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Eye Deep-Net: a deep neural network-based multi-class retinal disease diagnostic

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ABSTRACT:

Ophthalmologists rely heavily on retinal pictures to diagnose a wide range of eye conditions. Numerous retinal disorders may lead to microvascular alterations in the retina, and a number of studies have been conducted on the early identification of medical pictures to enable prompt and appropriate treatment. In order to identify various eye illnesses using color fundus pictures, this study develops a non-invasive, automated deep learning system. A multiclass ocular illness A productive diagnostic approach was created using the Remind dataset. A variety of augmentation strategies were used to make the structure robust in real-time after multi-class fundus pictures were collected from a multi-label dataset. Low computational demand images were processed in accordance with the network. The fundamental convolutional neural network (CNN) extracts appropriate characteristics from the input color fundus image dataset, and then processed characteristics were employed to make predictive diagnoses. This multi-layer neural network, called Eye Deep-Net, has been developed for training and evaluating images for the recognition of various eye problems. The performance of the suggested model is determined to be much better than numerous baseline state-of-the-art models. The strength from the Eye Deep-Net is assessed using different statistical metrics. The suggested methodology's effectiveness in

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classifying and identifying diseases using digital fundus pictures is shown by a thorough comparison with the most modern techniques.

INTRODUCTION

The prevalence of retinal disorders in people of all ages is rising. In the human eye, the retina is composed of a layer of optical nerve tissue known as photosensitive tissue. This layer converts the lens-focused light into brain signals. Sensing is carried out by the macula, which is located in the center of the retina. The macula gathers information, which the retina processes and sends via the optic nerve to the brain enabling visual identification. A variety of illnesses, including diabetic macular edema (DME) with Roth spots, optic disc drusen, and age-associated macular degeneration (AMD), may result in abnormalities in perception. AMD is the primary cause of visual loss in most industrialized nations for those between the ages of 50 and 60. Based on current studies, around 35 percent of persons in the US over the age of 80 have this condition. The most difficult aspect is identifying retinal disorders since there are so many different types of these conditions, making an accurate diagnosis need a highly skilled ophthalmologist. Likewise, retinal disorders are readily recognized and treated in their early stages using computer-aided diagnostic systems (CAD). The medical industry is one area where technological improvements have the most positive impact on people's lives. To increase the effectiveness and caliber of medical treatments, several strategies & models have been put forward. Advances on Automatic Disease Detection (ADD) have shown a considerable improvement in the social health system. Additionally, retinal symptom analysis—an ADD application—offers a special chance to advance eye care worldwide. In categorized segmentation, and detection of retinal disorders, several cutting-edge machine learning (ML) as well as deep learning (DL) algorithms have been developed presented recently. Due to the creation of multiple machine learning (ML) as well as deep acquiring (DL) models, such as recurrent neural networks (RNN), cone neural network (CNN), Alex's Reset, and VGN, we observe that gathering information and labelling are major challenges for the execution of ADDs, as stated by authors in and. Because of them, it is now easier for researchers and medical professionals to identify and classify these critical

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illnesses. A hybrid approach based on machine learning is introduced to automatically classify retinal disorders. In addition to using a Support Vector Machine, or SVM, classifier for classification, researchers in have suggested using U-Net segment for image pre-processing. A diagnosis accuracy of 89.3% was attained using the suggested method. Additionally, Yang et al. contributed the first annotated Eye Net dataset, which included 32 retinal disorders. The authors pointed out that transferring the whole map of features to the appropriate decoder requires a large amount of memory, which is a serious shortcoming of the U-Net. A crucial part of picture categorization is played by deep learning. on order to categorize multi-class eye illness detection, this study suggests a CNN model that is grounded on deep learning. The Eye Net Dataset was used to assess the suggested model. 32 files with associated photos for certain purposes make up the Eye Net dataset. With the remaining percentage being utilized for validation, 70% has been utilized in training. It was found via experimental assessment that the suggested model had an accuracy of 95%. To improve the traditional diagnosis approach, the CNN model with deep learning has been used for retinal-based critical disorders. This is the study's main contribution. The paper's main contributions are listed below. • The conventional diagnostic procedure for retinal-based critical diseases has been reinforced by the use of a CNN model based on deep learning. • An experimental assessment shows that the suggested CNN model performs better in the multi-class Eye Nets dataset, producing greater accuracy while using less memory than typical state-of-the-art approaches. The remaining sections of the document are organized as follows: The connected works are shown in this section. We provide a thorough explanation of the dataset utilized in the Section along with the suggested design. This section describes the experimental evaluation's findings, including how well the specified CNN model performed. The discussion and analysis are included in this section. This section provides future directions for the study effort and finishes it.

RELATED WORK

"Dermatologist-level classification of skin cancer with deep neural networks",

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A. Esteva, B. Kural, R. A. Novoa, J. Ko, S. M. Swatter, H. M. Blau, et al.,2017.

Skin cancer, the most common human malignancy, is primarily diagnosed visually, beginning with an initial clinical screening and followed potentially by thermoscopic analysis, a biopsy and histopathological examination. Automated classification of skin lesions using images is a challenging task owing to the fine-grained variability in the appearance of skin lesions. Deep convolutional neural networks (CNNs) show potential for general and highly variable tasks across many fine-grained object categories. Here we demonstrate classification of skin lesions using a single CNN, trained end-to-end from images directly, using only pixels and disease labels as inputs. We train a CNN using a dataset of 129,450 clinical images—two orders of magnitude larger than previous datasets consisting of 2,032 different diseases. We test its performance against 21 board-certified dermatologists on biopsy-proven clinical images with two critical binary classification use cases: keratinocyte carcinomas versus benign seborrheic keratoses; and malignant melanomas versus benign nevi. The first case represents the identification of the most common cancers, the second represents the identification of the deadliest skin cancer. The CNN achieves Across all tests, the artificial intelligence demonstrated efficiency on par with all evaluated specialists, indicating that it is competent enough to classify skin cancer on par with dermatologists. Mobile devices with neural networks that are deep installed may allow dermatologists to contact patients outside of their clinics. By 2021, there will likely be 6.3 billion users of smartphones worldwide (ref.), which means that everyone may have inexpensive access to essential diagnostic care.

"Automated detection and classification of fundus diabetic retinopathy images using synergic deep learning model",

K. Shankar, A. R. W. Sait, D. Gupta, S. K. Lakshmana Prabu, A. Khanna and H. M. Pandey, 2020.

Due to a sharp rise in blood glucose levels, the prevalence of Diabetic Retinopathy (DR), which affects the eyes, has increased recently. Almost half of all individuals under 70 worldwide suffer from serious diabetes. DR patients often experience visual loss if appropriate treatment and early diagnosis are not received. After identifying the warning indicators, the disease's severity must be confirmed in order to make judgments on the best course of action. The idea of classifying DR fundus photos using a network of deep learning algorithms according to severity degree is the main subject of the present research study. A deep learning-driven automated algorithm for fundus DR picture recognition and categorization is presented in this article. Preprocessing, segmentation, and classification are among the steps in the suggested technique. The approach starts with a preprocessing step that eliminates extraneous noise from the edges. After that, the image's valuable sections are extracted using a segmentation technique based on histograms. After that, different severity levels for the DR fundus photos were classified using the Synergic deep-learning (SDL) model. Using the Messi or DR dataset, the suggested SDL model was justified. The results of the experiment showed that the proposed SDL model provides superior categorization compared to the current models.

"Multi-retinal disease classification by reduced deep learning features",

R. Arunkumar and P. KarthigaiKumar, 2017.

The deep learning-based extraction of features approach for retina-based illness detection is presented in this study. By using this procedure, an automated screening system that can diagnose conditions including retinopathy, macular detachment, retinoblastoma, age-related molecular degeneration, and retinitis pigmentosa may be developed. The categorization of several of these disorders is challenging since they have a similar feature. Deep learning extraction of features and a multi-class classifier based on SVM are utilized to solve the aforementioned issue. The primary contribution of this study is the reduction in the dimension of characteristics needed for the classification of retinal diseases, which improves both high performance and the process of lowering the system need.

"Modified Alex net architecture for classification of diabetic retinopathy images",

T. Shanthi and R. S. Siberian, 2019.

A condition called retinopathy from diabetes (DR) is brought on by elevated blood glucose levels and affects the eyes. Half of all fatalities in the 70+ age range are related to diabetes. For many DR patients,

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early detection and effective treatment may minimize vision loss. The extent of the condition should be assessed after DR symptoms are identified in order to provide the appropriate treatment. In order to achieve a high degree of accuracy, this article focuses on the categorization of DR fundus pictures according to the degree of the illness using convolutional neural networks with appropriate Pooling, SoftMax, and Rectified Linear Activated Unit (Relu) layers used. Messi or the database have been used to verify the suggested algorithm's performance. Classification accuracy of 96.6 %, 96.2 %, 95.6 %, and 96.6 % have been attained for healthy pictures and images of diabetic retinopathy stages 1, 2, and 3.

METHODOLOGY

To implement this project we have designed following modules

1) Upload Dataset: This module will allow us to upload, read, and show datasets in the application.
2) Pre-process Dataset: This module will be used to eliminate missing values, normalize and shuffle the set of values, and divide the dataset into instructional and evaluation segments, with the application utilizing 80% of the data to teach and 20% for testing.
3) Train EYENET with SGD optimizer: With the use of train data and the SGD optimizer method, this module trained EYENET. The prediction accuracy of the trained model can then be determined using test data.
4) Train EYENET with ADAM optimizer: This module is used to train EYENET using the ADAM optimizer algorithm using train data as input. The prediction accuracy of the trained model may then be calculated using test data.
5) Train EYENET with ADAM & Valid optimizer: This module is used to train EYENET using the ADAM optimizer algorithm. It does this by utilizing train data as input, and then applying the trained model to test data to determine prediction accuracy.
6) Accuracy Comparison Graph: is capable of plotting a graph that compares all algorithms.
7) Upload Test Data: may be used to submit test photographs, and the extension model will forecast the results based on the test data.

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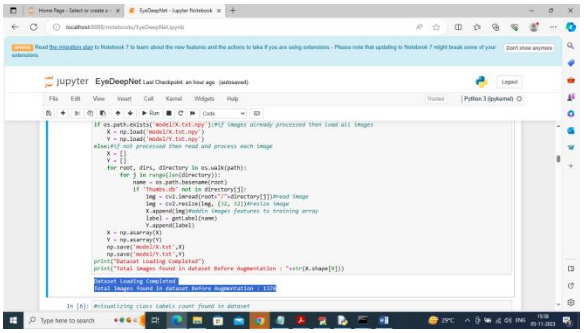
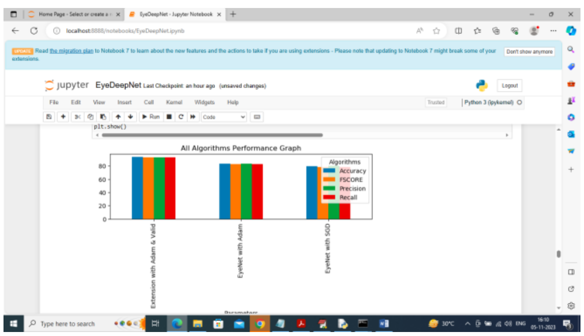
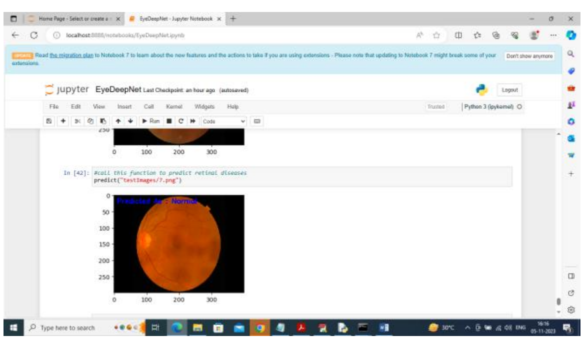
8) RESULT AND DISCUSSION



In above result reading all images from dataset and then resizing and adding to training array and after loading we can see dataset contains 1376 images without augmentation and this output displaying in blue colour text



In above result x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars and in all algorithm extension model got high accuracy



In above result can see predicted output from other test images

CONCLUSION

A deep learning-based CNN model is presented to handle the categorization of various retinal illnesses. The model is implemented using Eye Net, a set of data that includes 32 different retinal disorders. To evaluate the correctness of the suggested model, it is trained over many epochs. The model first obtained 95% validation accuracy after 10 epochs of training; after 15 epochs, it again attained 95% validation correctness with a different validation loss of 0.0279 in both instances. In comparison to other models regarded as state of the art, the model's overall performance is far better. The model what has been presented may be useful in the classification of retinal disorders. Its performance will be improved going forward with regular updates to the model and retraining on fresh data. This will be accomplished via using the growing availability of varied retinal disease datasets and the progress made in deep learning methods.

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