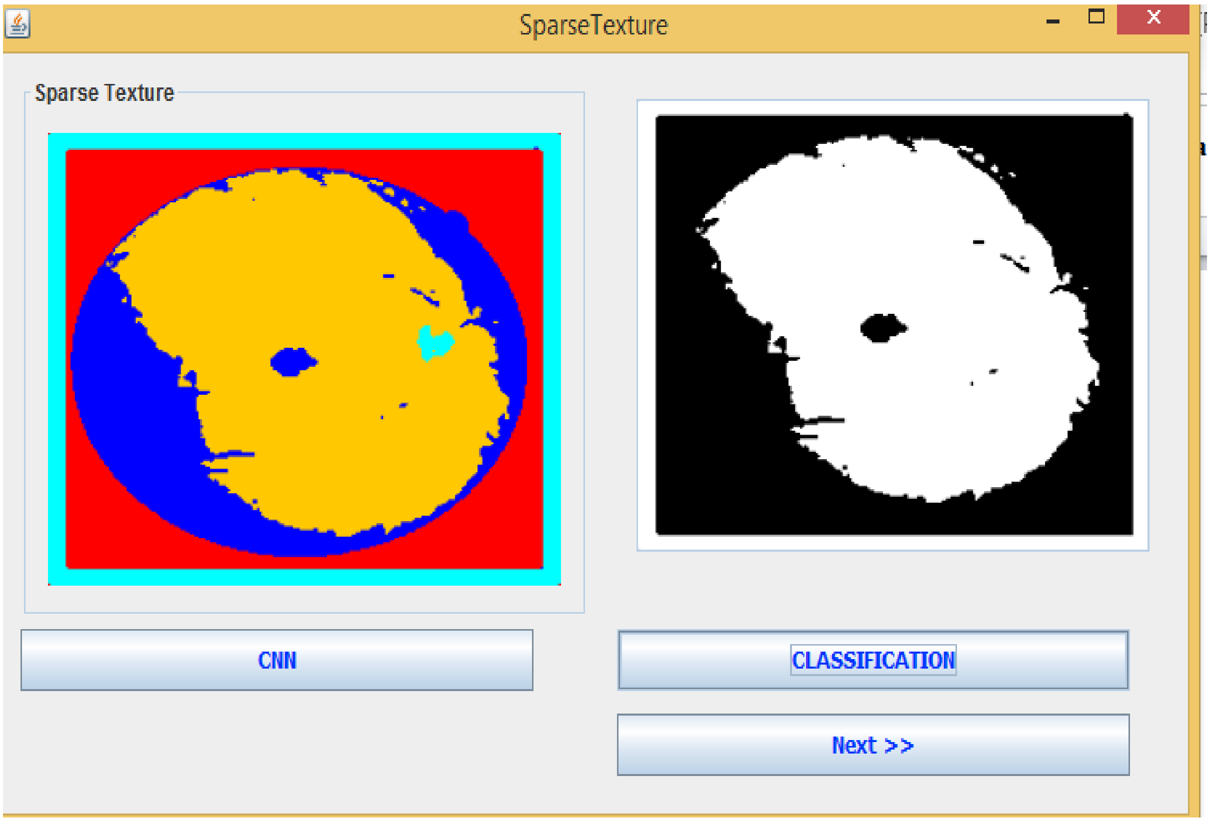

FIG:RESULT

IV.CONCULSION

An in-death look at the current state of diabetic eye disease detection methods. A thorough Evaluation of relevant papers was done to attain this purpose. We discovered that constructing an efficient neural network classifier necessitates careful consideration of both the network design on the data input after conducting considerable research on various classification systems and approaches. As a result, image processing is crucial in the development of high-accuracy diabetic eye disease classifiers. Specific work limits in the early classification of diabetic eye illness where identified as part of this investigation. First classification of DED at an early stage, and then classification of DR, GL and DME using a procedure that results in irreversible blindness. Finally the goal of this study was to offer a paradigm for early automatic DED identification in fundus pictures using deep learning, which fill the major research gaps.

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