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CNN Based Approach For Recognition Of Disease

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.**Abstract:**
A deep learning-based convolutional artificial neural networks structured a new image classification method approach was implemented in the study. Sample application was carried out with Diabetic Retinopathy disease. Obtaining information about the blood vessels and any abnormal patterns from the rest of the phonoscopic image and assessing thedegree of retinopathy is the problem itself. To solve this problem developed methodology and algorithmic structure of this new approach is presented in the study. An approach called care model was used in this study different from the classical CNN structure. The care approach is based on the idea that the best solution will be taken from the new data obtained by rescale the available data according to total number of pixels before the average data pool is created and then CNN processes will continue. In the care model approach, all data is multiplied by the number of elements by the number of epoch time eight tensors. The purposed care model includes VGG19 image classification model and developed mathematical model presented. Pre-trained model and all image dataset taken from kaggle and keras for implementation of case study. The purposed model provides train accuracy 87%, test accuracy 88%, precision 93% and recall 83%.

Introduction:

Deep learning health practices constitute a multidisciplinary field of study. Although computer image classification is now inevitably included in our daily lives, it requires the interpretation of software with health applications by expert healthcare professionals [1,2]. Today, when the state of the technology, data processing speed and data processing capacity are taken into account [3,4], disease diagnosis with image processing stands as a hot topic in front of many researches [5] in academia and private sector researchers [6,7]

Objective Of The System:

Each year in the world, diabetic retinopathy has caused for 12% of all new cases of blindness.

Therefore, today, the medical doctors are trying to diagnose this disease using several methods. Because this disease can occur in diabetics with the rupture of the vessels and blood accumulation behind the eyes, even if they sleep at night without showing much symptoms. Diabetic retinopathy can be detected using the following methods such as Visual acuity test, Pupil dilation, Ophthalmoscopy, Fundus Fluorescein angiography, Retinal vessel analysis and Optical coherence tomography.

Each of these methods is diagnosed by using different methods in itself and by analyzing the information obtained as a result of patient follow-up and time-consuming studies by the doctor. With a deep learning-based approach developed in this study, instant eye retina pictures of the patient are uploaded to diagnose a certain risk and disease. It is possible to provide a diagnosis with a few snapshots without the need for much time. The motivation for this study has been explained above.

LITERARTURE SURVEY:

In the definition of many hazards encountered in the field of bio-medicine, image processing is now used in the literature [8,9] in the diagnosis of brain tumour [10,11], cancer [12,13], microorganism detection [14,15], eye diseases [16,17], MRI imaging [18,19], lung, liver and other diseases. Deep learning is focused on computer programs that simulate human brain functions. Deep learning history, in 1943, McCulloch and Pitts used mathematics and neural reasoning to mimic thinking. It is focused upon the creation of an algorithm-based computational model [20]. In 1958 a supervised algorithm for the detection of teaching patterns was developed on the basis of a two-layer Rosenblatt neural computer network [21]. Ivakhnenko and Lapa used models with activation features of complex equations in 1965 to develop deep - learning algorithms [22]. In 1988, Fukushima, He suggested Neocognitrona hierarchical and multi-layered nerve network used to identify the compose and other patterns [23]. The Cresceptron process, which performs dimensional object recognition, was automated by Weng, Cohen and Herniou in 1992 for three mixed scenes [24]. Vapnik is using Cortes and Vector Support networks to identify two related category data in 1995 [25]. A paradigm called Long Short-Term Memory (LTSM) was suggested for learning in 1997 by Hochreiter and Schmidhuber to save knowledge for a long time with repeating back growth [26,27]. Deep Learning field which is one of the major research era that gained attention. Crafted by Google's analysis team in a 2012 study contains 16,000 processors and over a billion ties. The efficiency of algorithms for the identification of artificial designs is human [28]. Facial Recognition by adding 120 millionR-CNN parameters to tag users in images automatically uses the technologies of deep learning called DeepFace in 2014 [29]. Deep learning as a neural artificial network based on biological nervous system information processing techniques uses proven algorithms. Computers must then specify the meaning and model of each result.

Machine learning and Google Brain science team research is one of the most popular methods for deep learning, and has been developed by engineers [30]. TensorFlow is one of the most popular tools for deep learning. Artificial intelligence open source, a library for artificial learning and TensorFlow uses data flow graphs to construct a multi-layered and large-scale artificial neural network, used in vision, discovery, classification, understanding and predictive applications [31]. This experiment is also used in TensorFlow particularly for deep learning.

With the rapid entry of deep learning into our lives with the developing technology, the processing of big data and the development of its models have started. These models generally consist of deep artificial neural networks, convolutional neural networks, artificial neural networks and other models. The open-source image processing models using these networks are models such as googleNet, VGG16, VGG19, ResNet and Inception [32,33]. Another difficulty seen in the studies in the literature is related to the image data. The fact that each of the images obtained is in separate pixels, the drawing angles are different, the use of special lenses in some of them and their different resolutionsreduce the quality of the work. The situations mentioned above appear as noise in image datasets in analysis. For this, it is necessary to undergo a series of processes before using the ready image datasets. These operations are carried out to make image datasets trainablewith certain criteria. In this case, it directly increases the quality of the work done [34,35].

Deep learning and image processing models have been used actively for the last ten yearsin the diagnosis of eye diseases. Disease detection has become possible by using image datasets that can provide certain features with pre-trained models [36,37].

In this study, the sample application was carried out on such an eye disease. Models used in image processing and classification studies generally consist of many layers. These layers consist of Convolution layers, direct connected layers, maximum pool layer and softmax layers in CNN applications. A classification problem is created with a loss function, pretrained classification model, pre-trained label model, general classification model and ready image data sets [38,39].

The data used in classical CNN structures is not pre-processed in many methods and many unrelated data are involved in processing, which prolongs the processing times. This is the weakness of classical methods [40,41]. However, in practice, processing is done directly onthe picture without the need for any intermediate processing. In this case, it provides convenience. In fact, the care model, as used in this research, operates by prioritizing precision and accuracy in diagnosis and classification. This gave better results than most classical models in the literature.

Block Diagram

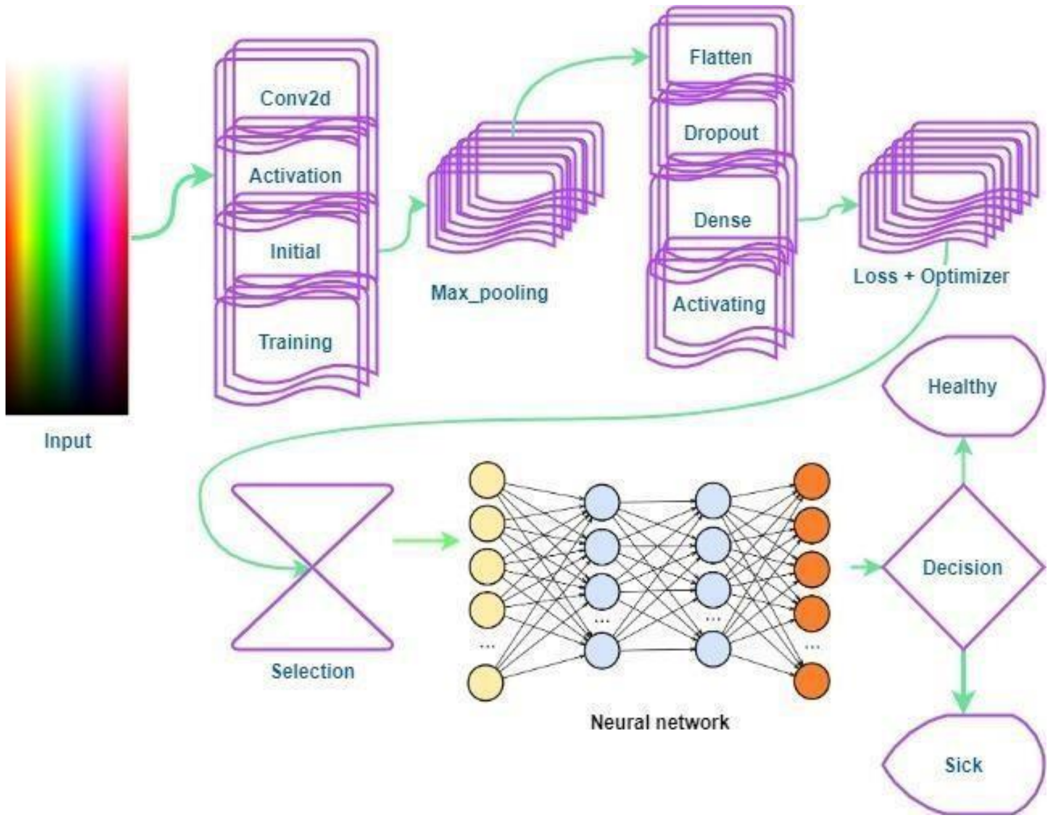


Figure:1 Convolutional neural network scheme for healthy or sick decision

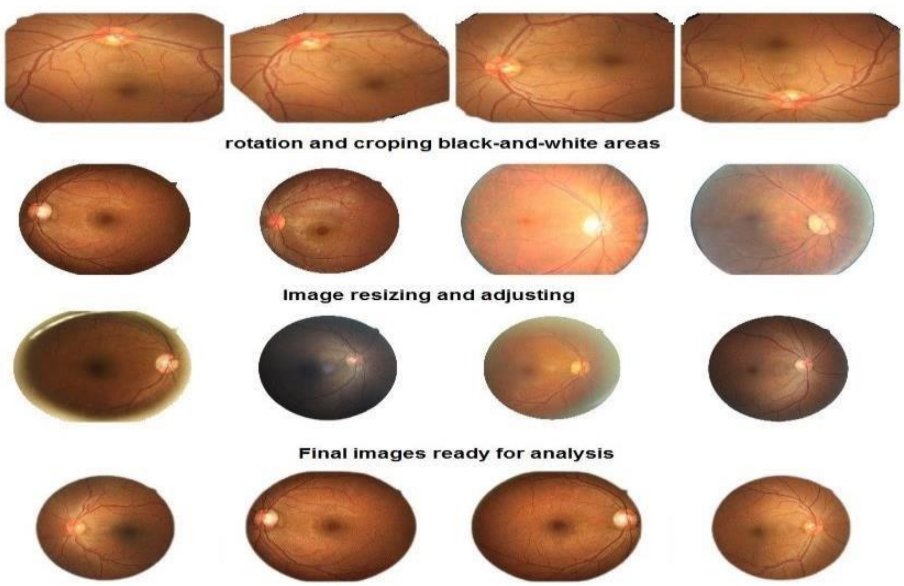


Figure 2. Image pre-processing steps

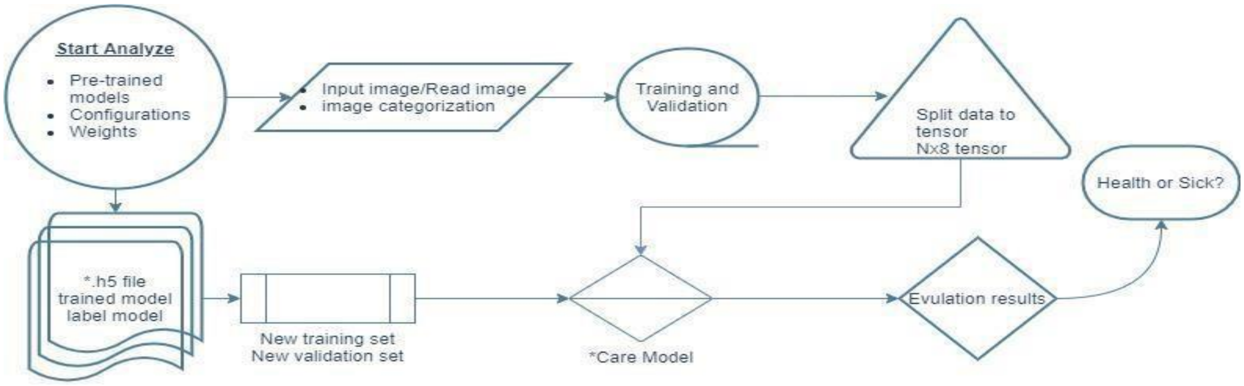


Figure 3. Deep learning model algorithm

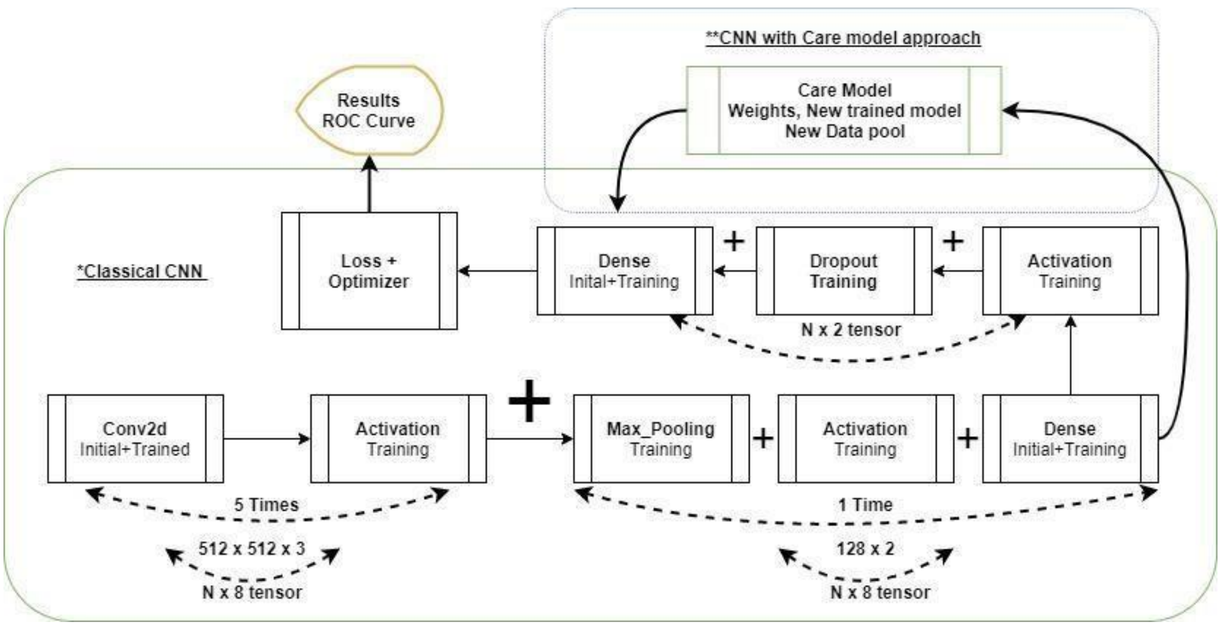
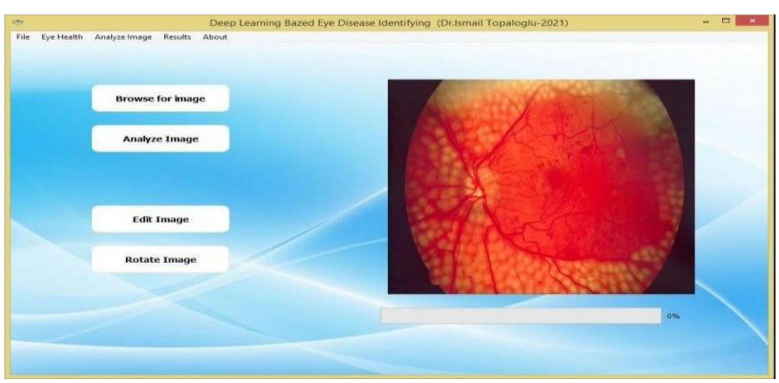
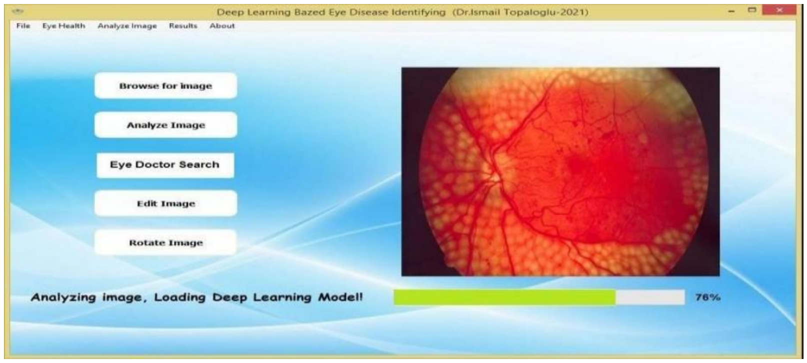


Figure 4. Care model approach scheme



(a)



(b)

Hardware requirements:

Hardware

Nvidia Tesla K80 CUDA Cores Graphic Cards (GPU) used for this study. This hardware provides us for calculation and implementation of all process 4992 CUDA cores and 2x GK120 GPUs.

Memory

GPU has 24 GB memory and test platform has approximately 77 GB free memory for the implementation of the study. It is inevitably clear that more computational capacity and more free space are needed for the targeted study.

Time

The total processing time was 2349.8 seconds. This equates to approximately 39.16 minutes. There are things that can be done both on the hardware and on the data side to shorten the processing time. On the data side, datasets containing only eye images with less noise and a stronger computation capacity on the hardware side will reduce the processing time.

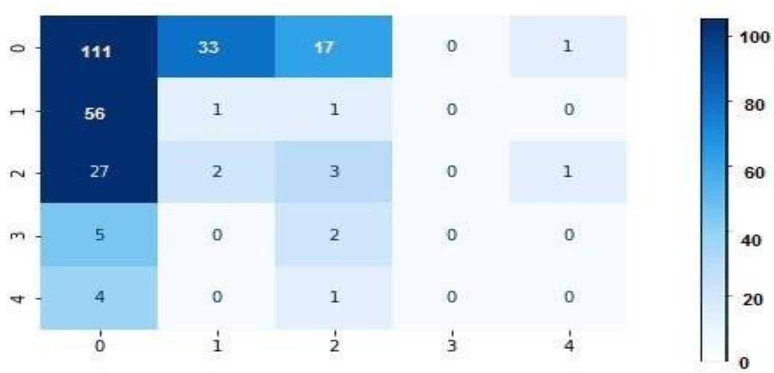


Figure10: Confusion matrix of purposed model

Conclusion:

In this study, a deep learning-based convolutional artificial neural networks structured a new image classification method approach, which can be used to identify eye diseases, was implemented. Care model approach implemented via using eye disease identifying software (edis) in python environment. Developed model approach explained in mathematically and has been realized in the study. Case study has been carried out diabetic retinopathy disease image. Image data of this disease have been taken from the kaggle site. Better results have been obtained with the newly developed model approach. The results were discussed in depth in the study and presented. The purposed model provides train accuracy 88%, test accuracy 87%, precision 93% F_1 0.83 and recall 83%.

Future Work:

The results are considered as evaluation metrics, hardware, memory and time, which are generally accepted and defined in the literature [19]. Evaluation metrics consist of three parts.

These are precision, recall and accuracy. Accuracy of model investigated for both test and train process. It is very important pre-processing for neural network. In this way, cropping the black and colourless areas in the picture, saving the process from unnecessary processing load and can work directly for the target in the image. The number of untrained elements remained at 13% of the total element. Figure 9 show that training curve of purposed model. Total loss is less than 1 almost in every iteration. Validated and trained data loss in every epoch can be seen in figure 9.

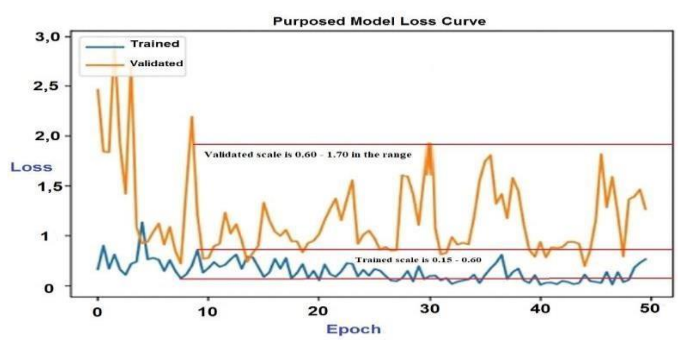


Figure 9. Training curve of purposed model

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