DEEP CONVOLUTIONAL NEURAL NETWORK BASED MULTICLASS RETINAL DISEASE DETECTION

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ABSTRACT: Ophthalmologists use retinal imaging as a crucial diagnostic tool for a range of eye conditions. Numerous retinal disorders can cause microvascular alterations in the retina, and a great deal of study has been done on early identification of medical pictures to enable timely administration of appropriate medication. The goal of this research is to create a non-invasive, automated deep learning framework that can identify various eye illnesses from color fundus photos. The RFMiD dataset for multiple classes of eye diseases was utilized to create an effective diagnosis system. A multi-label dataset was used to extract multi-class fundus images, and different augmentation strategies were then used to strengthen the framework in real time. The network's minimal computational demand guidelines were followed for processing images.

1. INTRODUCTION

Retinal diseases are spreading widely among humans of all ages. The retina contains a layer of optic nerve tissue called photosensitive in the human eye.

This layer transforms the light focused by the lens into brain impulses. Macula, positioned in the retina's middle, performs the sensing process. Information acquired by the macula is processed by the retina and transferred to the brain for visual recognition through the optic nerve [1]. Different types of diseases can cause abnormality in perception, such as age-related macular degeneration (AMD), optic disc drusen, Roth spot diabetic macular Edema (DME) [2], etc. In most of the developed countries, people belonging to the age group of 50 to 60 are losing vision due to AMD. According to recent research, in the United States (US), this abnormality is found in about 35% of adults in the age group of 80 [3]. Identifying retinal diseases is the most challenging task, as accurate diagnosis needs a highly experienced ophthalmologist due to the diversity of retinal diseases. Similarly, with computer-aided diagnostic systems (CAD), retinal diseases can easily be identified and treated at early stages.

[4]. Technology advancements have immense benefits in almost every field of

life, especially in the medical domain. Several approaches and models have been presented to improve the efficacy and quality of medical solutions. A significant improvement has been observed in the social health system with the advancement in Automatic Disease Detection (ADD) [5]. Furthermore, an ADD application, namely retinal symptom analysis, provides a unique opportunity to improve eye care globally [6]. Recently, many state-of-the-art ML and Deep Learning (DL) models have been proposed for the classification, segmentation, and identification of retinal diseases. We observe that data collection and labelling are significant challenges in the implementation of ADDs, as presented by authors in [7] and [8], due to the development of several machine learning (ML) and deep learning (DL) models, including Recurrent Neural Network (RNN), Convolution Neural Network (CNN), Alex Net ResNet and VGN. These have enabled researchers and physicians to detect and categorize such vital disorders [9] readily. An ML-based Hybrid technique is presented for the classification of retinal diseases automatically. Researchers in [10] have proposed to use U-Net segmentation for image pre-processing; they have also used a Support Vector Machine (SVM) classifier for the classification. The proposed technique achieved a diagnostic accuracy of 89.3%. Yang et al. also provided the first labelled Eye Net dataset containing 32 retinal diseases. It was noted by authors in [10] that the U-Net has a significant flaw of high memory consumption in moving the whole feature map to the corresponding decoder. Deep learning plays a Vitol role in the classification of images [11], [12], [13]. This research proposes a CNN model based on deep learning for classifying multi-class eye disease detection. The proposed model has been evaluated on Eye Net Dataset. The EyeNet dataset includes 32 folders, each containing related images for specific. 70% has been used for training and the rest for validation. From experimental evaluation, it has been observed that the proposed model achieved 95% accuracy. The deep learning-based CNN model has been applied for retinal-based crucial diseases to boost the conventional diagnostic method. This is the primary contribution of this study. The key contributions of the paper are as follows. A deep learning-based CNN model has been utilized to strengthen the traditional diagnosis process for retinal-based crucial disease.The proposed CNN model produces better outcomes while consuming low memory than standard state-of-art techniques.

. Experimental evaluation reveals that the performance of the proposed model on the multi-class Eye Net dataset produces higher accuracy.

2.LITERATURE SURVEY

2.1 Title: " Further Results on Mean-Square Exponential Input-to-State Stability of Stochastic Delayed Cohen-Grossberg Neural Networks **"**

Year: 2015

Authors: Wentao wang

Abstract: We examine the mean-square exponential input-to-state stability and global existence of solutions for a type of stochastic delayed Cohen-Grossberg neural networks that do not have a global Lipschitz requirement. We identify novel adequate criteria that guarantee the global existence and mean-square exponential input-to-state stability of the supplied neural network solutions under local Lipschitz constraints. Additionally, we compare our innovative results with those of Zhou et al. (2015) and provide a numerical example to illustrate the advantages of our work.

2.2. Title: " Prevalence of asymptomatic ocular conditions in subjects with refractive-based symptoms "

Authors: Langis Michaud*, Pierre Forcier

Year: 2013

Abstract: This study aims to investigate the prevalence of asymptomatic ocular conditions in individuals presenting with refractive-based symptoms. A cross-sectional study was conducted involving 500 subjects who visited an ophthalmology clinic with complaints of refractive errors. Each subject underwent a comprehensive eye examination, including visual acuity testing, refraction assessment, slit-lamp bio microscopy, intraocular pressure measurement, and fundus examination. Subjects were categorized into two groups: those with only refractive errors and those with additional asymptomatic ocular conditions.

2.3. Title: " Practical guide to genetic screening for inherited eye diseases "

Authors: Méjécase CMalka SGuan ZSlater AArno GMoosajee M

Year: 2020

Abstract: About one in 1000 people worldwide suffer from genetic eye illnesses, the majority of which have an unknown molecular cause. Understanding the ailment and its inheritance better is made possible by the discovery of the gene variant(s) responsible for the disease. Since autosomal recessive RPE65-retinopathy now has an approved retinal gene therapy and multiple ocular gene/mutation-targeted clinical trials are in progress, it is critical to establish a genetic diagnosis to enable patients to fully benefit from the most recent advancements in research and treatment options.

2.4. Title: "Age-related macular degeneration (ARMD) "

Authors: Riazi Esfahani HHajizadeh F

Year: 2021

Abstract: The eye condition known as age-related macular degeneration (AMD) can cause central vision impairment. It occurs when the macula, the area of the eye that regulates crisp, straight-ahead vision, is harmed by aging. The macula is a component of the retina, which is the back of the eye's light-sensitive tissue. AMD is a prevalent ailment that is the primary cause of vision loss in the elderly. AMD does not result in total blindness, but it can make it more difficult to drive, read, recognize faces, and perform close-up tasks like housework or cooking.

3.PROPOSED SYSTEM

The goal of the Eye Deep-Net model, the suggested system, is to provide a diagnostic framework for the early detection of different fundus diseases using a shared deep neural network. This would enable patients to receive treatment on schedule and take the required precautions to prevent their eyes from going blind. The primary contribution of the suggested approach is the development of a strong and efficient framework for the classification of fundus images and diagnosis of various eye illnesses using the suggested Eye Deep-Net model, a deep learning architecture. After converting an open-source multi-labelled dataset into a multiclass dataset, retrieved fundus images were processed and enhanced to handle real-world scenarios.

3.1 METHODOLOGIES

Dataset Collection

In the dataset collection phase, the focus is on gathering a comprehensive set of retinal images that represent various eye conditions. The RFMiD (Retinal Fundus Multi-disease Image Dataset) is utilized, which contains color fundus images labelled with multiple classes of eye diseases. The dataset encompasses a wide range of retinal conditions, ensuring that the model can learn to recognize different patterns and anomalies associated with each disease.

Data Preprocessing

Preprocessing prepares the raw images for the deep learning model by enhancing image quality and uniformity.

This involves standardizing the image dimensions, normalizing pixel values, and applying data augmentation techniques such as rotation, flipping, zooming, and brightness adjustments. Noise reduction filters are also implemented to enhance image clarity.

Training and Build Model

In this phase, the deep neural network is designed, trained, and fine-tuned to accurately classify retinal images. The process involves selecting an appropriate architecture, feeding pre-processed images into the model, and adjusting the model's weights through backpropagation using a labelled dataset. The model is evaluated on a validation set to tune hyperparameters and prevent overfitting, with optimization techniques applied to enhance performance.

Input Data and Predict Output Data

In the final module, the trained model is deployed to make predictions on new retinal images. The input images undergo the same preprocessing steps to ensure compatibility with the model. The model processes the input data and outputs probabilities or labels indicating the presence of various eye diseases. The model's output is interpreted to provide diagnostic information, and its predictions are continuously validated against actual medical diagnoses to ensure accuracy and reliability.

3.2 ALGORITHMS

CNN ALGORITHM

Deep Learning is turning into a very famous subset of laptop studying due to its excessive degree of overall performance throughout many sorts of data. An amazing way to use deep gaining knowledge of to classify pix is to construct a Convolutional Neural Network (CNN). Kera's library in Python makes it extraordinarily easy to construct a CNN. Computers see pictures of the usage of pixels. Pixels in pix are typically related. For example, a sure team of pixels may additionally signify a part in a photograph or some different pattern. Convolutions use this to assist become aware of images. A Convolution multiplies a matrix of pixels with a filter matrix or kernel and sums up the multiplication values. Then the convolution slides over to the subsequent pixel and repeats the identical technique till all the photograph pixels have been covered. Convolutional Neural Networks are very comparable to everyday Neural Networks; they are made up of neurons that have learnable weights and biases. Each neuron receives some inputs, performs a dot product and optionally follows it with a non-linearity.

Regular Neural Nets don’t scale nicely to full images. Consider a picture of measurement 32x32x3(32 wide, 32 high, three colour channels), so a single utterly related neuron in a first hidden layer of an everyday Neural Network would have 32*32*3 = 3072 weights. This quantity nevertheless appears manageable, however simply this completely linked shape does no longer scale to large images. For example, and photo of extra first-rate size, e.g.200x200x3, would lead to neurons that have200*200*3 = 120,000 weights. Moreover, all of us desire to have numerous such neurons, so the parameters would add up quickly! Clearly, this full connectivity is wasteful, and the massive variety of parameters would rapidly lead to overfitting.Convolutional Neural Networks take advantage of the truth that the entry consists of snap shots, and they constrain the structure in a greater good way. Unlike an ordinary Neural Network, the layers of a ConvNet have neurons organized in three dimensions:width, height, depth. For example, the enter photograph with dimensions XxYxZ (width, height, depth respectively), the neurons in a layer will solely be linked to a small vicinity of the layer earlier than it, rather of all of the neurons in a fully-connected manner, the remaining output layer would have dimensions(1,1,C), because with the aid of the quilt of the Connet architecture, it will limit the full photo into a single vector of category scores, organized alongside the depth dimension.

3.2.1 Layers in Convolutional Neural Network

- The convolutional layer will compute the output of neurons that are linked to local regions in the input, with each neuron computing a dot product between their weights and a small region in the input volume to which they are reconnected.
- At zero, the RELU layer will use an element-wise activation function, such as the max (0, x) thresholding.
- The POOL layer will undertake down sampling along the spatial dimensions (width, height).
- The FULLY linked layer will compute the class scores, producing in a volume of size [1x1xX], where X integers correspond to class scores.

3.2.2 Convolution layer

When dealing with excessive dimensional inputs such as images, as considered above it is impractical to join neurons to all neurons in the preceding volume. Instead, it will join every neuron to solely a nearby location of the enter volume. The spatial extent of this connectivity is a hyperparameter referred to as the receptive discipline of the neuron (equivalently this is the filter size). The extent of the connectivity alongside the depth axis is usually equal to the depth of the enter volume. It is vital to emphasize once more this asymmetry in how to deal with the spatial dimensions (width and height) and the depth dimension: The connections are nearby in house (along width and height), however constantly full alongside the complete depth of the enter volume.

Example 1. For example, believe that the enter extent has dimension [32x32x3], (e.g.anRGBCIFAR-10image)

. If the receptive field (or the filtersize) is5x5, then every neuron in the Convolution Layer will have weights to a[5x5x3] vicinity in the enter volume, for a whole of 5*5*3 =75 weights (and +1 bias parameter). Notice that the extent of the connectivity alongside the depth axis ought to be 3, due to the fact that this is the depth of the enter volume.

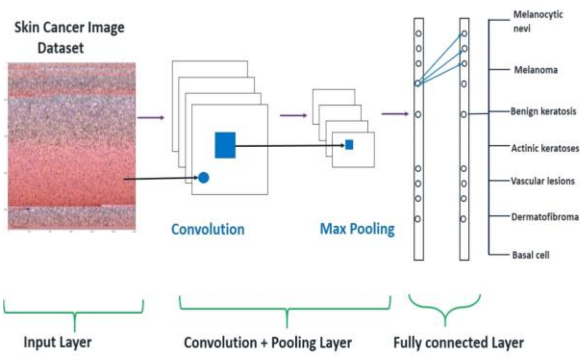

Fig 1: Convolutional- layer representation

An example red input volume (e.g., a 32x32x3 CIFAR-10 image) and an example volume of neurons in the first Convolutional layer are shown on the left. Each neuron in the Convolutional layer is spatially related only to a tiny region in the input volume, but to the entire depth (i.e., all colour channels). It should be noted that there are several neurons (5 in this case) along the depth, all of which are staring at the same place in the input.

Right: The neurons from the Neural Network chapter are unaltered: They still calculate a dot product of their weights with the input, followed by a nonlinearity, but their connectedness is now spatially limited to be local. 1) Convolutional Layer: In a typical neural network each input neuron is connected to the next hidden layer. In CNN, only a small region of the input layer neurons connects to the neuron hidden layer.

2)Reul Layer: - In this layer we apply activation function.

3) Pooling Layer: The pooling layer is used to reduce the dimensionality of the feature map. There will be multiple activation & pooling layers inside the hidden layer of the CNN.

4) Fully Connected layer: Fully Connected Layers form the last few layers in the network. The input to the fully connected layer is the output from the final Pooling or Convolutional Layer, which is flattened and then fed into the fully connected layer.

```
def SGDoptimizer():
   global eyenet_model
   #train eyenet model using SGD
optimizer fixed learning rate
   eyenet_model=
keras.models.Sequential([
keras.layers.Conv2D(filters=32,
```

```
kernel_size=(11,11), strides=(4,4),
activation='relu',
input_shape=(X_train.shape[1],X_train.sh
ape[2],X_train.shape[3])),
 keras.layers.BatchNormalization(),
  keras.layers.MaxPool2D(pool_size=(1,1),
strides=(2,2)),
keras.layers.Conv2D(filters=16,
kernel_size=(9,9), strides=(1,1),
activation='relu', padding="same"),
 keras.layers.BatchNormalization(),
 keras.layers.MaxPool2D(pool_size=(1,1),
strides=(2,2)),
keras.layers.Conv2D(filters=8,
kernel_size=(7,7), strides=(1,1),
activation='relu', padding="same"),
keras.layers.BatchNormalization(),
 keras.layers.MaxPool2D(pool_size=(1,1),
strides=(2,2)),keras.layers.
Conv2D(filters=8, kernel_size=(6,6),
strides=(1,1), activation='relu',
padding="same"),
 keras.layers.BatchNormalization(),
 keras.layers.MaxPool2D(pool_size=(1,1),
strides=(2,2)),
 keras.layers.Conv2D(filters=8,
kernel_size=(5,5), strides=(1,1),
activation='relu', padding="same"),
   keras.layers.BatchNormalization(),

keras.layers.MaxPool2D(pool_size=(1,1),
strides=(2,2)),
 keras.layers.Conv2D(filters=8,
kernel_size=(3,3), strides=(1,1),
activation='relu', padding="same"),
  keras.layers.BatchNormalization(),
   keras.layers.Conv2D(filters=8,
kernel_size=(3,3), strides=(1,1),
activation='relu', padding="same"),
  keras.layers.BatchNormalization(),
   keras.layers.Conv2D(filters=8,
kernel_size=(3,3), strides=(2,2),
activation='relu', padding="same"),
keras.layers.BatchNormalization(),
 keras.layers.MaxPool2D(pool_size=(1,1),
strides=(2,2)),keras.layers.Flatten(),
  keras.layers.Dense(64, activation='relu'),
  keras.layers.Dropout(0.2),
  keras.layers.Dense(64, activation='relu'),
   keras.layers.Dropout(0.2),
   keras.layers.Dense(y_train.shape[1],
activation='softmax') ])
```

4. RESULTS AND DISCUSSION

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases.

Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/ (TP + FP)

Recall: Recall is a metric in machine learning that measures the ability of model to identify all relevant instances of class.It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

Recall=TP/TP+TN

FINAL OUTPUT

Fig1: Model accuracy by implementing 10Epochs

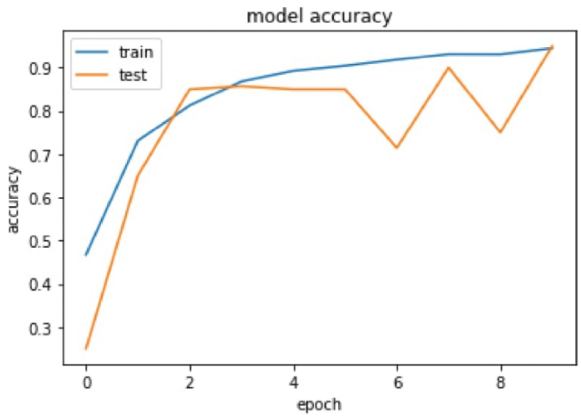

Fig2: Model accuracy at 15 Epochs

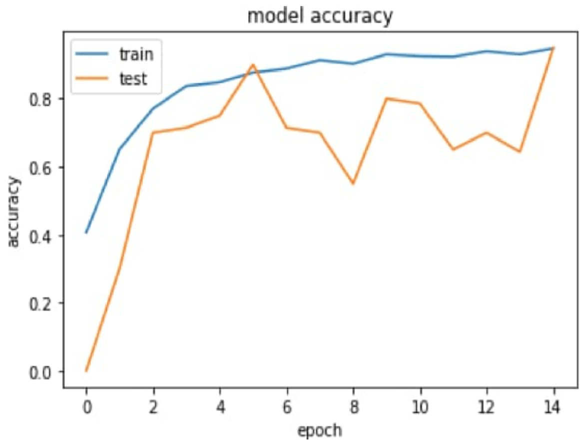

Fig3: Validation and training loss comparison at 15 Epochs

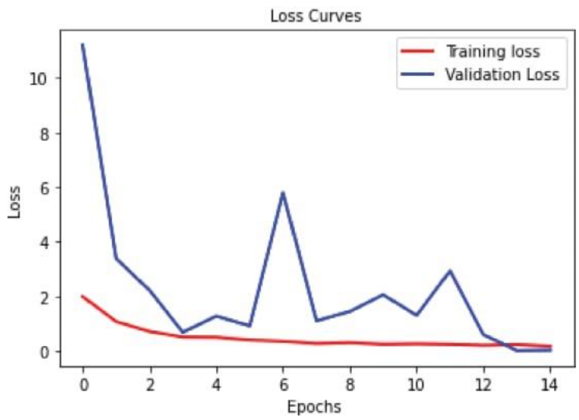

Fig4: Comparisons with state-of-the-art approaches

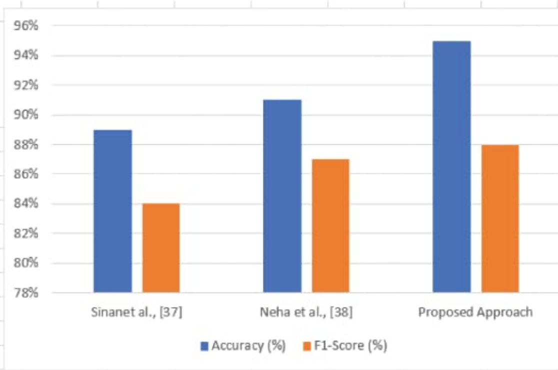

Table: Comparison of the proposed model with existing models

Models	Datasets	Detected classes	Accuracy
OCT-Net [14]	SERI-CUHK +A2A SD-OCT	4	99%
CNN(DL) [19]	STARE	15	80.93%
Neural Network [20]	STARE, DRIVE	1	95.2% 94.5%
SVM [21]	STARE, DRIVE	1	93.5% 94.3%
Fuzzy C-Means clustering [22]	STARE, DRIVE	1	89.7% 89.1%
Multi-scale differential [23]	STARE, DRIVE	1	92.4% 92.2%
U-Net Segmentation1+SVM [10]	Eye-Net	32	89.3%
Proposed Deep learning CNN	Eye-Net	32	95%

5. CONCLUSION

A CNN model based on deep learning is presented to handle the categorization of various retinal illnesses.The model's implementation is based on the EyeNet dataset, which includes 32 distinct retinal disorders. To assess the model's correctness, the suggested model is trained across several epochs. After training the model for 10 epochs, it obtained 95% validation accuracy. After training the model for 15 epochs, it again reached 95% validation accuracy with a different validation loss of 0.0279 in both cases the model performs significantly better overall than other models that are regarded as state-of-the-art. It is possible that the model presented will be useful in the classification of retinal disorders.

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