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Retinal Disease Detection Using Deep Learning For Biomedical Applications

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Abstract: The fast-spreading infection of the retina is affecting persons of every age. There is photosensitive optic nerve material within a person's retina. The objective of the proposed approach is to gather a dataset of retinal illnesses so that the model can be trained on a range of images utilizing an open resume to enhance our standing. To identify the thing by analyzing the images and videos. From the smallest set of images if the retina, a machine learning technique based Deep Convolutional Neural Network (Deep CNN) will be used to determine the major retinal issues. The architecture consists of five layers, of which the second hidden layer and the third convolution layer are utilized to enhance and sharpen the images. The high as well as medium range characteristics are improved when the low-level characteristics are retrieved. Based on an experimental assessment, the suggested framework outperforms the others utilizing the multi-class Based on each stage's ability to recall, efficiency, and duration consumption, a complete assessment is being created. ss Kaggle dataset in terms of validity. On the Kaggle dataset, the recommended technique yielded a 97% accuracy rate.

Keywords - Machine Learning, Deep CNN, Convolutional Neural Network, CAT Boost Algorithm.

I. INTRODUCTION

People of all ages are increasingly developing retinal disorders. The retina of the human eye has a layer of optic nerve tissue that is referred to as photosensitive. This stratum modifies the light converted into brain signals by the lens.The retina processes the data collected by the macula and sends it to the brain via the optic nerve so that it may be recognized visually. Perception irregularities can be caused by a number of eye disorders, such as Rothspot diabetic macular edema (DME), optic disc drusen, and age-related macular degeneration (AMD). About 35% of persons in the 80+ age bracket in the United States (US) have this anomaly, according to recent studies.

Recently, several state-of-the-art models for deep learning (DL) and machine learning (ML) have been proposed for the classification, subclassification, and diagnosis of retinal illnesses. The implementation of ADDs presents notable challenges in terms of data collection and labeling, as noted by many authors Numerous machine learning (ML) and deep learning (DL) models, including Recurrent Neural Network (RNN), Convolution Neural Network (CNN), Alex Net ResNet, and VGN, are credited with this development. A hybrid method based on machine learning is introduced for automatically classifying retinal disorders. This study suggests a CNN model for multi-class eye illness detection classification that is based on deep learning. The EyeNet Dataset has been used to assess the suggested model. 32 folders with associated photos for various purposes make up the EyeNet dataset. The remaining 70% was used for validation and the remaining 70% for training. The experimental assessment indicates that the proposed model achieved 95% accuracy.

Another suggest for detecting retinal disease is to use the CAT boost algorithm, which can handle both categories and characteristics and makes quick, accurate predictions. Retinal disease detection and classification accuracy is the aim of the CAT Boost algorithm. The algorithm can assist in identifying possible ailments early on for prompt intervention and treatment by examining different aspects and patterns in the photos.The experimental assessment indicates that the proposed model achieved 93% accuracy.

1.1Overview

Convolutional neural networks (CNNs), commonly referred to as convents, are a sort of deep learning model that are nearly always utilized in computer vision applications. For this reason, the study was developed to evaluate retinal images using CNNs. Convnets, which are made up of several processing layers, have the essential quality of being able to automatically identify interesting features in training data without the requirement for human feature engineering. This is particularly helpful for issues involving very high-dimensional input samples, such as retinal fundus pictures. It can measure minute variations in feature expression and identify distinct and subclinical characteristics that seem below the threshold of a human observer.

CATBOOST algorithm, an open-source machine learning algorithm, stands out for its process in handling categorical features seamlessly within the gradient boosting framework. It proving particularly effective in scenarios with categorical variables. Its competitive performance and user-friendly nature make it a valuable tool for machine learning tasks, contributing to its widespread adoption.

II. Literature Review

PUSPITA DASH (2018), This research, Optical Coherence Tomography (OCT) is a non-invasive eye-imaging modality for detecting macular edema both in its early and advanced stages. The main aim of this work is to present the automatic detection of edema of the retinal layers particularly around the macula in diabetic patients. After detection and extracting certain features in the OCT retinal images a classification of the type of Diabetic Macular Edema is done.[8]

ZENGQIANG YAN (2019), A three-stage deep learning model for accurate retinal vascular segmentation is presented in this paper. The way the model works is that it goes through three unique stages, each focused on a different component of vessel delineation, Multiple phases can create complexity that raises processing needs and makes real-time applications difficult or resource-intensive, especially in healthcare contexts where quick analysis is crucial.. Its practical value and dependability in real-world retinal imaging conditions could be improved with more optimization and validation work [15].

FARHAN HASSAN MALIK (2020), In this paper, human diseases that can be diagnosed through fundus images are reviewed. Several publicly available fundus datasets which are helpful in the screening of these abnormalities are briefly discussed. This work aims to show the importance of retinal images in the diagnosis of different human diseases. The main challenges and difficulties faced in effective diagnosis are presented and discussed. We believe that this work will guide the researchers in addressing the challenges in existing solutions and assist doctors in the proper diagnosis of various diseases."[10].

NARGES SAEEDIZADEH (2022), The method uses a TV-UNet to detect the retinal pigment epithelium (RPE) layer in retinal optical coherence tomography (OCT) images, and it is device-independent and shape-preserving. The objective of this technique is to precisely align OCT pictures from various devices while maintaining the retina's structural integrity. It is able to precisely align by identifying the RPE layer through the use of a TV-UNet. However, TV-UNet's computational complexity may be a drawback, preventing its real-time implementation, particularly in situations demanding quick image alignment or processing [6].

ASIF NAWAZ (2023), A deep convolutional neural network (CNN) with low memory consumption is presented in this research. It is intended for the identification of various retinal disorders. This CNN architecture optimizes memory utilization without sacrificing accuracy, making it well-suited to manage a range of retinal illnesses. The model performs well in classifying a variety of diseases;

however, there may be a trade-off between memory efficiency and network complexity, which could limit the model's scalability or affect the overall accuracy of classification when working with larger datasets or more complex disease manifestations. Furthermore, additional validation using different datasets or imaging settings can provide a more thorough assessment of its performance and generalizability [1].

III. METHODOLOGY

3.1 CNN Architecture

The input image has to be collected from the Kaggle dataset. The implementation is done in Python by using Thonny software. The image will then be provided as input, and the preprocessing method will display the preprocessed image after first converting the normal image to a grayscale image. Next, feature extraction is used to transform this preprocessed image into binary data. Following that, the data will undergo training using several epochs until it reaches the desired level of accuracy.

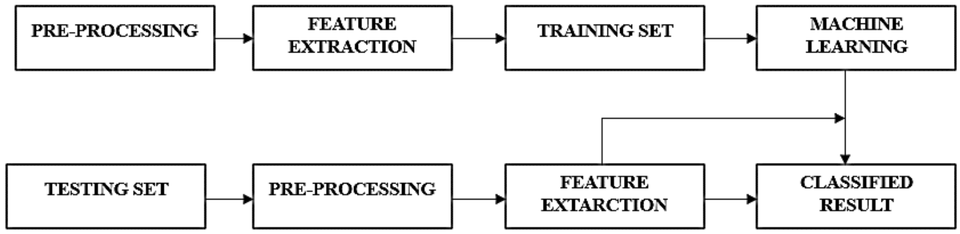

Figure 3.1: Block Diagram for CNN

3.2 CAT Boost Algorithm

The gathered dataset is subjected to feature extraction. certain characteristics are based on shape, texture, or intensity. traits that aid in the distinction between a healthy and sick retina.Using the training dataset, the cat boost algorithm is trained to identify patterns and connections between the associated retinal illness and the retrieved attributes. The testing dataset is used to evaluate the trained model in terms of accuracy, precision, recall, and other performance parameters. It aids in assessing the algorithm's detection and classification accuracy for retinal disorders. The model can be used to forecast the occurrence of retinal disorders once it has been trained and assessed. These forecasts can help with early identification and timely medical intervention.

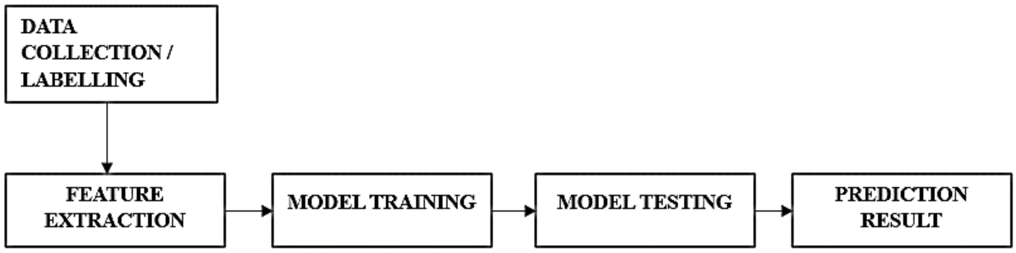

Figure 3.2: Block diagram for CAT Boost Algorithm

IV. RESULT AND DISCUSSION

The dataset is divided into two subsets such as training and validation. The input image has to be collected from the Kaggle dataset mention in the table 4.1. The implementation is done in python by using Thonny software. Then the image will be given as input, it can first convert the normal image into a grayscale image further the preprocessed image will be displayed by the preprocessing method. Then this preprocessed image is converted to binary data by feature extraction. After that data will be trained with different epochs and achieved its accuracy in training phase.

Table 4.1: Dataset Description

DATASET	CLASS LABEL
Kaggle	1.Cotton wool spots
	2.Fibrosis
	3.Fundus Neoplasm
	4.Maculopathy
	5.Myelinated Nerve Fiber
	6.Optic Atrophy
	7.Peripheral retinal degeneration and break
	8.Possible Glaucoma
	9.Preretinal Hemorrhage
	10.Severe Hypertensive Retinopathy

CNN ARCHITECTURE

Preprocessing

Input Image Gray Scale Image Pre Processed Image

Figure 3.3: Preprocessing

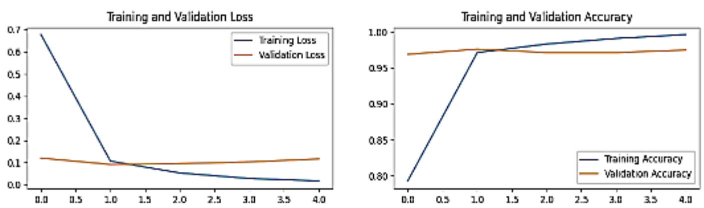

Figure 3.4: Training Phase

Table 4.2: Comparision

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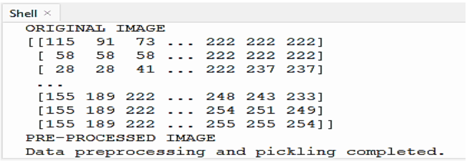
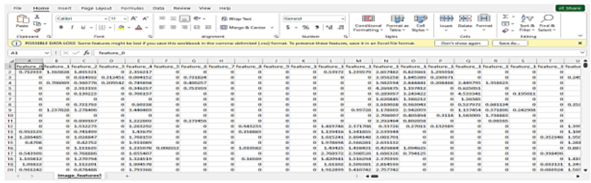
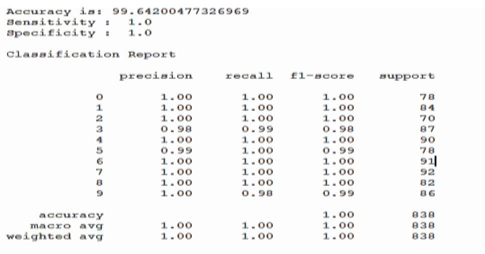
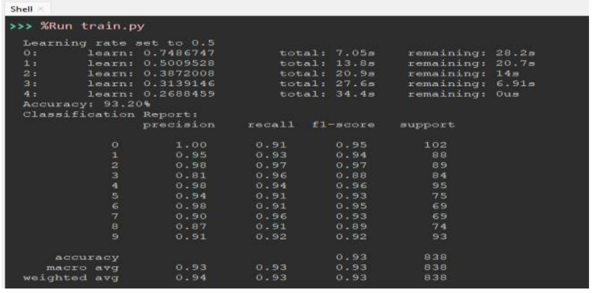
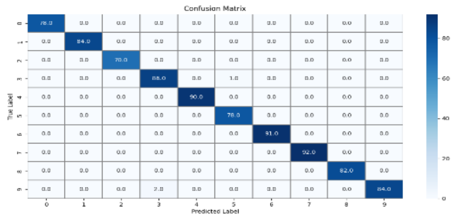
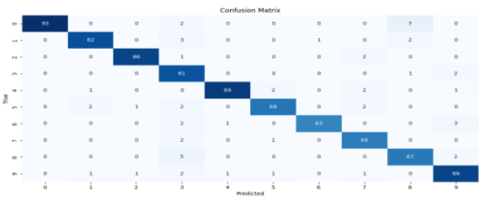
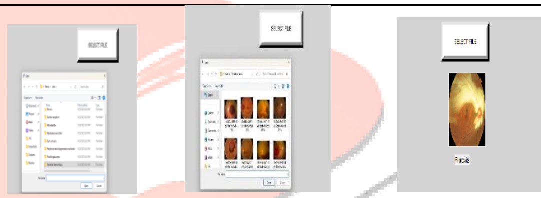
<tr><td>FEATURE EXTRACTION</td><td></td><td></td></tr>
<tr><td>CLASSIFICATION REPORT</td><td></td><td></td></tr>
<tr><td>CONFUSION MATRIX</td><td></td><td></td></tr>
<tr><td>TESTING PHASE</td><td></td><td></td></tr>
</table>

V. Conclusion

The classification of the different retinal disorders is addressed by presenting a CNN model based on deep learning. Kaggle, a dataset containing various retinal diseases, is the basis for the model's implementation. The proposed model is trained on different epochs to test the model's accuracy. Initially, the model was trained at 5 epochs and achieved 97% validation accuracy with 0.1156 validation loss.

Another implementation is done by using CAT Boost algorithm and the objective of using CAT Boost algorithm is to accurately classify and detect the retinal disease. By analyzing various features and patterns in the images, the algorithm can help identify potential diseases early on for timely intervention and treatment. It uses an innovative approach called ordered boosting, which takes advantage of the natural ordering of categorical variables.

CNN are built for picture data, they can automatically extract pertinent characteristics for the identification of retinal diseases. This is because CNNs can learn hierarchical features directly from pixel values. By utilizing the knowledge gained from a variety of image types, pre-trained CNN models on huge datasets can be improved for the identification of retinal diseases. If your dataset includes both retinal images and a combination of numerical and categorical variables.

CatBoost is a suitable option because it works well with tabular data. CatBoost simplifies the preprocessing procedures by handling category features effectively. By offering feature importance ratings, CatBoost makes it possible to determine which features have the most influence on predictions. But comparatively CatBoost alone might not be the best option. It might work well when used with pre-trained CNNs for feature extraction. CatBoost may not capture intricate spatial relationships in images as effectively as CNNs.

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Biography

Dr. L. Malathi, She received her Ph.D. in the field of VLSI under Faculty of Information and Communication Engineering (ICE) from Anna University, Chennai in the year 2023. She received her M.E. degree in Applied Electronics in the year 2008. She received her B.E. degree in Electronics and Communication Engineering in the year 2005. Currently she is working as Assistant Professor (Sr. Gr.) in Department of Electronics and Communication Engineering at Sri Ramakrishna Institute of Technology, Coimbatore, Tamilnadu, India. She is having 15 years of teaching experience. She has presented and published papers in various National and International Conferences, Journals and patents. Her field of interest is VLSI, Digital Signal Processing and Embedded Systems. She acted as resource person in seminar and workshop, session chair and reviewer in conferences. She is a lifetime member of professional bodies such as ISTE, IAENG and ACM.

Ms.R.Madhumitha, Ms.S.Pavithra and **Ms.S.Snekha** are UG scholars in Department of Electronics and Communication Engineering at Sri Ramakrishna Institute of Technology, Coimbatore, Tamilnadu, India.

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