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A research Paper on Ocular Disease Recognition using Convolutional Neural Networks

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ABSTRACT :

However, eye cancer can be a rare disease that corresponds to a malignancy.It is the most common form of cancer. It is curable in many cases, comparable to other types of cancer, if diagnosed correctly, but the diagnostic approach is complex and the most difficult to manage eye cancer. This paper presents an automated technique to identify eye skin, using a convolutional neural network (CNN) with grayscale victim conversion to higher image resolution. 200 pre-diagnosed square measurements based on traditional data, scaled and median filtered to a low-resolution paste image, and finally fed to complex neural network specification fit. While the technology is expected to require extensive computation, the high 92.5% accuracy rate exceeds the conservative victim rate. The built-in neural network classifier for feature classification and neural network extraction can be used to extract options from the image.

Keywords: Image fusion; Eye tumour detection; Canny operators

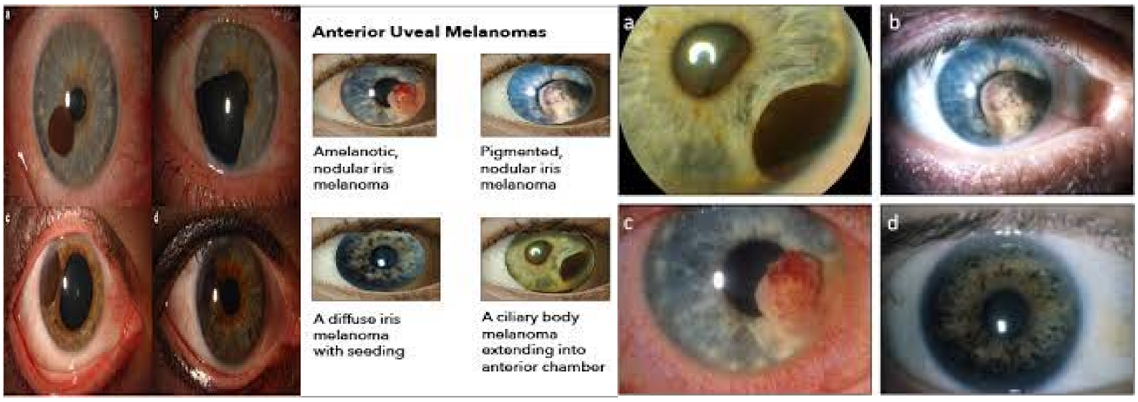
INTRODUCTION:

Early detection of eye illness is a cost-powerful and efficacious way to prevent blindness giving rise to diabetes, glaucoma, cataracts, aged macular degeneration (AMD) and masses of others. As stated thru the manner of the World Health Organization (WHO), at the least 2.2 billion people worldwide are visually impaired, of which at the least 1 billion have preventable vision defects. In the early 2000s, the amount of maximum cancer deaths worldwide grows to be 6.2 million. Although people can live on if their illness is detected initially.

Tumours of the eye and surrounding tissues (called tumours) can be useful tumours, specifically subcutaneous lesions but they can also hazard tumours which include myofascial sarcoma striae and Neuroblastoma. Iris tumour is the most appreciably recognized iris tumour, but most cancers are rare.

Reflexology is a systematic technique that examines the shape, colouring, and exclusive hallmarks of the iris simply so the wellbeing of a person can be detected. Analysing strange modifications in cells, the iris can deliver hints and inclusive facts in which several doctors can diagnose tumours. Also, the Depletion of vision and blind spots for the sufferer can be automated to come upon eye illnesses after imparting clinical photographs from orbit. Well-beingImage processing techniques are typically applied in several fields of medicine. Resemblance compression is one of the typically used packages for interior imaging visualization. The indicated application is critical withinside the clinical problem because of the truth lowering the file duration permits more photographs to be stored in a given aggregate, extent, unique disk or remembrance. Considering such tasks, photo processing techniques were used together with artificial intelligence gadget which includes neural networks to acquire the most important and accurate results.

The purpose of the paper is to format a strong tool to come upon several iris tumours using photo processing methodology. A positive proposed tool uses iris photographs obtained from the overall public dataset available on the Internet.



Fig(a) Uveal melanoma. **Fig(b) Ocular Melanoma.** **Fig(c)Iris melanocytic tumours**

PYTHON:

Python is an interpreter, class-primarily based totally application-orientated programming language with dynamic connotations. Python's syntactic simplicity and simplicity of gaining knowledge of emphasize clarity and therefore lessen application preservation tariff. It helps modules and packages, encouraging reuse of modules in help of all primary platforms, and may be freely distributed.

Its format philosophy is likewise pretty excellent. The predominant cause is to offer code clarity and enhance developer prolificacy. Although released, it likely comes up with inherited classes, a couple of base facts types, and exception handling. The maximum substantially used variations are Python 2. x and 3. There is lots of opposition among the two, and genres appear to have exclusive fan bases.

OPEN CV :

OpenCV (Open-Source Computer Vision Library) is an open-source computer vision and computer software library. it is designed to provide a common infrastructure for computer vision applications and to accelerate the use of machine sense in commercial products. OpenCV started as the brainchild of Gray Brodsky, formerly a computer vision engineers at Intel, around the early 2000s. Brodsky and a team of engineers, mainly from Russia, developed versions.

JUPYTER NOTEBOOK :

This is the latest web-based interactive development environment for notebooks, code and data. Its flexible interface allows users to configure and organize workflows in data science, scientific computing, computer journalism, and machine learning. The modular design invites extensions to extend and enrich the functionality.

PIL :

Python Visual Library is a free and open source plugin library for Python. It is available for Windows, Mac OS X and Linux. It integrates lightweight image processing tools that make it easy to edit, create, and save images. As an alternative to PIL for future use, Pillow supports a large number of image file formats, including BMP, PNG, JPEG, and TIFF. The library encourages adding support for loading new formats to the library by creating a new file decoder.

CONVOLUTIONALNEURALNETWORKS:

It is a type of artificial neural network used in image recognition and processing specifically designed to process pixel data vision, including image and video recognition and `NLP`. A neural network is a hardware or software system that is modelled on the behaviour of neurons in the human brain. Traditional neural networks are not ideal for image processing and must provide fragmented images at reduced resolutions. CNN uses the same system as a multilayer perceptron designed to reduce processing requirements and normalize layers. Eliminate limitations and increase image processing efficiency, resulting in a simpler and more efficient system for trains that limit image processing and natural language processing

Each neuron operates in its own receptive field and is connected to other neurons in a way that covers the entire visual field. The limited region of the visual field is called the receptive field. first and more complex patterns faces, objects, etc. By using CNN.

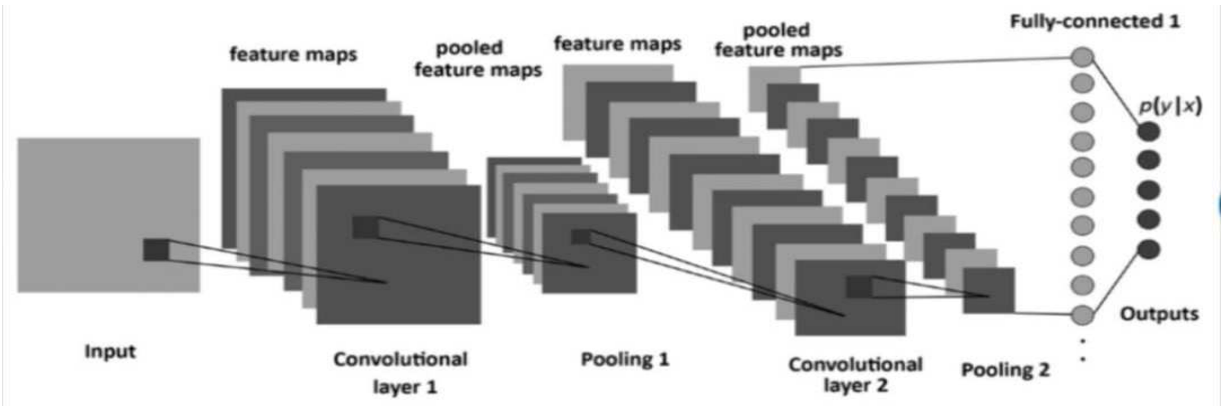


Fig. General configuration of a convolutional neural network (CNN)

CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE :

A CNN typically has three layers: a convolutional layer, a pooling layer, and a fully connected layer.

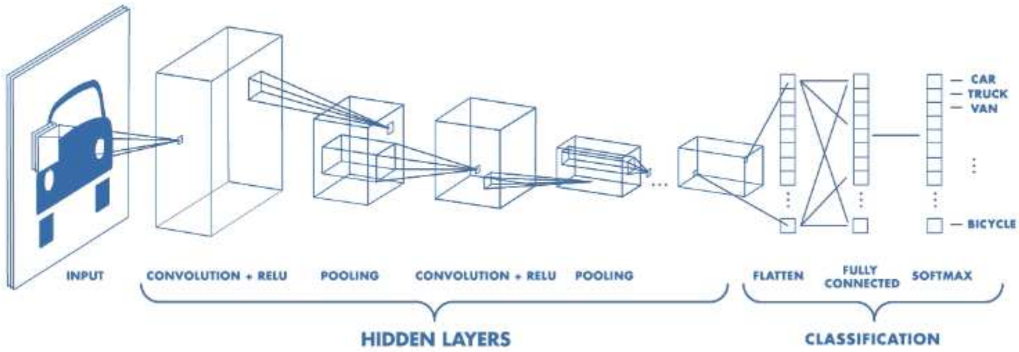


Fig shows. Convolutional Neural Network Architecture

1. **CONVOLUTIONAL LAYER:**

   It carries most of the network's computational load. This class performs a point product between two matrices, where the set of learnable parameters is called the kernel and another limited part of the receiving field. His central space is smaller than the image but has more depth. This means that if the image consists of three channels (RGB), the height and width of the kernels will be spatially small, but the depth extends to all three channels.

2. **POOLING LAYER:**

   The group layer replaces network stores at certain locations by taking summary statistics from neighbouring stores. This reduces the spatial size of the representation, thereby reducing the amount of computation and weight required. Group operations are processed on individual slices, functions such as rectangular neighbourhood average, rectangular neighbourhood L2 level, and weighted average based on distance from central pixels . The most common process is the maximum aggregate, which gives the maximum output of the quarter

3. **FULLY CONNECTED LAYER:**

   The neurons in this layer are fully capable of connecting with all neurons in the anterior and posterior layers, as seen in normal FCNN. That's why it can be calculated as usual by matrix multiplicationfollowedby bias effect.The FC layer helps in mapping the representation between input and output

METHODOLOGY

IMAGE PROCESSING

Eye Disease Recognition (ODIR) is a structured ophthalmic database of 5,000 elderly patients, colourbackground images of left and right eyes, by Shang gong Medical Technology Co., Ltd. In these institutions, fundus images are taken by various cameras on the market, such as Canon, Zeiss and Kowa, resulting in different image resolutions. Comments have been tagged by trained readers who have quality control managers. They classified patients into eight labels, including normal (N), diabetic (D), glaucoma (G), cataract (C), AMD (A), hypertensive (H), myopa (M) and other diseases / abnormalities (O) .

IMAGE ACQUISITION:

This step is also known as pre-processing in image processing. It involves getting an image from a source, usually a hardware source.Machine vision, image acquisition is the act of obtaining an image from a source, usually hardware systems like cameras, sensors, etc. This is the first and most important step in the workflow chain because, without the image, the system would not be able to do the actual processing. The image obtained by the system is usually not processed.

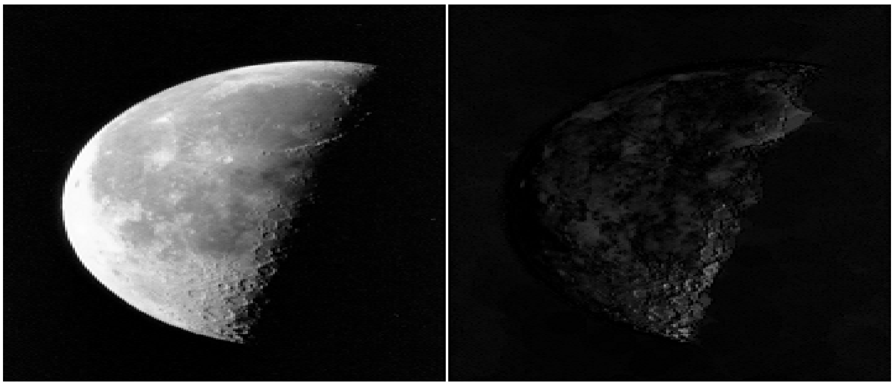
COLOUR IMAGE PROCESSING:

Colour image processing includes several techniques for creating colour models in the digital domain. This step has become important due to the widespread use of digital images on the Internet. The human visual system can distinguish hundreds of thousands of different shades and shades of colour, but only about 100 shades of Gray. Thus, in an image, a large amount of additional colour information can be contained, and this additional data can then be used to simplify image analysis, colour pattern recognition, and extraction. Export objects based on colour.

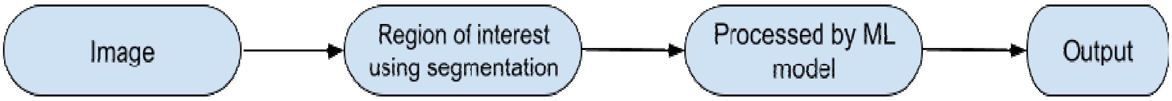
IMAGE RESTORATION:

It is the process of improving the appearance of an image. Errors can come in many forms such as motion blur, noise, and poor camera focus. Image restoration is done through inverting and blurring the image by taking the point source image and using the point source image, known as point propagation function (PSF) for restoration. Image information is lost when blurring the image.

IMAGE SEGMENTATION:



Segmentation is one of the most difficult steps in image processing. It involves the division of an image into its constituent elements or objects. Image segmentation is a method in which digital images are divided into different subgroups known as image segmentation; this method reduces image complexity to simplify image processing or analysis.Picture.Segmentation simply means labeling pixels. All elements or pixels in the image that belong to the same label are assigned a common label. For example, consider a problem where an image needs to be provided as input for object detection. Instead of processing the entire image, the detector can be partitioned with a selected area.



Approaches in Image Segmentation :

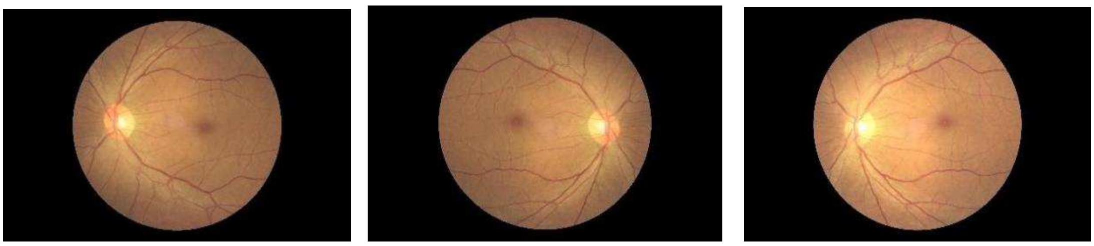
1. **Similarity approach:**This approach is based on detecting the similarity between pixels of an image to form a segment, based on a threshold. ML algorithms like clustering rely on this kind of approach to segment an image
2. **Discontinuity approach:**This approach is based on the discontinuity of the intensity values of the image pixels. Line, point, and edge detection techniques use this type of approach to obtain intermediate segmentation results that can be further processed to obtain the final segmented image.

DATASET:

Eye Disease Recognition (ODIR) is a structured ophthalmic database of 5,000 elderly patients, left and right eye color backgrounds, and physician diagnostic keywords. These base, Fundus images taken by different cameras in the market, such as Canon, Zeiss and Kowa resulting in different image resolutions. Reviews have been scored by trained readers with quality raters. myopia (M) and other diseases/abnormalities

DATA PRE-PROCESSING:

At first, we want to resize the "on the fly" image, using the TensorFlow dataset object. The images were resized while training the model. This is not a good decision, running an epoch can take even 15 minutes, so we created another function to replace it. resize the image before creatingTensor Flow dataset objects. As a result, the data is scaled only once and saved in a different folder, so we can test different training methods using training execution much faster. Initially, all images were scaled to 32x32 pixels, but we quickly realized that compressing at such a small size, while speeding up the training process, lost a lot of important image information.so, the accuracy is very low. After some tests, we found that Size 250 x 250 pixels is the best in terms of training speed and accuracy of tricks, so we kept this size on all images for testing. more.Second, the images are labelled. There is a problem with image captions in the data.csv file because these labels are for both eyes (left and right) at the same time while each eye can have a different disease. For example, if the left eye has a cataract and the right eye has a normal fundus, this label will be cataract, not indicating the diagnosis for the right eye. Fortunately, the diagnostic keywords involved botheyes. Cumulativediagnoses, ignoring the fact that eyes can be healthy. From an end-user perspective such a model is not reasonable and it is better to get separate predictions for each eye, e.g., to know which eye should be adjusted treat. Therefore, I enriched the data set by creating a mapping between diagnostic keywords and disease labels.



(a) Originalimage **(b)right-letrotation** **(c) random brightness**

Fig.2:Exemplary data augmentation results

It is developed very similar to the object shown in the official TensorFlow documentation for loading images. Since the library is complex and not easy to use for beginner TensorFlow users, here we share my summary of the findings. about building scalable and fast inlet pipelines. The ft. data API allows you to build complex input pipelines from simple, reusable parts. For example, the image model pipeline can aggregate data from files in a distributed file system Data. The API introduces. A dataset summary represents a sequence of items, where each item is made up of one or more components. By shuffling, the dataset fills the buffer with entries, and then randomly samples the items from that cache, replacing the selected items with new ones.

EXPERIMENTS AND RESULTS:

For the sake of simplicity, we wanted to start our study with easy proof-of-concept experiments, on a smaller, less challenging dataset, to test whether all previous hypotheses are correct or not. The images are labeled as N (normal) or C (cataract). The results are very satisfying, using a relatively simple network over 12 epochs my model achieved a validation accuracy of 93%. This shows that using CNN can automatically detect cataracts. Crystals in the eye! In each subsequent test, we added images from another layer to the dataset. The fourth test was performed on the full ODIR dataset, achieving close to 50% validation accuracy. The results of the experiments are presented in Table 1. As we can clearly see, the overall model has weak results because it is very difficult to train it to accurately detect diabetes, because diabetic eyes Street, nearly the same line as eyes with normal orbits. Detecting nearsightedness or cataracts is a much easier task because these images are very different from normal images. Illustrations of different selected diseases are shown in Fig.

Class	Precision	Recall	F1 score	Accuracy
N/C	0.9328	0.9328	0.9328	0.9328
N/C/M	0.8800	0.8709	0.8754	0.8722
N/C/M/A	0.8310	0.8253	0.8281	0.8281
ALL	0.4763	0.4617	0.4689	0.4953
N/D	0.5778	0.5778	0.5778	0.5778

Table 1: Experiments results. Legend: N – normal, C- cataract, M – myopia, A – AMD, D – diabetes, ALL –model trained on entire ODIR dataset

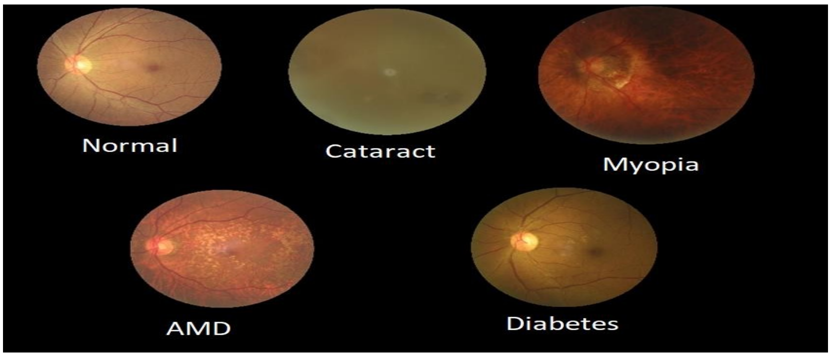


Fig. 4: As shown in figure Clearly Diabetes seems to be the most challenging in detecting and cataract is the easiest as varies the most from normal fundus.

For all tests, the same neural network architecture was used. The only difference is the number of epochs needed for each test to show allresults (some need to stop early; othersneed more epochs to find out). Except for the full dataset, theSoftMax activation function and cross-entropy loss of the classifier were used, as these are multi-class, not multi-label, classification problems.

FINAL OUTPUT:

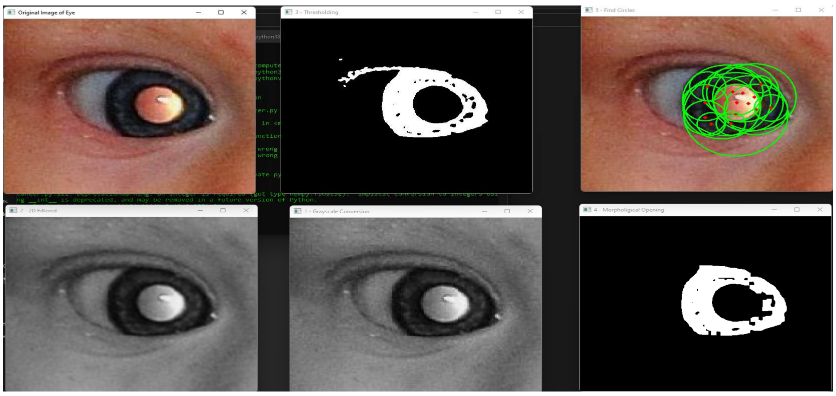


Fig. Final Output

CONCLUSIONS:

This paper presents a deep learning-based method for automatic diagnosis of ocular malignancies using a complex neural network. The processed images are passed into the architecture. CNN is because its formation is quite simple and has fewer parameters than ANN. TRAINING PARAMETERS FOR CNN Parameters Cross entropy Learning Algorithm Stochastic Gradient Descent Hyperparameters Momentum.76 Passed previous work on ANN. The main objective of this study was to provide a simple, accurate, and non-invasive method for the automated detection of ocular melanoma. In the future, automated iris tumor detection and classification will be performed using the deep learning engine to treat eye care and increase the chances of survival.

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