e-ISSN:2582-7219

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH IN SCIENCE, ENGINEERING AND TECHNOLOGY

Volume 7, Issue 7, July 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 7.521

6381 907 438 6381 907 438 ijmrset@gmail.com www.ijmrset.com

| ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 7.521| Monthly, Peer Reviewed & Referred Journal|

| Volume 7, Issue 7, July 2024 |

| DOI:10.15680/IJMRSET.2024.0707155 |

Deep Learning Based Automated Detection of Diabetic Retinopathy Using Inception V3 Architecture

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ABSTRACT: Diabetic Retinopathy (DR) is a diabetes-related complication that affects the eye, caused by damage to the blood vessels in the retina's light-sensitive region at the rear. It is the leading cause of blindness among working-age individuals, particularly when diabetes is poorly managed. While current detection methods aimed at Diabetic Retinopathy require manual examination of retinal pictures through an ophthalmologist, the proposed approach aims to automate DR detection using deep learning techniques. Specifically, the Inception V3 architecture is employed in this approach. With 35,126 retinal photos made available to the public by eyepatch on the Kaggle websitethe model reached an accuracy of about 81% after being trained on a GPU.By employing deep convolutional neural networks to evaluate retinal pictures, the Inception V3 architecture improves detection efficiency and accuracy. The Inception V3 architecture, a portion of the Inception family of models, introduces several key features that enhance its performance. It incorporates factorized convolutions, which break down traditional convolutions into smaller, more manageable operations, thus reducing computational cost while maintaining high accuracy. Additionally, the usage of auxiliary classifiers helps to mitigate the vanishing gradient problem and improve model convergence during training. The architecture also employs batch normalization extensively, which stabilizes and accelerates the training process. These innovations enable the Inception V3 model to analyze more complex patterns and features in retinal images, leading to more reliable DR detection. By leveraging these advanced techniques, the future model offers a robust and scalable solution for automated DR diagnosis.

KEYWORDS: Ophthalmologist, Diabetic Retinopathy

I.INTRODUCTION

Computational models with several processing layers can learn different levels of abstraction for data representations thanks to deep learning. The state-of-the-art has been greatly advanced by these techniques in several sectors, including drug discovery and genomics, as well as speech recognition, visual object recognition, and object detection. Deep learning uncovers intricate structures in large datasets by employing the backpropagation algorithm, It instructs a machine on how to modify its internal parameters in order to compute the layer's representation based on the layer's representation before it. While recurrent networks have shown remarkable proficiency in processing sequential data, such as text and voice, deep convolutional networks have made substantial strides in processing pictures, video, speech, and audio.

What is Machine Learning?

Machine Learning describes a framework for computer algorithms capable of learning from examples and improving autonomously without explicit programming by a developer. It is a subsection of artificial intelligence that integrates data with statistical tools to predict outputs, enabling actionable insights.

The breakthrough lies in the concept that a machine can autonomously learn from data (i.e., examples) to generate accurate results. Machine learning is closely intertwined with data mining and Bayesian predictive modeling. In this process, the machine takes data as input and employs algorithms to generate responses.

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II.SYSTEM MODEL AND ASSUMPTIONS

IMPLEMENTATION
Multi-Layer Perceptron (MLP)

- Dataset
- Importing the necessary libraries
- Retrieving the images
- Splitting the dataset
- Building the model
- Apply the model and plot the graphs for accuracy and loss
- Accuracy on test set
- Saving the Trained Model

MODULES DESCSRIPTION:

Dataset:
In the first module, we developed the system to get the input dataset for the training and testing purpose. We give the data set in model folder.

The dataset consists of 2222 Diabetic Retinopathy images.

Importing the necessary libraries:
We will be using Python language for this. First we will import the necessary libraries such as karas for building the main model, sklearn for splitting the training and test data, PIL for converting the images into array of numbers and other libraries like NumPy, pandas, and matplotlib and TensorFlow.

Retrieving the images:
We will retrieve the images and their labels. Then resize the images to (224,224) as all images should have same size for recognition. Then convert the images into NumPy array.

Splitting the dataset:
Split the dataset into train and test. 80% train data and 20% test data.

Inception Networks
This is how an inception block looks:

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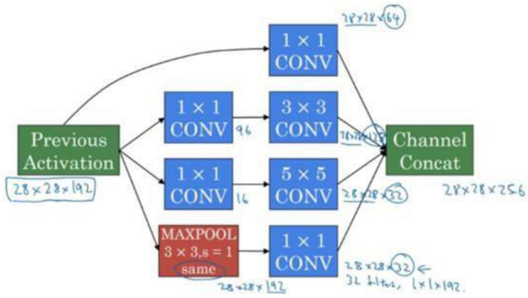

Fig :2 Module Diagram

Inception v3

The Premise

The supplementary classifiers didn't really help until the very end of the training procedure, when accuracies were getting close to saturation, according to the authors. They contended that, particularly in the case of BatchNorm or Dropout operations, they serve as regularizers.

Possibilities to improve on the Inception v2 without drastically changing the modules were to be investigated.

The Solution

1. **Inception Net v3** incorporated altogether of the above upgrades stated for Inception v2, and in addition used the following:
2. Respro Optimizer.
3. Factorized 7x7 convolutions.
4. Batch Norm from the Auxiliary Classifiers.
5. Label Smoothing (A type of regularizing component added to the loss formula that avoids the network's overconfidence about a class. Prevents over fitting).

Building the model:

The concept of convolutional neural networks. They are very successful in image recognition. The key part to understand, which distinguishes CNN from traditional neural networks, is the **convolution** operation. Having an image at the input, CNN scans it many times to look for certain **features**. This scanning (convolution) can be set with 2 main parameters: stride and padding type. As we see on below picture, process of the first convolution gives us a collection of new frames, shown here in the second column (layer). Each frame contains an information about one feature and its presence in scanned image. Resulting frame will have larger values in places where a feature is strongly visible and inferior standards where there are no or little such features. Afterwards, the process is repeated for each of obtained frames for a chosen number of times. In this project I chose a classic InceptionV3 model which contains only two convolution layers.

The latter layer we are convolving, the more high-level features are being searched. It works similarly to human perception. To give an example, below is a very descriptive picture with features which are searched on different CNN layers. As you can see, the application of this model is face recognition. You may ask how the model knows which features to seek. If you construct the CNN from the beginning, searched features are random. Then, during training process, weights between neurons are being adjusted and slowly CNN starts to find such features which enable to meet predefined goal, i.e. to recognize successfully images from the training set.

III. EXISTING MODELS

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Inception Networks
This is how an inception block looks:

IV. PROPOSED MODEL

In this proposed system, we propose an automatic deep-learning-based method for phase discovery of diabetic retinopathy by single photography for the human fundus. The method presented can serve as a screening tool for initial discovery of diabetic retinopathy because to its high sensitivity. The model was developed using
Keras with TensorFlow backend for Python, highlighting its capability to efficiently process and analyze retinal images for diagnostic purposes. The planned framework is implemented using Inception V3 architecture.

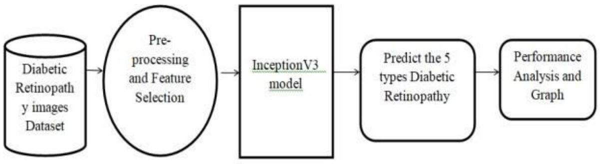

Fig :1 Proposed Architecture

The dataset used in the proposed technique is freely accessible for download from numerous internet sources. It consists of images captured from different individuals, using various cameras, and varying in size. Given the inherent noise in this data, multiple preprocessing steps were necessary to standardize all images into a suitable format for training purposes.

V. RESULT AND DISCUSSION

Detecting diabetic retinopathy (DR) usage of deep learning techniques has become a significant area of research and application in medical imaging and ophthalmology. The primary aim is to classify and categorize retinal abnormalities caused by diabetes, which can lead to vision impairment and blindness if left untreated. Here's a summary of key results and advancements in the field:

1) Key Results in Diabetic Retinopathy Detection using Deep Learning

Accuracy and Sensitivity: Convolutional Neural Networks (CNNs), in particular, are deep learning models that have shown excellent sensitivity and accuracy in identifying diabetic retinopathy from retinal pictures. Some models have achieved performance metrics comparable to or even surpassing that of human experts. For instance, Google's DeepMind developed a deep learning system that achieved an accuracy of 94.5% for referable DR detection .

Automated Screening: Automated screening systems based on deep learning can significantly reduce the workload of ophthalmologists by efficiently recognizing patients who require further examination. These systems can process large

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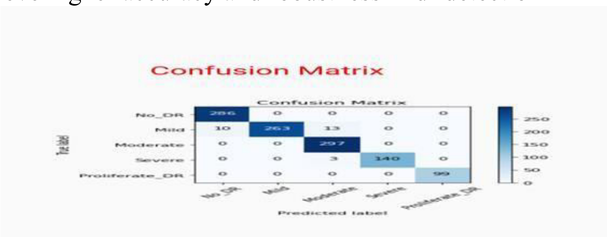
volumes of retinal images quickly, providing rapid preliminary diagnosis and prioritizing cases that need immediate attention .

Grading Severity: Deep learning models are not limited to capable of detecting the existence of diabetic retinopathy but also of grading its severity. Models trained on large, annotated datasets have been able to classify DR into various stages (e.g., mild, moderate, severe) with a high degree of accuracy, this is essential for choosing the right treatment programs.

Real-world Applications: Several deep learning-based DR detection structures have been deployed in realworld settings, such as primary care clinics and telemedicine platforms. These systems have been authorized across diverse populations and are being integrated into healthcare workflows to improve screening programs, especially in regions where access to ophthalmological services is limited.

VI. CONCLUSION

given the limited availability of clinicians for manual detection of diabetic retinopathy (dr), an automated approach can significantly alleviate the manual labor involved in diagnosis. the presented model utilizes deep convolutional neural networks (cnns) based on the inception v3 additional data and iterative training can further leverage the strengths of the inception v3 architecture to achieve higher accuracy and robustness in dr detection



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