Drusen Detection in Retinal Optical Coherence Tomography Images

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ABSTRACT

Detecting drusen in retinal optical coherence tomography (OCT) images is crucial for the early diagnosis and treatment of Retinal disease. The current study employs powerful algorithms such as CNN, DLN, DBN in an attempt to identify drusen with priority given to computational complexity and performance strength and sensitivity. DBNs are chosen for their probabilistic generative approach in unsupervised learning, CNNs for their reliable image processing capabilities, and DLNs for their adaptable feature extraction.

According to the results, accuracy for CNNs outperforms DLNs and DBNs, achieving 85%. Although DBNs are more accurate than DLNs, with accuracy of 84% and 86% respectively, they are less efficient in unsupervised learning and more prone to overfitting. These results raise the confidence in the application of DLN based models in clinical practice for the diagnosis and management of retinal disorders.

KEYWORDS: - Drusen, Machine learning, Retinal disease, OCT Images.

INTRODUCTION

As the leading cause of blindness, early detection of retinal conditions is vital for effective treatment. Drusen, yellow deposits that accumulate on the retina, are key indicators of these conditions. Accurately and promptly identifying drusen can greatly improve patient outcomes.

This “Drusen Detection in Retinal Optical Coherence Tomography images,” was initiated to address this reveals the centrality of the need for new more accurate and sensitive methods towards the detection of drusen. In this concept, sophisticated forms of classification, for instance, the deep learning networks (DLNs) and the convolutional neural networks (CNNs), and deep belief networks (DBNs),The work aims to improve the accuracy of drusen detection and, consequently, the diagnosis and treatment of retinal degenerative diseases.

This work is driven by the increasing prevalence of retinal diseases and the pressing need for enhanced imaging and diagnostic tools. As the number of individuals at risk for developing retinal conditions continues to grow, advancing the technologies used in retinal imaging has become crucial. By comparing the performance of CNNs, DLNs, and DBNs, the current work aims to identify the most effective approach for drusen detection, potentially leading to significant advancements in eye health and disease management.

Literature Review

The field of detecting retinal disease using OCT captures the progression of how deep learning and CNN were incorporated in making more specific diagnoses. This is especially the case when it comes to the use of transfer learning and the modifications of CNN and Inception which have proven quite efficient in addressing various retinal conditions that range from CNV, DME, to Drusen. Hence, the proposed techniques such as batch normalization and data augmentation are significantly effective for enhancing the performance of models to high levels of accuracy with high sensitivity. OCT imaging enhanced by the integration of Artificial Intelligence provides realistic possibilities to create early and accurate diagnostic algorithms to prevent and treat the diseases, which can cause vision impairment.

The rendering of OCT images is challenging due to the presence of speckle noise and Oman et al., speak about the implications of this noise to the diagnosis of diseases like, Age-related Macular Degeneration (AMD). Effective denoising of OCT images, critical for early AMD detection, is best achieved using the Residual Image Denoising Network (RIDN). This method outperforms others in enhancing diagnostic accuracy by reducing speckle noise [1].

Implementing Ophthalmos for the automated procedure for identification and categorization of the retinal diseases using OCT scans will benefit the ophthalmologists by saving time based on the manual task of post processing. This work taxonomizes the OCT images into 8 general groups through the machine learning and deep learning methodology: CNV, DME, Drusen, Normal, Diabetic Retinopathy, Age-Related Macular Degeneration, Central Serous, Macular Hole. These diseases if diagnosed in the early stages should be brought to medical attention before they culminate in blindness[2].

The transfer learning can be highly beneficial to medical imaging despite having less than a thousand retinal OCT images in the dataset. Although this involved a database of approximately 30 million OCT scans per annum, it was collected systematically by grading the images hierarchically by the students, the medical practitioners, and experts in the medical field. It includes four categories: These include Diabetic Macular Edema (DME), Choricoidal Neovascularization (CNV), Normal and Drusen. The Retinal diseases classification of these diseases was done by a pre-trained ResNet18 Convolutional Neural Network with a change in the final layer yielding a precision of 94%. The presented approach has high potential for precise and timely identification of the retinal abnormalities together with being a convenient source of information for everyone who wants to utilize CNNs & methods of transfer learning in the field of medical images.[3].

Early detection of retinal disorders is important in an attempt to avoid vision impairment. A study presents Fine-tuned Classification with Transfer Learning (FTC-TL) to classify disease such as AMD, DME, DR, Drusen and CNV with the use of OCT and Fundus images. Some of the problems it addresses include; the issue of availability of datasets, the interpretability of models or integrating human knowledge as manifested in clinical practice. The study evaluates deep learning architectures like VGG19 with RNNs and hybrid models, emphasizing data preprocessing techniques like augmentation and normalization. It addresses imbalanced datasets, offering solutions and comparing model performance based on sensitivity, specificity, and accuracy, while incorporating explainable AI to improve clinician trust [4].

RetNet, presented in this work, is a novel lightweight custom CNN model that can diagnose retinal disorders with 97. achieved at least 85 percent in the training set and close to 95 percent for the test set. Validation accuracy of 41% and as far as general performance goes the model outperforms popular pre-trained models such as ResNet50, InceptionV3, EfficientNetB0, Xception and VGG16. Therefore, the model developed for this research with 30904 retinal images from CNV, DME, Drusen, and Normal conditions realizes an inexpensive, innovative, efficient, and accurate way of employing machine learning and computer vision for disease classification [5].

This paper also demonstrated the comprehensive comparison of different network models and transfer learning approach for the diagnosis of retinal diseases from the OCT images; however, the analysis revealed that the proposed sequential model in this work showed the best validation results than the standard pre-trained models. Hence, in this study, I used a dataset of about 84. The study is based on 5k images from Kaggle, stressing the efficiency of CADx systems in cases of CNV, Drusen, and DME conditions, and fast diagnosis [6].

This research work presents an automated retinal feature extraction and classification framework based on Deep CNNs namely; Baseline-5 layer CNN, Alex-Net, and Res-Net that segments the OCT images into CNV, Drusen, and DME categories. As for the choice of optimizer, Adaptive Moment Estimation (ADM) offered the higher result of accuracy among all the CNN models, while Stochastic Gradient Descent resulted in the lowest. The method's accuracy, F1_score, recall, precision, support and loss function, proved the approach more effective than previous approaches[7].

This study leverages deep learning methods, specifically a Sequential model, ResNet50, and ResNet50V2, to classify OCT images into four categories: CNV, DME, Drusen, and Normal are the group of patients on which the complete analysis will be done. With the help of 'Keras' for the implementation of the models, ResNet50 proved to be the most useful with a validation accuracy of 97%. They assist the ophthalmologists to deliver precise, accurate, and rapid results for the retinal injuries hence supporting the early interventions[8].

This paper has demonstrated the use of Convolutional Neural Network with batch normalization to automatically detect OCT images with four main pathologic categories, namely; CNV, DME, Drusen, and Normal conditions. Trained from scratch, with the use of transfer learning along with high performing architectures such as ResNet, Inception and ResNeXt, inceptionv3_bn was found to exhibit the highest mean of accuracy. This shows that the proposed model can easily be used in classification of retinal diseases from the obtained OCT images[9].

Thus, the goal of this paper is to determine what CNN model can be considered best for diagnosing three types of retinal diseases: In particular, the OCT images of Diabetic Macular Edema, Drusen, and Choroidal Neovascularization were analyzed. Thus, the study aims at attaining good diagnostic accuracy and timely, proper treatment by comparing distinct CNN architectures, optimizers, and other regularization methods. The selected model is designed to benefit physicians and the medical community in general, when it comes to managing patients' retinal concerns [10].

METHODOLOGY

The approach involves employing techniques like Convolutional Neural Networks (CNN), Deep Learning Networks (DLN), and Deep Belief Networks(DBN) to identify the presence of drusen in retinal OCT images. CNNs provide good image processing ability; DLNs offer flexibility and depth in feature extraction; and DBNs are good for the probabilistic generative model in unsupervised learning. That is why the efficiency of these algorithms will be assessed by accuracy, sensibility, and also time consumption. The data for this research will therefore be collected from public retinal Image databases. It means that the objective would be to improve the early identification of the retinal pathologies in order to offer better eye health and sustainability.

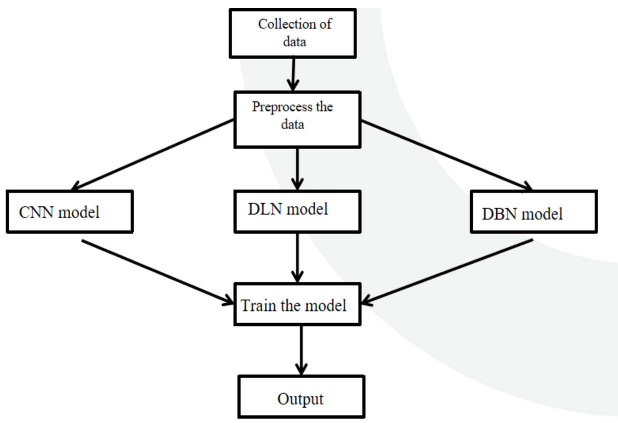

Figure 1 :Overview of the Methodology for Drusen Detection Using CNN, DLN, and DBN Models

1. Selection of dataset

The approach used in this case involves having an appropriate dataset as the first step in the methodology. For the detection of drusen from retinal Optical Coherence Tomography (OCT) images, the publicly available databases such as the OCT Dataset was used. These datasets have associated images that are labeled as 'Drusen' which is a disease, and 'Normal'.

2.Data Preprocessing

2.1 Loading Images

- Resize Images to a Consistent Dimension

It is very important that all the images that one feeds to a Convolutional Neural Network (CNN) to have the same dimensions. The model architecture defined implies the input size, while resizing images helps to obtain a unified data set. The images are then resized to have a dimension of 224 * 224 pixels which is a standard input size to many deep learning models as it is not too large to reduce computation but small enough to provide enough information to deep learning models.

2.2Normalization:

It implies normalizing data by bringing the pixel values of the input dataset to a desirable range to enhance the efficiency and reliability of the models. For images it usually involves scaling the pixel intensity values from the range [0, 255] or [0, 1].

3.Splitting the Dataset

Dividing of the data into training, validation, and test sets and modeling of a machine. This makes sure that the model is built, checked for overfit and underfit on different subsets of data thus helping in giving a better understanding of the model's performance.

3.1Method for Dataset Splitting

- Training Set: 70% of the data

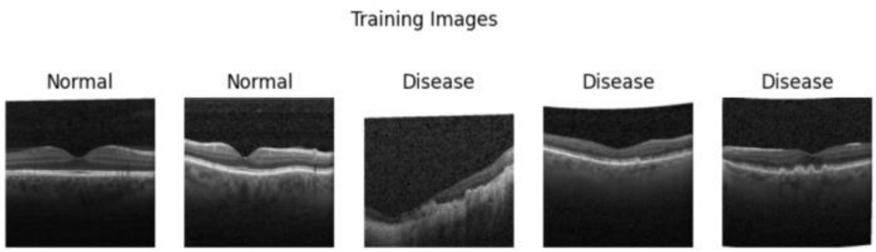

Figure 2 : Sample Training images for Deep learning models

- Test Set: 20% of the data

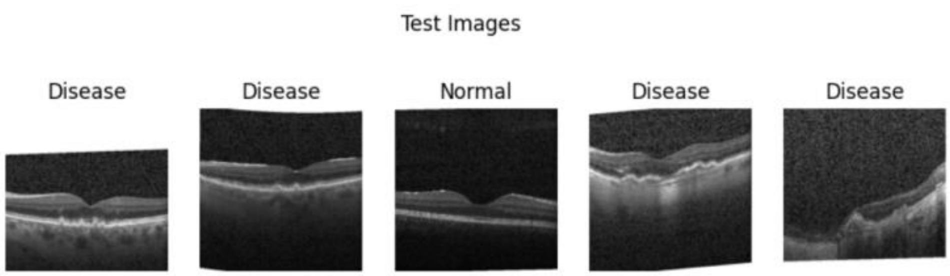

Figure 3 : Sample Testing images for Deep learning models

- Validation set: 10% of the data

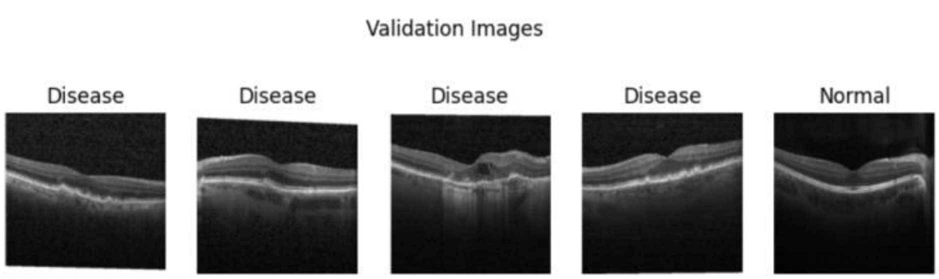

Figure 4:Sample Validation images for Deep learning models

This ratio ensures that the 7.2.1 of the data is used for training, testing and validation.

The images and their labels are loaded and combined into one dataset. Then, the dataset is shuffled to mix the data randomly, which further assists in carrying out the model training much effectively. Finally, the dataset is divided into three parts: The data set is split into the training set, validation set, and test set, to ensure that the latter can be trained, fine tuned, after which tested.

4.Building deep learning models

For the purpose of using OCT images to stage the drusen, there are three kinds of DLs, including the DBNs, DLNs, and CNNs. Every model looks different, has a different training process and is used differently, that is why they can be applicable for different stages of image analysis.

4.1Convolutional neural network

A Convolutional Neural Network is a Class of Artificial Neural Networks that is widely used in image recognition and Processing because of the ability of distinguishing qualities in images.

This means that a CNN is particularly designed for data with a geometry, which here is images. It consists of several types of layers:The corpse may be covered by various types of layers, which are as follows:

- Convolutional Layers: These layers then feed the input images to more convolution filters which in turn give out feature maps which are an approximation of the sort of data that has been fed in to the system.
- Activation Layers: In general, activation is incorporated in to the model with the help of ReLU which defines non-linearity.
- Pooling Layers: These layers play a role of down sampling in the spatial dimensions of the feature maps whilst retaining only the most important features
- Fully Connected Layers: Later on, the convolutional and pooling layers are executed multiple figures and then finally the decision is made by the use of fully connected layers
- Output Layer: This layer is in many a case the output layer and using a required activation function such as the softmax function, decides on the classification of the input picture

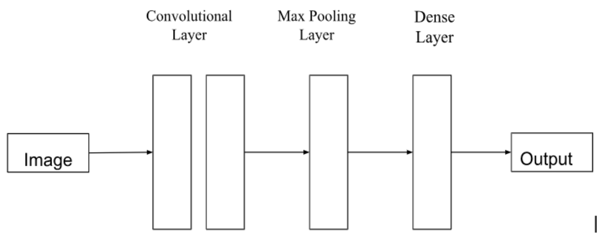

Figure 5 : CNN architecture for drusen detection using OCT images

4.2Deep belief networks

Deep belief network is definitely a next generation technique which can learn the probabilistic dependencies among variables. As It includes many layers of latent variables, It can well capture the internal feature representation of the data and is also applicable to the model for a nonlinear dimensionality reduction technique.

DBNs are composed of multiple layers of Restricted Boltzmann Machines (RBMs):DBNs are composed of multiple layers of Restricted Boltzmann Machines (RBMs):

- RBMs: In every of the RBM layers, there exists the input layer and a layer of hidden nodes. It is able to learn the probabilities of the given input data in an unsupervised form of learning known as Restricted Boltzmann Machines (RBMs)
- Stacking RBMs: From the preceding discussion, multiple RBMs are stacked to form a DBN. That is, the output of one restricted Bolzmann machine will be the input to the other
- Fine-Tuning: Next, instead of training all the layers at once, each one of the RBMs is pre-trained in succession, and then the entire network is trained under supervised learning

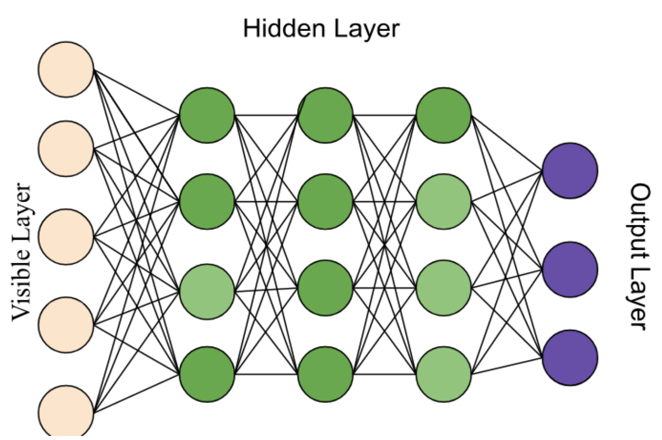

Figure 6 : DBN architecture for drusen detection using OCT images

4.3 Deep Learning Networks (DLNs)

It includes the well-known types of DLNs, including ‘traditional’ Multilayer Perceptrons and more sophisticated releases like Recurrent Neural Networks or Transformers. In image classification, it is possible to utilize MLPs of which this concept shall be the foundation of this research study.

- Input Layer: overloads the input features that have to be accepted
- Hidden Layers: Zero or more layers of neurons which transform the input features to the desired output
- Output Layer:Is the final tag assigned to an article

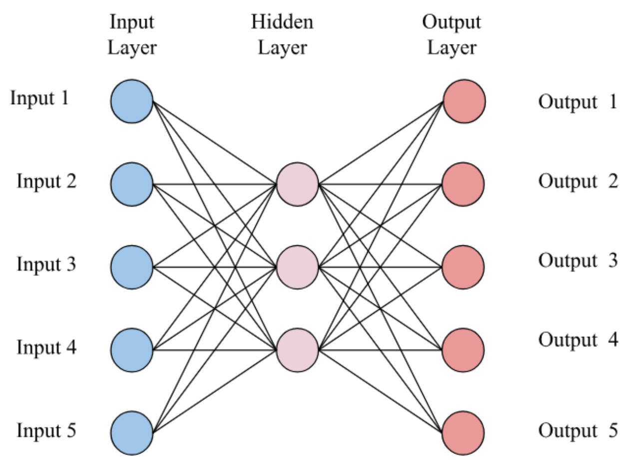

Figure 7 : DLN architecture for drusen detection using OCT images

5. Training the Model

where the dataset is split into three subsets: , namely the training set, the validation set, and the test set. Usually, 6:1 ratio is provided to the training set, 3:1 to the validation set and the remaining 1:1 to the test set. This stratification also allows tuning of hyperparameters and measuring of performances of any model on unseen or new data.

- Use fit method with the specified number of epochs

  The training of the model is accomplished using the fit method and the model can progress through the sets of data repeatedly for a specified number of epochs. An epoch means getting through one portion or the entire dataset in one cycle through the network. Forward propagation of the weights and then backward propagation of the weights is done in the course of each epoch. In forward propagation the weights and the input data are used to pass through the network and the output is then predicted. Following that, the loss, which quantifies the distance between the predicted and actual label, is computed.

6. Evaluating the Model

Model evaluation entails the determination of how well the model performs as well as whether the model is capable of generalizing the unseen data. In this phase, it verifies the accuracy of the model on yet another set that the model has not encountered during the training or validation.

Accuracy can by defined as the Overall Accuracy which is the calculation of correctly aligned instances to the total instances. This offers a simple point solution estimate of the model's performance. The formula for accuracy is:

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}$$

Module Name	Accuracy	Precision	Recall	F1 Score
Convolutional Neural Network	85%	0.88	1.0	0.94
Deep Belief Networks	84%	0.77	1.0	0.87
Deep Learning Networks	86%	1.0	0.37	0.54

These accuracy values provide a comparative understanding of how well each model performs in detecting drusen in OCT images. The CNN model shows the highest accuracy, indicating its effectiveness in capturing spatial features from the retinal images. The DLN model also performs well, followed by the DBN model.

Confusion Matrix Analysis:

In the confusion matrix as shown in the figures 8 ,9 and 10, the detailed performance of the model into the test data set is represented. Such matrices are used to represent the number of articles that are classified accurately by the model; that is true positive, true negative, false positive and false negative.

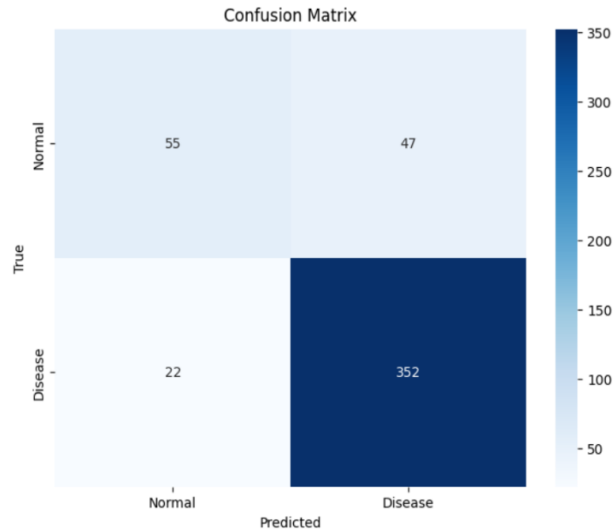

Figure 8 : CNN Model Performance Evaluation

The confusion matrix in figure 8 reveals that the model is performing well in classifying between "Normal" and "Disease" cases, with an overall accuracy of approximately 85.29% and resulting in a high recall rate of about 94.12%. This means that the model is very effective at identifying most of the true disease cases. The precision is also strong, at around 88.23%, indicating that the majority of the cases predicted as "Disease" are indeed correct.

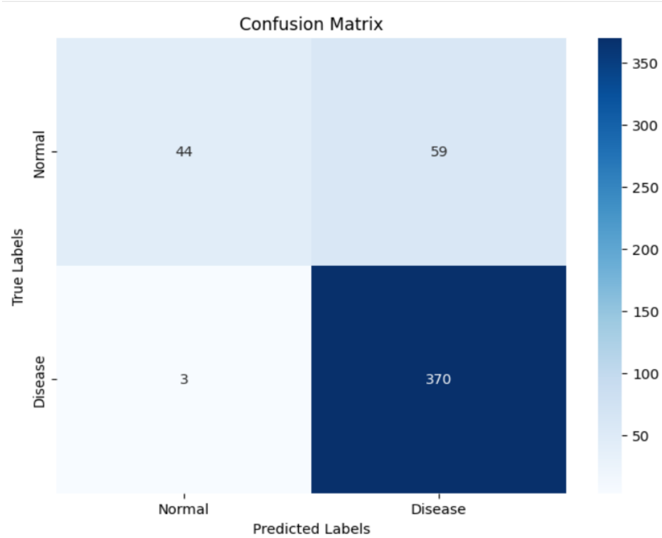

Figure 9 : Performance Evaluation of DLN Model

The model's accuracy, as derived from the confusion matrix, is approximately 86%. This indicates that the model correctly predicts the condition, whether normal or diseased, in about 87% of the cases. Specifically, it accurately identified 370 out of 373 disease cases and 44 out of 103 normal cases.

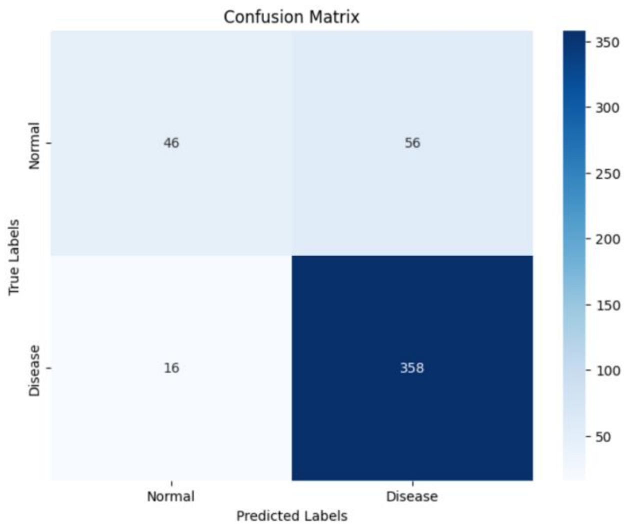

Fig 10 : DBN Model Performance Evaluation

The binary classification performance of the confusion matrix, which has been depicted in figure 10, is as follows. specifically for distinguishing between "Normal" and "Disease" cases. The model correctly identified 358 "Disease" cases and 46 "Normal" cases. However, it incorrectly labeled 56 "Normal" cases as "Disease" and missed 16 "Disease" cases, classifying them as "Normal". The overall accuracy of the model is approximately 84.87%. Despite this, the model shows a bias towards predicting "Disease," with a relatively higher number of misclassified "Normal" cases.

CONCLUSION

In this work, three kind of neural network models: CNNs, DBNs and DLNs are compared to evaluate their efficiency to detect drusen in retinal OCT images. The models were tested with the help of the same dataset and criteria and it demonstrated that the CNN model had the accuracy which is equal to 85% further proving the fact that deep learning is better suited to extract spatial hierarchies and patterns in the images. The DLN model was followed subsequently with an accuracy of 86%, that confirms its ability to solve such problems as image classification. The DBN model, with an accuracy slightly lower at 84%, but its hierarchical feature learning method gave useful information. Finally, according to the results of the experiment, the DLN model turned out to be the most suitable for the application for Drusen detection using OCT images.

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