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GLAUCOMA DETECTION USING DEEP LEARNING AND STREAMLIT WITH SEGMENTATION

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Abstract - Glaucoma is a condition affecting the vision of the human eye. This illness is considered an irreversible sickness that causes visual degeneration. So far, many deep learning (DL) models have been built to accurately find glaucoma. So, this research proposes an architecture for effective glaucoma diagnosis based on deep learning and the use of a convolutional neural network (CNN). The CNN can differentiate between glaucoma and non-glaucoma patterns. The CNN generates a hierarchical structure of pictures for distinction. The proposed work may be assessed using six tiers. The dropout method is also employed to provide satisfactory performance in glaucoma detection. The datasets used in the experiments are the SCES and ORIGA.

***Key Words*:** Eye disease, Gluacoma detection, preventive measures, recommendation.

I. INTRODUCTION

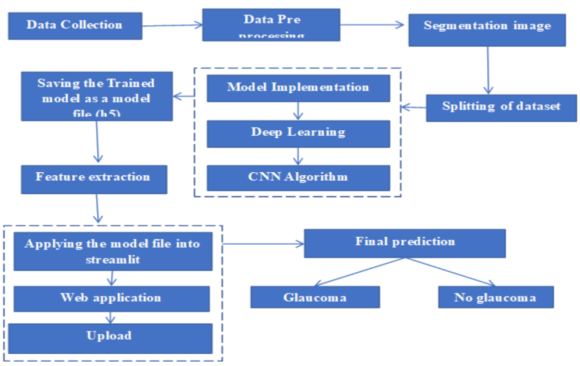
Handwritten Glaucoma is a collection of eye conditions that cause damage to the optic nerve, which transports information from the eye to the brain, and can worsen over time, eventually leading to blindness. Glaucoma must be discovered as early as possible to receive adequate treatment. In this research, we provide a Convolutional Neural Network (CNN) system for early diagnosis of glaucoma. Initially, ocular pictures are supplemented to produce data for deep learning. The eye photos are then pre-processed to reduce noise using the Gaussian Blur method, preparing them for further processing. The system is trained on pre-processed photos, and when new input images are fed into it, it classifies them as normal, or glaucoma eyes based on the characteristics retrieved during training. Glaucoma is frequently connected to a buildup of pressure inside the eyes. Glaucoma runs in families, and it develops later in life. Increased pressure in the eyes, known as intraocular pressure, can damage the optic nerve, which transmits pictures to the brain. If the damage progresses, glaucoma can result in permanent vision loss or complete blindness within a few years.

II. PROBLEM STATEMENTS

Glaucoma, a progressive eye disease leading to irreversible vision loss, necessitates early detection for effective management. While various deep learning (DL) models have been developed for glaucoma diagnosis, there remains a need for an architecture that ensures both accuracy and efficiency in distinguishing glaucomatous from non-glaucomatous patterns. This research aims to address this gap by proposing a Convolutional Neural Network (CNN)-based system tailored for precise glaucoma detection. Leveraging the hierarchical structure generated by CNNs, the proposed architecture undergoes evaluation across six tiers to ensure robust performance. Additionally, the utilization of dropout methodology enhances the model's reliability in glaucoma identification. Experimental validation is conducted using datasets such as SCES and ORIGA. By offering a comprehensive solution for early glaucoma diagnosis, this research endeavors to contribute significantly to the timely intervention and management of this sight-threatening condition.

III. SYSTEM DESIGN

3.1 SYSTEM ARCHITECTURE: It provides a high-level overview of how different parts of the system are organized and how they communicate with each other to achieve the system's goals. Architecture diagrams serve as a valuable communication in designing, developing, and maintaining the system. This help facilitate discussions, clarify design decisions, and ensure that everyone has a shared understanding of the system's architecture. Additionally, architecture diagrams can aid in troubleshooting, scalability planning, and documentation of the system over time.



For this project, ocular images from datasets such as SCES and ORIGA were collected. These datasets contain various images depicting normal and glaucomatous eyes, providing a diverse and representative sample for training and evaluation purposes.

3.2 DATA PRE-PROCESSING: Prior to model training, the ocular images underwent preprocessing steps to enhance their quality and facilitate feature extraction. Techniques such as Gaussian Blur were applied to reduce noise and improve image clarity, ensuring that the input data were suitable for further processing.

3.3 SEGMENTATION OF IMAGES: Image segmentation techniques were employed to partition ocular images into meaningful regions or segments. This process helps in isolating specific features relevant to glaucoma diagnosis, such as the optic disc or retinal nerve fiber layer, enabling more targeted analysis by the model.

3.4 SPLITTING OF DATASET: The dataset was divided into training, validation, and test sets to facilitate model training and evaluation. The training set was used to train the model, while the validation set was utilized for hyperparameter tuning and model optimization. Finally, the test set was reserved for evaluating the final performance of the trained model.

3.5 SERVING THE TRAINED MODEL AS MODEL FILE: Once the model was trained and optimized, it was saved as a model file using a suitable format such as HDF5 or TensorFlow's SavedModel format. This allowed for easy deployment and integration of the trained model into the web application for real-time predictions.

3.6 MODEL IMPLEMETATION: The trained CNN model was implemented using a deep learning framework such as TensorFlow or PyTorch. The model architecture, including layers, activation functions, and optimization algorithms, was defined, and the model was trained using the preprocessed ocular images.

3.7 DEEP LEARNING: In general, we will execute two activities all the time, consciously or subconsciously: classify what we felt via our senses (such as feeling hot, chilly, etc.). Prediction, for example, forecasts future temperatures based on past temperature data. In our daily lives, we categorize and forecast a variety of occurrences or activities, including the following:

• Holding a cup of tea, water, or coffee, which might be hot or cold.

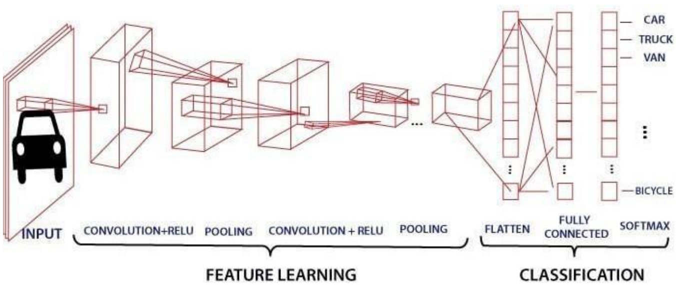
• Email classification, such as spam or non-spam.

• Daylight time is classified as either day or nighttime.

• Prediction is the long-term planning of the future based on our current situation and the resources we have.

Every creature in the world will perform these tasks at some point in their lives. For example, a crow will decide whether to build a nest, a bee will decide when and where to get honey, and a bat will come at night and sleep in the morning based on day and night categorizations.

3.8 ALGORITHM: CNN are a key category for image classification and identification in neural networks. Convolutional neural networks are widely used in many applications, including scene labelling, object identification, and facial recognition. CNN accepts a picture as input, which is categorized and processed under a certain category such as dog, cat, lion, tiger, etc. The computer perceives a picture as an array of pixels, which is determined by the image's resolution. Image resolution is represented by the equation h*w*d, where h represents height, w represents width, and d represents dimensions. RGB images are 6 * 6 * 3 matrix arrays, whereas grey scale images are 4 * 4 * 1 matrix arrays. Each input picture in CNN will go through a series of convolution layers, pooling, fully linked layers, and filters (also known as kernels). Following that, we will use the Softmax algorithm to categorize an item with probabilistic values between 0 and 1.



Convolution Layer: The convolution layer is the first layer that extracts information from an input picture. The convolutional layer maintains pixel relationships by learning visual properties from a tiny square of input data.

- The dimension of the image matrix is h×w×d.
- The dimension of the filter is fh×fw×d.
- The dimension of the output is (h-fh+1) ×(w-fw+1) ×1

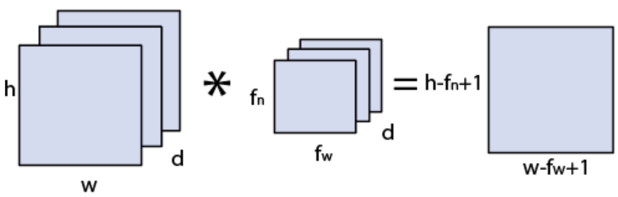
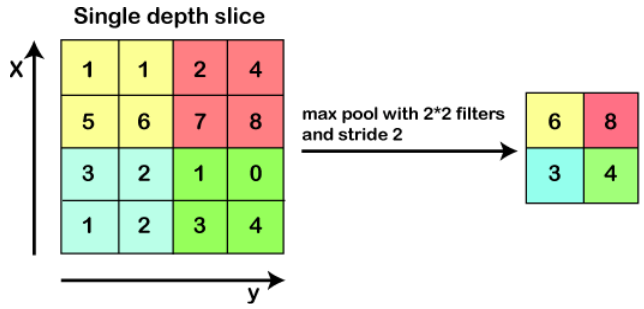


Image matrix multiplies kernl or filter matrix

3.9 Working of CNN:
Input: A picture with 32 widths and 32 heights and three R, G, and B channels will include the raw pixel values ([32x32x3]).
Convolution: computes the output of neurons connected with input areas. Each neuron calculates a dot product between weights and a tiny region inside the input volume. For example, including 12 filters would result in a volume of [32x32x12].
ReLU Layer: This Layer applies activation functions elementwise, such as maximum (0, x) thresholding at zero. It

yields ([32x32x12]), indicating that the volume's size remains constant.

Pooling: This layer down samples along spatial dimensions (width, height), resulting in a volume of [16x16x12].



3.10 FEATURE EXTRACTION: During model training, the CNN automatically learned to extract relevant features from ocular images. These features capture key characteristics indicative of glaucoma, such as optic disc morphology or retinal nerve fiber thickness, enabling the model to make accurate predictions based on input images.

3.11 APPLYING THE MODEL INTO STREAMLIT: The trained model was integrated into a Streamlit web application, allowing users to upload ocular images and receive real-time predictions for glaucoma diagnosis. Streamlit provided an intuitive and interactive interface for users to interact with the model and visualize its predictions.

3.12 FINAL PREDICTION: Upon uploading an ocular image through the Streamlit interface, the model processed the image and generated a prediction indicating whether the eye exhibited signs of glaucoma or not. The prediction was displayed to the user along with any relevant confidence scores or probabilities.

3.13 GLAUCOMA/ NO GLAUCOMA: The final prediction generated by the model indicated whether the input ocular image was classified as exhibiting signs of glaucoma (positive prediction) or not (negative prediction). This binary classification output helped users understand the diagnostic outcome of the model.

3.14 WEB APPLICATION: The entire system, including data preprocessing, model training, and prediction serving, was integrated into a web application using Streamlit. This web application provided a user-friendly interface for uploading ocular images, visualizing model predictions, and obtaining rapid glaucoma diagnosis results in real-time.

IV METHODOLOGY

4.1 DATASET COLLECTION: One of the datasets utilized in this study is a private database (RETINA), which contains 45 colour fundus photos from patients with early-stage glaucoma and 33 fundus images from healthy patients. Images of 2896 × 1944 pixels were captured from both eyes using a non-mydriatic DRI OCT Triton, Topcon camera. We incorporated the ACRIMA dataset as well as some photos from the RIM-ONE dataset, resulting in a total of 856 colour fundus images that are equally distributed.

4.2 DATA PROCESSING: The initial stage in preprocessing was to manually clip the retinal pictures around the Optic Nerve Head (ONH). As a result, we carefully cropped the photographs to focus just on the ONH and its surrounds. The cropped photos were then normalized (the pixel values were lowered to a range of 0 to 1) and standardized. To mimic a larger dataset, the picture augmentation approach was used. Data augmentation is most used in the medical imaging industry since there is typically insufficient data available. Data augmentation applies a variety of picture alterations to the photos, including rotation, zooming, vertical and horizontal flipping, brightness, and shearing. Modified copies of the photos in the dataset are created, imitating a larger dataset while avoiding overfitting. In the current investigation, the photographs were vertically and horizontally flipped and rotated in the range [0,360]. To match the DenseNet121 network input size, the photos were downsized to 224 × 224 x3 pixels. The photographs are automatically labelled by placing them in two subfolders: glaucomatous images and normal images. The glaucomatous pictures were labelled as 0 and the normal ones as 1. The photos were then divided into training and validation sets using the guideline of 80% for training and 20% for validation (686 for training and 170 for testing).

4.3 SEGMENTATION: In an image classification job, the network labels (or classifies) each input picture. However, imagine you want to know the form of that thing, which pixel corresponds to which object, and so on. In this situation, you must give a class to each pixel in the image—a process known as segmentation. A segmentation model provides far more comprehensive information about a picture. Image segmentation has several uses, including medical imaging, self-driving automobiles, and satellite imaging.

4.4 SPLITTING OF DATASET: Splitting data into two or more sections is known as data splitting. In a two-part split, the model is frequently trained in one part and the data is analyzed or tested in the other. Data splitting is an essential component of data science, particularly for creating data - driven models. Two thirds of the data points in a modeling dataset should be assigned to the training set and one third to the testing set. Consequently, prior to being applied to the test set, the model is trained on the training set. We may evaluate our model's performance using this way.

4.5 MODEL IMPLEMENTATION: Deep learning models are being used for this project. Convolutional neural networks are extensively employed in several applications, such as facial recognition, object identification, and scene categorization. When an image is sent to CNN, it is first classified and then sorted into one of several categories, such as dog, cat, lion, or tiger. The resolution of an image determines how an array of pixels appears to the computer while viewing it. The formula h * w * d, where h stands for height, w for width, and d for dimensions, describes image resolution. A grayscale image is a 4 * 4 * 1 matrix array, while an RGB image is a 6 * 6 * 3.

4.6 FEATURE EXTRACTION: Feature extraction is part of the dimensionality reduction process, which involves dividing and reducing an initial collection of raw data into more understandable categories. So, when you want to process, it will be simpler. The most essential feature of these enormous data sets is that they contain many variables. To handle these variables, many computational resources are required. So, feature extraction helps to extract the best features from large data sets by choosing and merging variables into features, so lowering the amount of data. These qualities are simple to understand while accurately and uniquely describing the real data set.

4.7 IMPLEMENTING INTO STEAM LIT: Using this training model, we can predict if a patient has glaucoma or not. Streamlit is an open-source application framework written in Python. It enables us to quickly construct web apps for data science and machine learning. It is compatible with popular Python libraries including scikit-learn, Keras, PyTorch, SymPy (latex), NumPy, pandas, and Matplotlib. 5.8 PREDICTION Finally, the forecast will be made based on the presence or absence of glaucoma illness.

V. RESULT

The project successfully developed and implemented a Convolutional Neural Network (CNN) for the early diagnosis of Glaucoma, offering a more efficient and timely approach that could save many people’s vision. By focusing on the Region of Interest (ROI) and applying Gaussian blur to reduce noise, the pre-processed images were effectively analyzed by the CNN. The results indicate that densely connected neural networks can accurately diagnose glaucoma from images alone, bypassing the need for additional, often expensive tests. These neural networks excel in identifying the subtle, early-stage changes associated with glaucoma, which are typically undetectable by the human eye. Moreover, the densely connected neural network outperformed residual neural networks in terms of diagnostic accuracy.

VI. CONCLUSION

In conclusion, In this project, we created and implemented a Convolutional Neural Network. Our method will give a better approach for diagnosing Glaucoma in the initial stages in less time, saving many people's visions. To accomplish this project, we utilized the part of Interest (ROI) to choose the only part of the image where Glaucoma may be identified, as well as Gaussian blur to eliminate noise from the image, and then sent the pre-processed image into CNN. The results show that densely connected neural networks may accurately diagnose glaucoma by evaluating photos (without the need for extra tests). They demonstrated the ability to correctly diagnose early glaucoma pictures, which contain extremely minute alterations caused by glaucoma that are not apparent to the human eye and often require extra costly inspection.

Furthermore, the densely connected neural network utilized in this study performs better in terms of accuracy than residual neural networks.

VII REFERENCES

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