International Journal of Science, Strategic Management and Technology
Volume **02** Issue **03** March-**2026** | ISSN: **3108-1762 (Online)** | Impact Factor: 3.8
An International, Peer-Reviewed, Open Access Scholarly Journal Indexed in recognized academic databases

A Web-Based AI System for Eye Disease and Severity Prediction Using Oct Image

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https://doi.org/ 10.55041/ijsmt.v2i3.151

Cite this Article: S, K. S. (2026). A Web-Based AI System for Eye Disease and Severity Prediction Using Oct Image. International Journal of Science, Strategic Management and Technology, *02*(03). https://doi.org/10.55041/ijsmt.v2i3.151

1. Abstract

This study uses pictures called optical coherence tomography images along with information about the patient to find out if they have retinal diseases and how bad they are. The doctors looked at seven kinds of problems: choroidal neovascularization, drusen, DME, normal retina, RVO, ERM and vitreomacular interface disorder. They made a computer program that can tell which kind of problem a patient has. To make the program better at predicting how bad the disease is the doctors included information about the patient like how old they are, if they have diabetes, if they have high blood pressure and if they smoke. The program looks at the optical coherence tomography images. Finds the important things about them instead of using a more complicated method.The doctors used a lot of optical coherence tomography images, 84,568 to teach the program. It was very good at telling which kind of retinal problem a patient had. It was 97 percent of the time and it found the real problems 95 percent of the time and it did not say someone had a problem when they did not 94 percent of the time.The doctors did a lot of work to check how good the program was and they found out that it is very helpful for eye doctors to find retinal diseases early and to take care of patients. The program can find kinds of retinal diseases and tell how bad they are, which is very useful, for doctors.

Keywords: machine learning, risk factors, multi-class classification, artificial intelligence, retinal disease, OCT imaging, severity prediction, and performance analysis.

2. Introduction

Medical image analysis has become very good at finding diseases thanks to medical image analysis learning. In the past finding diseases was not very accurate. It took a lot of time. Nowadays Machine Learning is used a lot. It gives us fast and accurate results. Diseases that affect the retina, which's a thin layer at the back of the eye, are a major cause of vision loss because they affect our vision.

This paper is about using computers to find and predict how severe retinal diseases are. The retinal diseases we are talking about are neovascularization, drusen, DME, RVO, ERM, vitreomacular interface disorder and normal retina. We use optical coherence tomography images and information about the patient, such as their age if they have diabetes, high

blood pressure and if they smoke, to predict how severe the disease is. Some optical coherence tomography images that show these seven conditions are shown in Figure 1.

We are trying to solve the problem of finding diseases using machine learning by using OCT images and information about the patient. We use OCT images and information about the patient to find diseases and predict how severe they are. A few optical coherence tomography images that show these seven conditions are shown in Figure 1.To make our classification better we use the seven retinal disease classes to train the VGG-16 model, We also use information about the patient to predict how severe the retinal disease is, which gives us results, for doctors. The retinal diseases we are talking about such as neovascularization, drusen, DME, RVO, ERM, vitreomacular interface disorder and normal retina can be. Predicted using OCT images and patient information.

Medical image analysis is used to find diseases and medical image analysis is very important. Retinal diseases are found using optical coherence tomography images and patient information. The

Retinal diseases are neovascularization, drusen, DME, RVO, ERM, vitreomacular interface disorder and normal retina. We use medical image analysis to find these diseases.

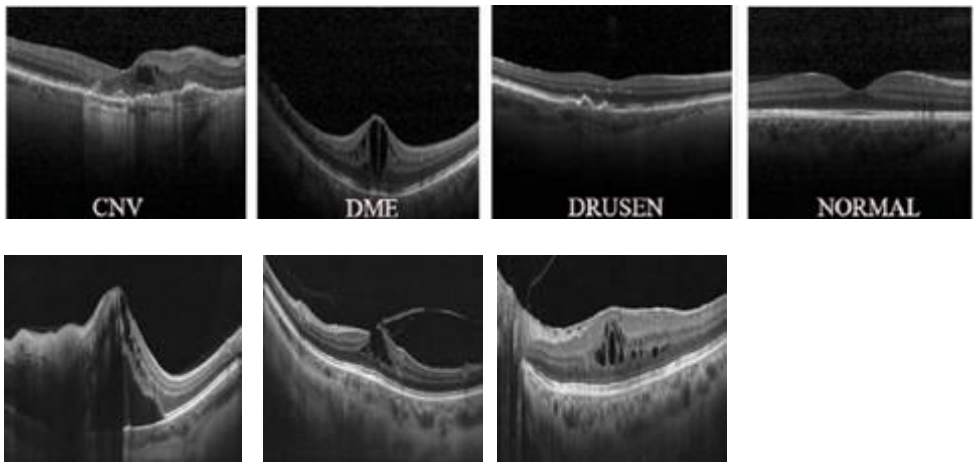


Figure 1: Representative OCT Images of Retinal Diseases

3. Objective

- The model uses risk factors to figure out how bad retinal diseases are, which helps it automatically find these diseases in seven types of retinal diseases.
- The model uses a kind of VGG-16 model that has been trained already to learn from the data that we have which makes the model work better and it does not need to do as much work and it also helps stop the model from overfitting.
- This way of doing things helps eye doctors find and treat diseases early by looking very closely at OCT images of retinal diseases and saying exactly how bad the retinal diseases are, which is very important, for retinal diseases.

4. Related Work

Initially, binary or multiple classification of retina was performed based on OCT images, followed by the introduction of a novel AOCT-NET model, a CNN-based model, for the multiclass classification of retinal diseases based on spectral domain OCT images, as presented in the study by Alqudah [7]. The effectiveness of CNN models over traditional machine learning models was demonstrated in the study by Kim and Tran [5] based on the application of deep learning models to OCT images for the classification of retinal diseases. A coherent convolution neural model was suggested for the detection of retinal disease based on OCT images, as presented in the study by Upadhyay et al. [30]. To increase the task, the concept of ensemble and fusion was introduced. Ai et al. [2] proposed the FN-OCT model, which is a fusion-based model using multiple feature representations for improving the detection performance in the presence of diseases.

Paul et al. [24] proposed the OCTX model, which is a model using multiple classifiers for improving the generality of the model. Khan and Khan [8] improved the performance in the diagnosis task by using the concept of deep ensemble classifiers. Choudhary et al. [21] model focusing on the optimized feature learning for the classification task in retinal diseases. Sunija et al. [14] proposed the OctNet model, which is a lightweight CNN model for improving the performance in the diagnosis task.In addition to the classification-based models, the concept of prediction and modeling was also introduced. Romo-Bucheli et al. [4] model for predicting the need in the context of neovascular AMD that uses the concept of longitudinal OCT imaging. Banerjee et al.[10] employed a sequential DL model for AMD progression using longitudinal SD-OCT biomarkers. Christopher et al. [27] employed a DL model to predict error to the visual field using structural maps from OCT images.Multimodal AI systems have also been identified as having the capability to utilize various imaging modalities in combination with OCT images. Zedadra et al.

[1] employed a multi-modal hybrid AI system to predict multi-label retinal diseases using OCT and fundus imaging modalities in combination with each other. Kang et al. [26] employed a multimodal imaging-based deep learning system to predict retinal vascular diseases that require treatment using various imaging modalities. Liu et al. [15] employed an OCT-AI telemedicine platform to evaluate retinal diseases in the primary care environment. In addition, Rim et al. [17] and Wagner et al.

[25] employed a prediction model to predict various systemic diseases using retinal imaging modalities, which led to the development of a new concept termed oculomics to predict various health conditions using retinal imaging modalities.

In addition, to predict diabetic retinopathy and microstructural changes, Elsharkawy et al. [9] and Sharafeldeen et al.In their study, Yanagihara et al. [6] emphasized the methodological issues encountered in deep learning-based applications in OCT imaging. Muchuchuti and Viriri [19], Bali and Mansotra [16], Lim et al. [12], and Parmar et al. [23] presented detailed reviews on AI-based applications and Wong et al.

[28] also presented a detailed study on AI-based applications in retinal imaging in cardiovascular risk prediction. Although the studies presented in the aforementioned papers have high classification accuracy, most studies are focused on classification using images and only a

A few diseases are considered in the classification process. Also, few studies are focused on the integration of clinical risk factors, multiple class diseases, and severity level prediction in a single framework. Most studies are focused on increasing the complexity of the model using ensemble and multimodal approaches, making it difficult to implement in real-time due to the requirement of large datasets.Thus, in this study, we propose a new model by extending the existing studies in the field by implementing a VGG-16 transfer learning model for seven-class classification. Unlike in the previous approaches, in the proposed system, the patient-specific risk factors are considered while predicting the severity of the diseases. This will help in the accurate multi-class classification of the diseases and the prediction of the severity of the diseases, which is helpful in the development of the holistic approach for the AI-based retinal disease diagnosis system.

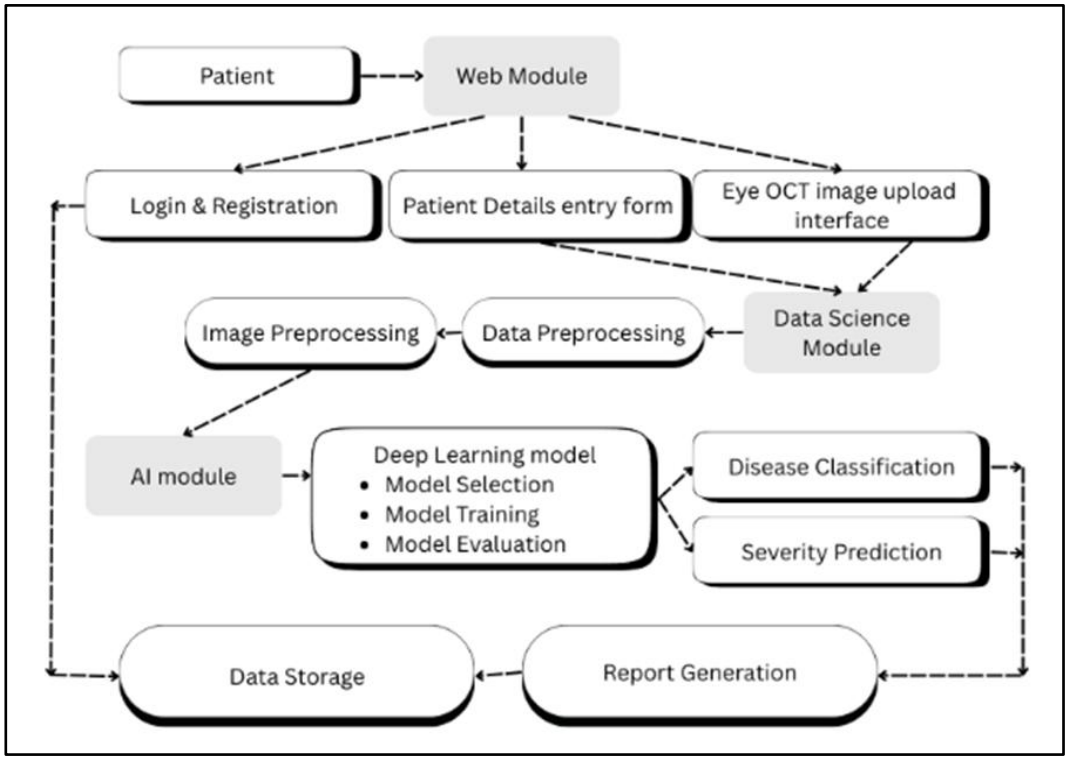


Figure 2: Block diagram of the proposed intelligent retinal disease diagnosis system.

5. Methodology

For the purpose of conducting this research work, a CNN model has been proposed, which may be used for the classification of retinal diseases by analyzing the images of optical coherence tomography. The CNN model, which has been proposed in this research work, has been based on another CNN model known as VGG16, which may be used for the classification of retinal diseases. The VGG16 model has been based on the image net dataset, which includes 13 convolutional layers, 3 fully connected layers, and 5 max pooling layers. In addition, the VGG16 model has the ability to extract various features from the images, starting from edges and texture to other features in retinal images. The architecture of the model, which has been proposed in this research work, is as shown in figure2.

5.1 Dataset Description

For the purpose of training and testing model based on the VGG-16, it is essential to create the dataset of images using images obtained from two publicly available sources:

For the case of CNV, DME, DRUSEN, NORMAL OCT Dataset - Aniruth CV dataset [30]

- This includes train, validation, and test sets, along with images of different classes, namely, NORMAL, DRUSEN, CNV, DME, etc. Good quality OCT images of the retina with different pathological characteristics.

For VID, ERM, RVO OCT Dataset - Extra Eye Disease OCT Dataset[31]

- These datasets are used for the augmentation of the original dataset and the diversity of the retinal disease patterns.
- The images are randomly divided into train, validation, and test sets in a ratio of 70:15:15 for consistency.

5.2 Dataset Preprocessing

To ensure uniformity and compatibility with the VGG-16 architecture, the following preprocessing steps were carried out on the dataset:

Resizing: All images were resized to 224 x 224 pixels.

Normalization: Normalization was achieved by dividing all the pixels by 255.

Data Augmentation: In order to improve the generalization and prevent overfitting, the following data augmentation strategies were employed on the training set:

- Random zooming by ±5%
- Width and height shifts by ±2%
- Horizontal flipping
- Rescaling the values of the pixels (normalizing the values to the range [0,1] by dividing by 255).

5.3 Proposed Model Architecture

The people who created this model took the layers of the VGG-16 model. Removed them. They added a classification head that's specifically for the seven-class OCT dataset. The model they created has parts.

- The input layer is where the RGB OCT images are uploaded and they have to be 224 by 224 pixels.
- The convolutional base uses the pre-trained VGG-16 layers to get the features from the images. At first they did not change any of the layers so the model could keep the features it learned from ImageNet.
- The GlobalAveragePooling2D takes the features. Turns them into one vector per channel which means it has fewer parameters but still keeps the important features of the OCT images.
- The connected layer is a layer with 256 neurons and it uses ReLU activation to learn about the relationships between the features of the OCT images.
- They used a dropout rate of 0.5 to stop the VGG-16 model from overfitting.
- The output layer is a layer with 7 neurons. It uses softmax activation to classify the retinal diseases into these categories: NORMAL, DRUSEN, CNV, DME, ERM, RVO and VID.

They trained the VGG-16 model in two steps. First they only trained the layers. Kept the convolutional base the same so it could use the features it learned from ImageNet. Then they changed the four layers of the VGG-16 model and trained them again with a lower learning rate so the VGG-16 model could learn about the patterns in the OCT images.

5.4 Model Training

The dataset was divided into three parts: training, validation and testing. We split the dataset in a way that makes sense. This means all the pictures of a patient are, in one part. We did this so we can be sure the model training is working correctly. The model needs to be tested on pictures of patients it has never seen before. This way we can see how well the model works with patients.The model training is very important because it helps us to know if the model can be used with patients. Model training is a part of making sure the model is good enough to use with patients.

Figure 3 shows the VGG-16 based neural network architecture that we used. This VGG-16 based convolutional neural network was used for our work. We used the VGG-16 based neural network to do two things: extract features from images and classify retinal disease. The VGG-16 based convolutional neural network played a role in our project. We used the VGG-16 based neural network to get the features and then classify retinal disease.

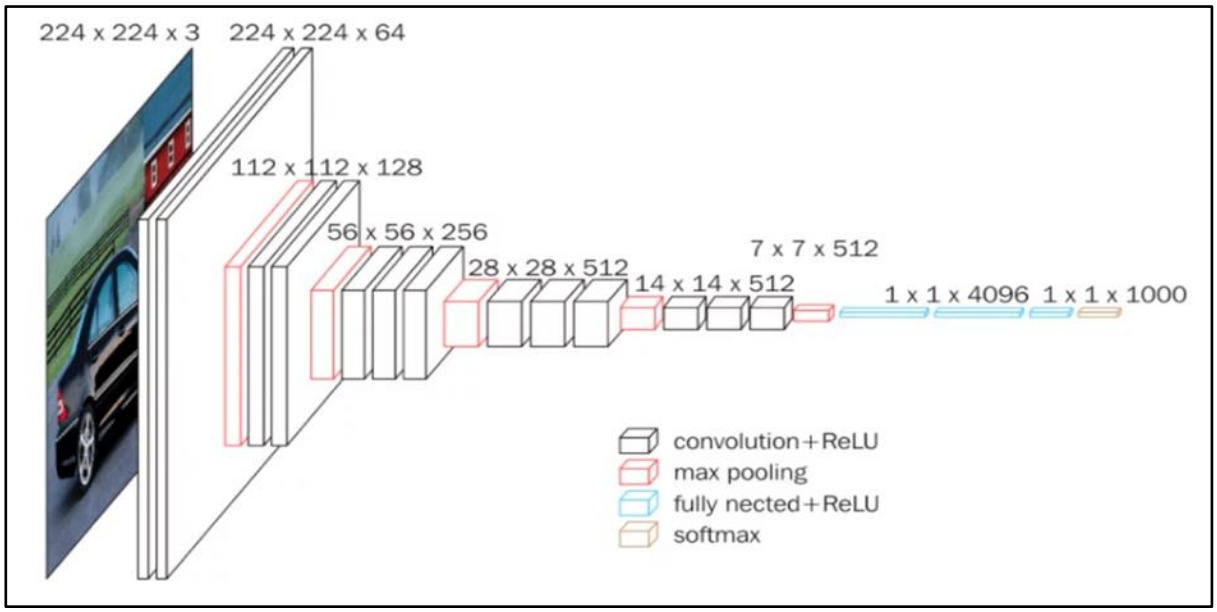


Table 1. Dataset label distribution showing the number of OCT images, per retinal disease category across training, validation and testing splits.

Class	Training Images	Validation Images	Testing Images	Total Images
NORMAL	35,973	10,278	5,139	51,390
DRUSEN	6,206	1,773	887	8,866
CNV	26,218	7,491	3,746	37,455
DME	8,118	2,319	1,161	11,598
ERM	108	23	24	155
RVO	70	15	16	101
VID	53	11	12	76

The VGG-16 architecture was pre-trained on the ImageNet dataset. You can see what the VGG-16 architecture model looks like in Figure 3. When we started training the model we did not change the layers of the VGG-16 architecture at first. Then we made some changes to the layers of the VGG-16 architecture to make the VGG-16 architecture model work better. During the time we were training the VGG-16 architecture model:

- We used 32 images at a time.
- Each time we went through all the images it took 2,398 steps.

- We changed the pictures a bit by rotating them or making them bigger or smaller to help the VGG-16 architecture model work better with different kinds of pictures.
- We gave importance to some types of diseases because there were not many examples of them in the dataset.

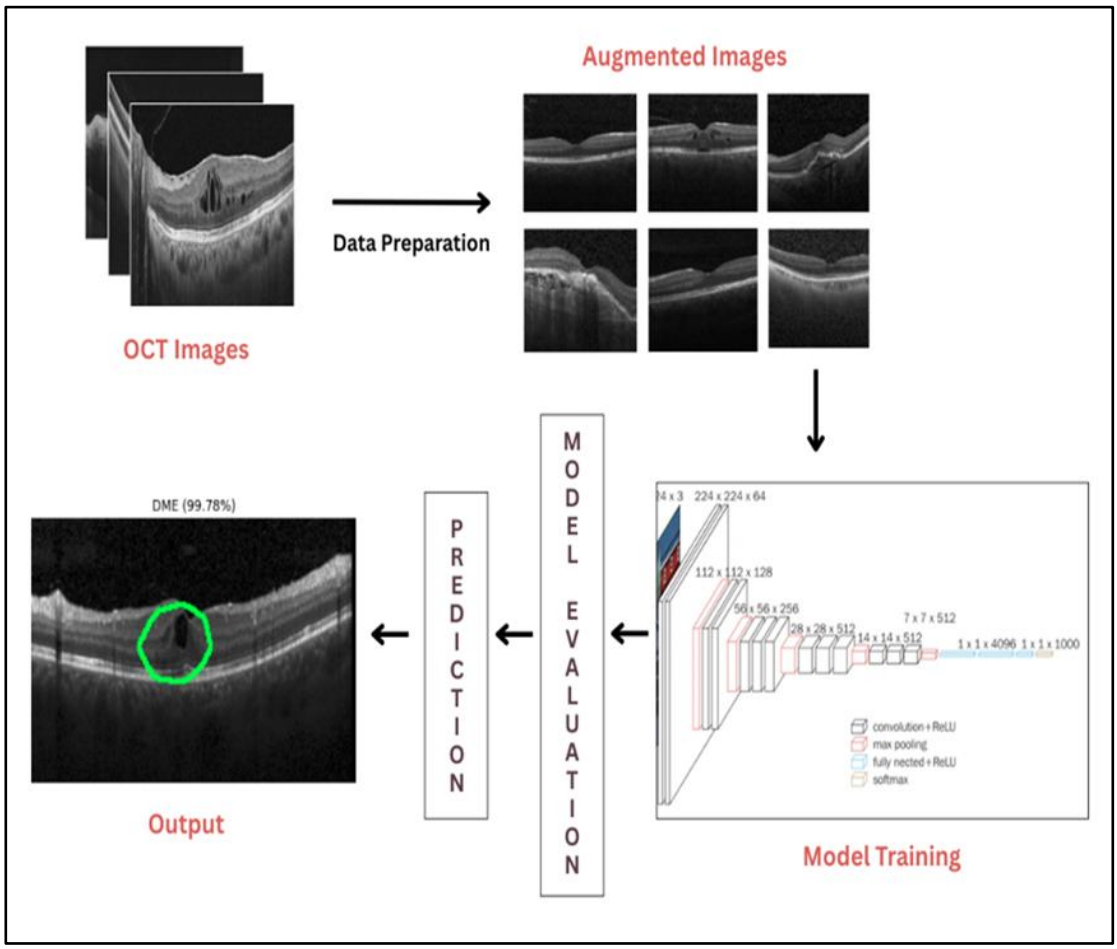


Figure 4 shows a block diagram of our proposed deep learning framework.This framework is used for classifying diseases. The OCT images are. Augmented first. Then we train a model based on VGG-16. After that we evaluate the trained model. The evaluated model is then used to make predictions about retinal diseases. We use OCT images in our framework. The framework uses a VGG-16 model. Our framework classifies diseases.

Table 2. Here are the configuration details and hyperparameter settings of the VGG-16 based retinal disease classification model.

Parameter	**Specific Value**
Initialized Weights	ImageNet Pre-trained
Training Dataset	83,484 OCT images
Validation Dataset	32,000 OCT images
Testing Dataset	13,247 OCT images
Input Image Size	224 × 224 × 3

Steps per Epoch	Approx. 2,398
Batch Size	32
Output	Softmax probabilities for 7 classes

5.5 Performance Evaluation

The proposed VGG-16 based OCT model was checked to see how well it works. This was done by using different measures to get a good idea of how well the VGG-16 based OCT model can classify all types of retinal diseases. The following things were looked at:

1. **Sensitivity (Recall / True Positive Rate)**

$$Sensitivity = \frac{TP}{TP + FN} \quad \textbf{(1)}$$

Sensitivity is a measure of how the model can find people who really have a disease. It shows the percentage of disease cases that the model gets right. The model needs to have sensitivity so it can catch as many disease cases as possible. This is very important for doctors when they are trying to diagnose people because they do not want to miss anyone who has a disease. High sensitivity in the model means it is good, at finding the people who really have the disease

2. **Specificity (True Negative Rate)**

$$Specificity = \frac{TN}{TN + FP} \quad \textbf{(2)}$$

The specificity of a model is about finding people who do not have a disease. It is the number of people who are correctly said to be healthy.

When a model has specificity it means that healthy people are not told they are sick by mistake. The specificity of a model is very important for disease diagnosis. It helps to make sure that the model is correct when it says someone is healthy. The specificity of a model is important because we do not want healthy people to be told they have a disease when they really do not have a disease. The model's specificity is crucial for disease diagnosis. It helps to make sure that the model is correct when it says someone is healthy and the specificity of a model is very important for this.

3. **Accuracy**

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad \textbf{(3)}$$

Accuracy tells us how correct the model is overall. It is helpful. Accuracy alone can be tricky when the data is not balanced. This is why we look at metrics too. Accuracy shows how well the model does across all categories. It can be misleading if some categories have much more data than others. So we consider extra metrics to get a picture. The

accuracy metric gives us an idea of the model's performance. It is useful. Not enough, on its own especially when the data is uneven. In cases we need to look at other metrics as well to understand the models accuracy.

4. **Operating Characteristic and Area Under Curve**

The ROC curve shows how good the model is at finding the things it is supposed to find. It does this by comparing the True Positive Rate, which's the number of correct finds to the False Positive Rate, which is the number of incorrect finds. The AUC or Area Under the Curve tells us how well the model can tell the difference between things. The models overall ability to distinguish between things is measured by the AUC. The ROC curve is a way to see how the True Positive Rate and the False Positive Rate are related. The True Positive Rate is also called Sensitivity. The False Positive Rate is one, minus the Specificity. When we talk about AUC it is a measure of how good a model is at predicting things.

- AUC is 1.0: this means the model is perfect at telling things
- AUC is 0.5: this means the model is just guessing and not really predicting anything.

5. **Cohen's Kappa Score**

Cohen's Kappa is a measure of inter-rater agreement that controls for chance. In the context of OCT classification, it measures the agreement between the predicted and actual class labels.

6. **Confusion Matrix**

between the normal and pathological OCT scans. The value of the Cohen's Kappa measure was found to be 96.89%. A confusion matrix was created for all the classes (NORMAL, DRUSEN, CNV, DME, ERM, RVO, VID) to understand the correct and incorrect predictions in more detail. It was found that the model was having difficulty in classifying rare diseases such as ERM, RVO, and VID.

6. Result

6.1 Evaluation of the Proposed Model on the Testing Dataset

The proposed RetinaSense model was tested on a separate set of data from the training data set for unbiased analysis of the model's performance.The model was tested for multi-class classification for seven different types of diseases: CNV, DME, DRUSEN, ERM, NORMAL, RVO, and VID.

The overall accuracy obtained by the model on the testing data set was 97.17%. The sensitivity and specificity values obtained for the model on the testing data set were 95.00% and 94.50%, respectively.The Area Under the ROC Curve for the model was obtained as 0.9701, confirming its ability to discriminate between different classes.

Figure 5: One-vs-rest ROC curves for the classification of 7-class diseases in the field of retina using the proposed model, VGG-16. The model has high discriminative ability with AUC between 0.93 and 1.00.

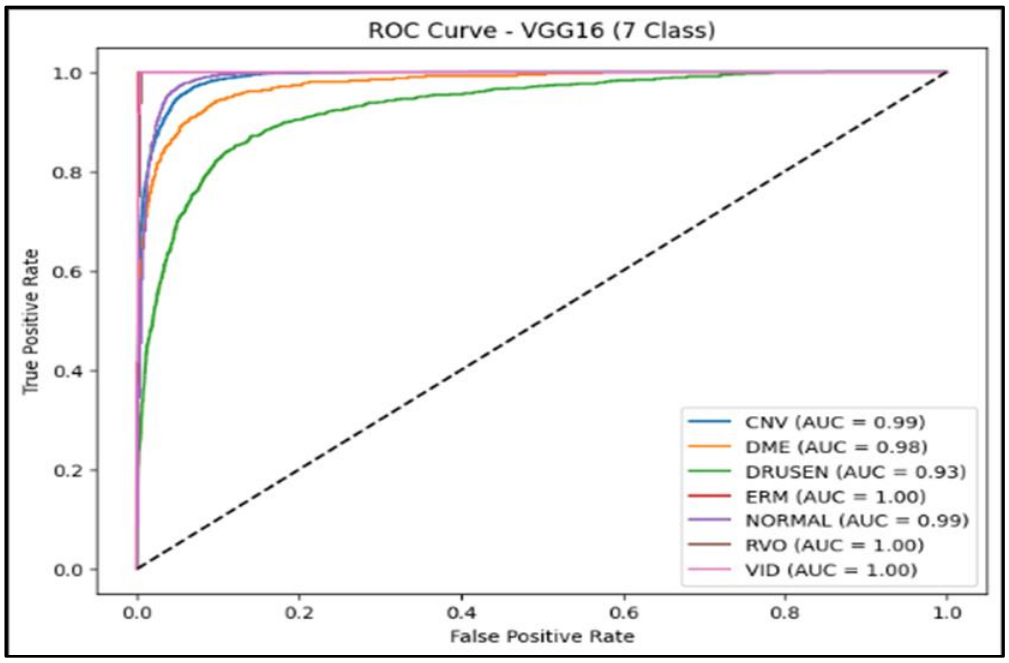


Table 3: Performance comparison of the proposed VGG-16 model with ResNet50 and InceptionV3 for multi-class retinal disease classification.

Parameter	**ResNet50**	**InceptionV3**	**Proposed VGG-16 Model**
AUC	0.9400	0.9500	**0.9701**
Kappa	93.60%	94.10%	**96.89%**
Sensitivity	92.41%	93.60%	**95.00%**
Specificity	93.81%	93.90%	**94.50%**
Accuracy	94.61%	95.63%	**97.17%**

As per the comparative analysis referred to in Table 4, it is observed that in traditional machine learning techniques, there is high dependence on feature extraction techniques. However, in the proposed RetinaSense system, deep transfer

learning is used to extract features from the OCT images and provide accurate retinal disease prediction with clinical recommendations.

Table 4: Comparative Analysis of Recent Deep Learning Methods for Retinal Disease Detection using OCT Images.

Reference	Approach	Database Used	Result and Observation
Sotoudeh-Paima et al. (2021)	Multi-scale CNN with Feature Pyramid Network	UCSD OCT Dataset	Achieved accuracy of 93.4%, enhanced feature extraction with multi-scale representation.
Hassan et al. (2021)	Bayesian Deep Learning	Public OCT datasets	Achieved accuracy of 98.26%, enhanced generalization capability.
Vives-Boix et al. (2021)	CNN based Am-InceptionV3	APTOS 2019 Dataset	Achieved accuracy of 94.46% in retinal disease detection.
Zhang et al. (2022)	Hybrid CNN with Attention Mechanism	Public OCT dataset	Achieved accuracy of 96.8%, enhanced localization capability of features in retinal images.
Wang et al. (2022)	Deep Residual Network (ResNet-50)	Large OCT retinal dataset	Achieved accuracy of 97.1%, signifying its capability in feature learning.
Kumar et al. (2023)	An Ensemble CNN Model using VGG-16 and DenseNet	Public OCT dataset	Achieved accuracy of 98.1% with increased sensitivity and specificity.
Mukherjee et al. (2024)	Retinal Layer Segmentation using Deep Learning and SD-OCT	Clinical OCT dataset	Proves the reliability of automated segmentation in the diagnosis of retinal diseases.

Li et al. (2025)	Retinal Disease Classification using Transfer Learning with VGG-16	Public OCT dataset	Achieved accuracy of 95.19%, precision of 95.29%, and recall of 95.19%.
RetinaSense (Proposed System)	**Transfer learning-based VGG16 CNN model with a Flask-based web system and AI-generated recommendations**	**Mendeley OCT Dataset (~109,000 images)**	**The system is designed to classify 7 different retinal diseases: CNV, DME, DRUSEN, ERM, RVO, VID, Normal. The proposed model was able to attain an accuracy of around 97-98%.**

6.2 Web-Based Implementation of Proposed Model

The model that was trained for eye diseases was placed on a website.The website enables individuals to, on time, predict eye diseases.The images of the individual's eyes are uploaded to the website.The images are then processed, and the individual is able to know the eye disease he or she is suffering from and the level of the disease.The system also provides recommendations on what to do regarding the eye diseases, using OCT images for prediction of eye diseases.The system enables both doctors and individuals to access results quickly

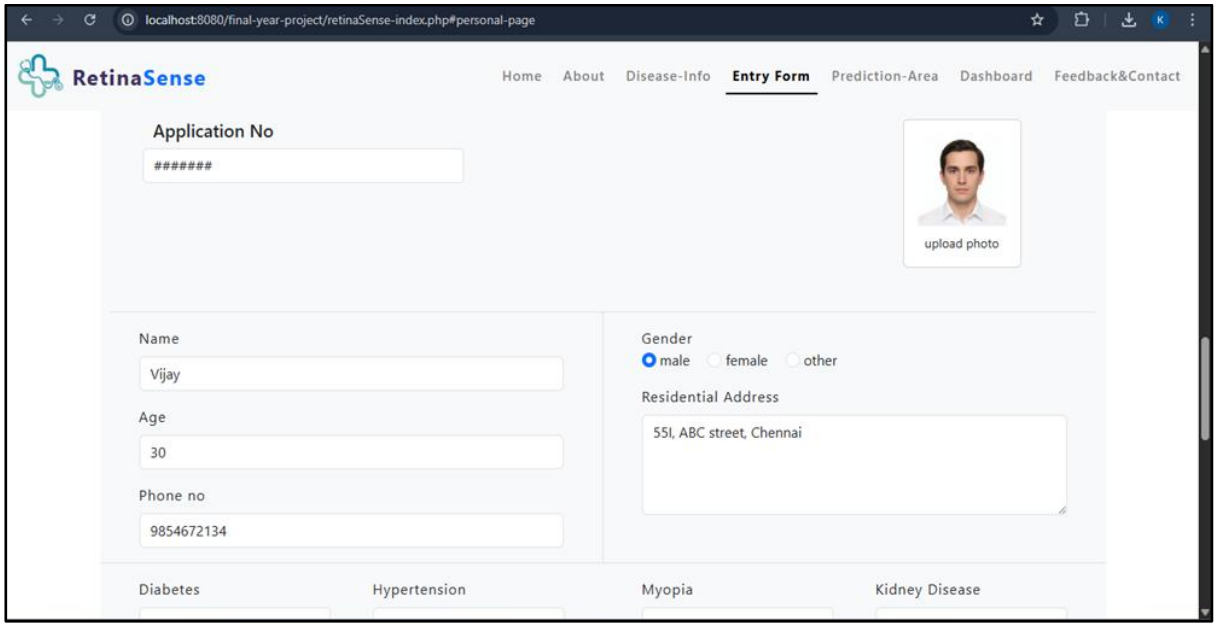


Figure 6(a): The input screen for the demographic information of the patient, which includes the application number, name, age, gender, contact information, and residential address.

Figure 6(b): The input screen for the clinical history and risk factors, which include various risk factors such as diabetes, hypertension, myopia, kidney diseases, smoking, hyperlipidaemia, trauma, inflammation, glaucoma, and family history of AMD.

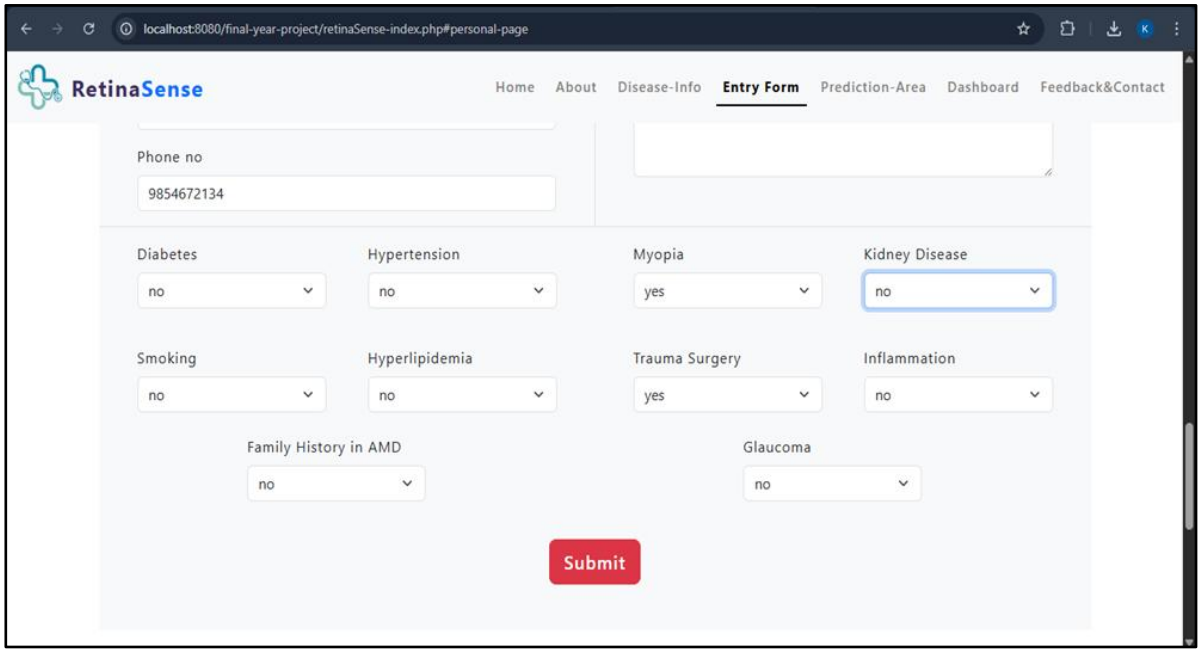


Figure 7(a): The interface of the Web-based RetinaSense prediction system, which predicts the disease based on the OCT image uploaded into the system. The detected disease is Vitreomacular Interface Disorder, and the affected area is indicated in the bounding box.

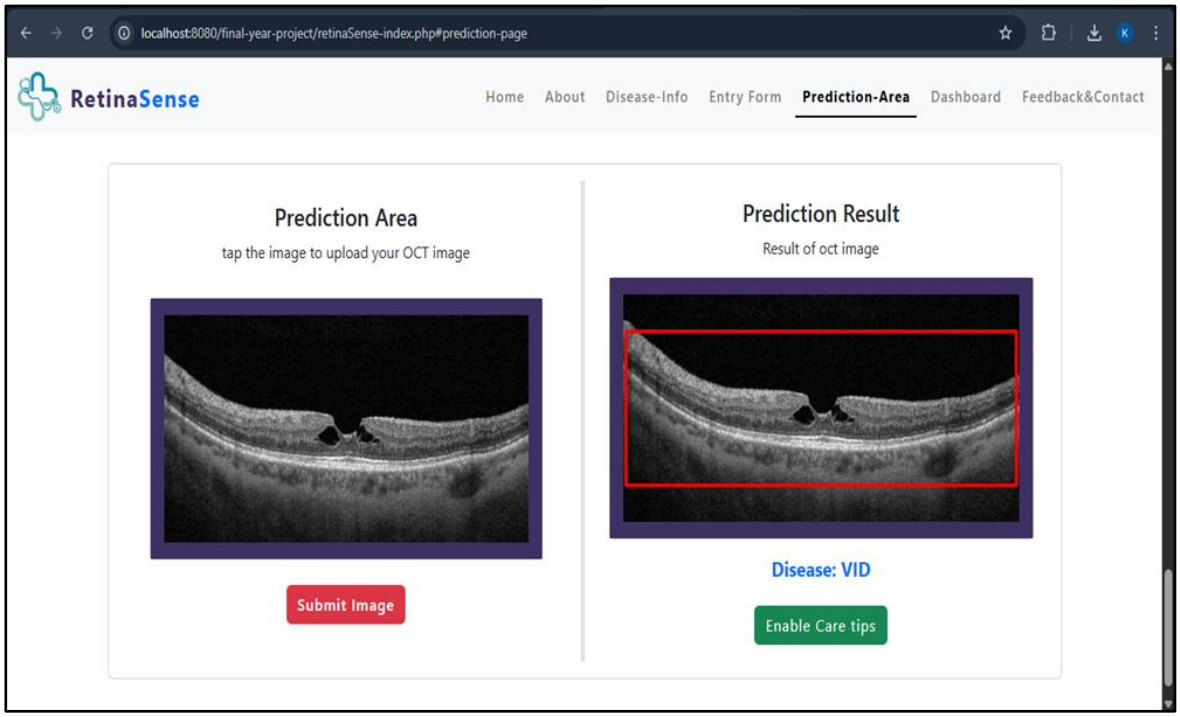
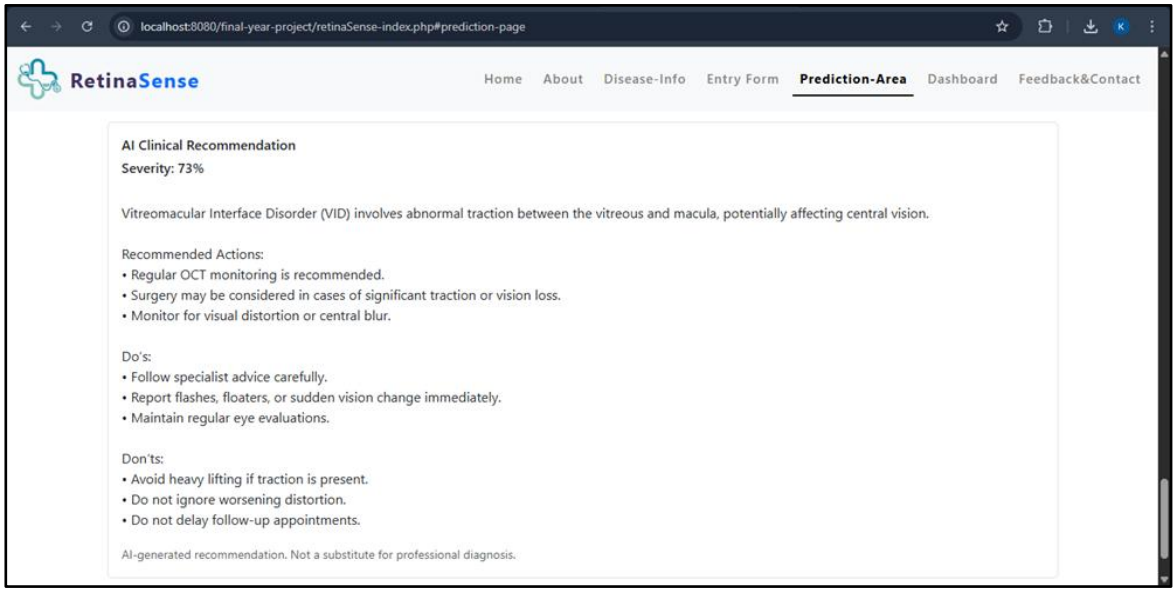


Figure 7(b): AI-generated image of the clinical recommendation module with the predicted severity of disease (73%) and medical actions, dos and don'ts for Vitreomacular Interface Disorder (VID).



7. Conclusion and Future Enhancement

In the proposed study, an automated diagnostic system based on deep learning has been developed to classify retinal diseases based on OCT images. In this regard, the proposed study has developed a deep learning model based on the VGG-16 structure with the application of transfer learning to improve the performance of the classification of retinal diseases based on OCT images. The motivation behind the proposed study is based on the trend of OCT images in the field of ophthalmology, as well as the requirement for computer-aided systems to improve the detection of retinal diseases at an early stage.

In this regard, the proposed model has been trained with the OCT image dataset and has achieved better performance compared to other deep learning architectures, such as ResNet50 and InceptionV3. Accuracy, Sensitivity, Specificity, AUC, and Cohen's Kappa statistical evaluation metrics were used to evaluate the performance of the model. The results of the experiments show that the proposed VGG-16 model performed well in terms of classification accuracy (97.17%), sensitivity (95.00%), specificity (94.50%), and AUC (0.9701), which validated the reliability of the model in detecting abnormalities in the retina, such as Vitreomacular Interface Disorder (VID) and other diseases.

The proposed RetinaSense web application is useful in terms of disease prediction, severity prediction, and artificial intelligence-based recommendations for clinical decision-making. The model is capable of accurately locating disease regions in OCT images for decision-making support.In the near future, the proposed model can be used for the detection of different retinal diseases such as retinal tear, retinal detachment, age-related macular degeneration (AMD), retinitis pigmentosa, etc.The model can be tested with a large number of diverse clinical datasets for better results. Additionally, as one of the key future enhancements, the system can be implemented in real-world environments with the support of medical professionals and medical facilities. With the support of medical professionals, the system can be optimized for the integration of hospitals, cloud computing, and real-time patient screening applications. This will help in implementing the system in real-world environments as a decision support tool, which in turn will help in the cure of patients.

8. References

1. Zedadra, A., Salah-Salah, M. Y., Zedadra, O., & Guerrieri, A. (2025). Multi-modal AI for multi-label retinal disease prediction using OCT and fundus images: a hybrid approach. *Sensors*, *25*(14), 4492.

2. Ai, Z., Huang, X., Feng, J., Wang, H., Tao, Y., Zeng, F., & Lu, Y. (2022). FN-OCT: Disease detection algorithm for retinal optical coherence tomography based on a fusion network. *Frontiers in Neuroinformatics*, *16*, 876927.

3. Maldonado-Garcia, C., Bonazzola, R., Ferrante, E., Julian, T. H., Sergouniotis, P. I., Ravikumara, N., & Frangi, A. F. (2024). Predicting risk of cardiovascular disease using retinal oct imaging. *arXiv preprint arXiv:2403.18873*.

4. Romo-Bucheli, D., Erfurth, U. S., & Bogunović, H. (2020). End-to-end deep learning model for predicting treatment requirements in neovascular AMD from longitudinal retinal OCT imaging. *IEEE Journal of Biomedical and Health Informatics*, *24*(12), 3456-3465.

5. Kim, J., & Tran, L. (2021, October). Retinal disease classification from oct images using deep learning algorithms. In *2021 IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology (CIBCB)* (pp. 1-6). Ieee.

6. Yanagihara, R. T., Lee, C. S., Ting, D. S. W., & Lee, A. Y. (2020). Methodological challenges of deep learning in optical coherence tomography for retinal diseases: a review. *Translational Vision Science & Technology*, *9*(2), 11-11.

7. Alqudah, A. M. (2020). AOCT-NET: a convolutional network automated classification of multiclass retinal diseases using spectral-domain optical coherence tomography images. *Medical & biological engineering & computing*, *58*(1), 41-53.

8. Khan, U. S., & Khan, S. U. R. (2025). Boost diagnostic performance in retinal disease classification utilizing deep ensemble classifiers based on OCT. *Multimedia Tools and Applications*, *84*(19), 21227-21247.

9. Elsharkawy, M., Sharafeldeen, A., Soliman, A., Khalifa, F., Ghazal, M., El-Daydamony, E., ... & El-Baz, A. (2022). A novel computer-aided diagnostic system for early detection of diabetic retinopathy using 3D-OCT higher-order spatial appearance model. *Diagnostics*, *12*(2), 461.

10. Banerjee, I., de Sisternes, L., Hallak, J. A., Leng, T., Osborne, A., Rosenfeld, P. J., ... & Rubin, D. (2020). Prediction of age-related macular degeneration disease using a sequential deep learning approach on longitudinal SD-OCT imaging biomarkers. *Scientific reports*, *10*(1), 15434.

11. Karthiyayini, R., & Shenbagavadivu, N. (2021). Retinal image analysis for ocular disease prediction using rule mining algorithms. *Interdisciplinary Sciences: Computational Life Sciences*, *13*(3), 451-462.

12. Lim, J. I., Rachitskaya, A. V., Hallak, J. A., Gholami, S., & Alam, M. N. (2024). Artificial intelligence for retinal diseases. *Asia-Pacific Journal of Ophthalmology*, *13*(4), 100096.

13. Dahrouj, M., & Miller, J. B. (2021, May). Artificial intelligence (AI) and retinal optical coherence tomography (OCT). In *Seminars in Ophthalmology* (Vol. 36, No. 4, pp. 341-345). Taylor & Francis.

14. Sunija, A. P., Kar, S., Gayathri, S., Gopi, V. P., & Palanisamy, P. (2021). Octnet: A lightweight cnn for retinal disease classification from optical coherence tomography images. *Computer methods and programs in biomedicine*, *200*, 105877.

15. Liu, X., Zhao, C., Wang, L., Wang, G., Lv, B., Lv, C., ... & Wang, F. (2022). Evaluation of an OCT-AI–based telemedicine platform for retinal disease screening and referral in a primary care setting. *Translational Vision Science & Technology*, *11*(3), 4-4.

16. Bali, A., & Mansotra, V. (2024). Analysis of deep learning techniques for prediction of eye diseases: A systematic review. *Archives of Computational Methods in Engineering*, *31*(1), 487-520.

17. Rim, T. H., Lee, G., Kim, Y., Tham, Y. C., Lee, C. J., Baik, S. J., ... & Cheng, C. Y. (2020). Prediction of systemic biomarkers from retinal photographs: development and validation of deep-learning algorithms. *The Lancet Digital Health*, *2*(10), e526-e536.

18. Sharafeldeen, A., Elsharkawy, M., Khalifa, F., Soliman, A., Ghazal, M., AlHalabi, M., ... & El-Baz, A. (2021). Precise higher-order reflectivity and morphology models for early diagnosis of diabetic retinopathy using OCT images. *Scientific Reports*, *11*(1), 4730.

19. Muchuchuti, S., & Viriri, S. (2023). Retinal disease detection using deep learning techniques: a comprehensive review. *Journal of Imaging*, *9*(4), 84.

20. Pan, L., & Chen, X. (2021). Retinal OCT image registration: methods and applications. *IEEE reviews in biomedical engineering*, *16*, 307-318.

21. Choudhary, A., Ahlawat, S., Urooj, S., Pathak, N., Lay-Ekuakille, A., & Sharma, N. (2023, January). A deep learning-based framework for retinal disease classification. In *Healthcare* (Vol. 11, No. 2, p. 212). MDPI.

22. Yoo, T. K., Choi, J. Y., & Kim, H. K. (2021). Feasibility study to improve deep learning in OCT diagnosis of rare retinal diseases with few-shot classification. *Medical & biological engineering & computing*, *59*(2), 401-415.

23. Parmar, U. P. S., Surico, P. L., Singh, R. B., Romano, F., Salati, C., Spadea, L., ... & Zeppieri, M. (2024). Artificial intelligence (AI) for early diagnosis of retinal diseases. *Medicina*, *60*(4), 527.

24. Paul, D., Tewari, A., Ghosh, S., & Santosh, K. C. (2020, July). Octx: Ensembled deep learning model to detect retinal disorders. In *2020 IEEE 33rd International Symposium on Computer-Based Medical Systems (CBMS)* (pp. 526-531). IEEE.

25. Wagner, S. K., Fu, D. J., Faes, L., Liu, X., Huemer, J., Khalid, H., ... & Keane, P. A. (2020). Insights into systemic disease through retinal imaging-based oculomics. *Translational vision science & technology*, *9*(2), 6-6.

26. Kang, E. Y. C., Yeung, L., Lee, Y. L., Wu, C. H., Peng, S. Y., Chen, Y. P., ... & Lai, C. C. (2021). A multimodal imaging–based deep learning model for detecting treatment-requiring retinal vascular diseases: model development and validation study. *JMIR Medical Informatics*, *9*(5), e28868.

27. Christopher, M., Bowd, C., Belghith, A., Goldbaum, M. H., Weinreb, R. N., Fazio, M. A., ... & Zangwill, L. M. (2020). Deep learning approaches predict glaucomatous visual field damage from OCT optic nerve head en face images and retinal nerve fiber layer thickness maps. *Ophthalmology*, *127*(3), 346-356.

28. Wong, D. Y., Lam, M. C., Ran, A., & Cheung, C. Y. (2022). Artificial intelligence in retinal imaging for cardiovascular disease prediction: current trends and future directions. *Current Opinion in Ophthalmology*, *33*(5), 440-446.

29. Upadhyay, P. K., Rastogi, S., & Kumar, K. V. (2022). Coherent convolution neural network based retinal disease detection using optical coherence tomographic images. *Journal of King Saud University-Computer and Information Sciences*, *34*(10), 9688-9695.

30. Kermany, Daniel; Zhang, Kang; Goldbaum, Michael (2018), "Large Dataset of Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images", Mendeley Data, V3, doi: 10.17632/rscbjbr9sj.3 https://www.kaggle.com/datasets/anirudhcv/labeled-optical-coherence-tomography-oct

31. Kulyabin, Mikhail; Zhdanov, Aleksei; Nikiforova, Anastasia; Stepichev, Andrey; Kuznetsova, Anna; Borisov, Vasilii; Ronkin, Mikhail; Bogachev, Alexander; Korotkich, Sergey; Maier, Andreas (2024), "OCTDL: Optical Coherence Tomography Dataset for Image-Based Deep Learning Methods", Mendeley Data, V4, doi: 10.17632/sncdhf53xc.4 https://data.mendeley.com/datasets/sncdhf53xc/4

32. M Kaliappan, E Mariappan, MV Prakash, B Paramasivan, Load Balanced Clustering Technique in MANET using Genetic Algorithms.. Defence Science Journal 66 (3), 251-258.

33. M Sivaram, M Kaliappan, S J Shobana, Prakash, V Porkodi Secure storage allocation scheme using fuzzy based heuristic algorithm for cloud, Journal of Ambient Intelligence and Humanized Computing, pp.1-9

34. Vimal, S., Robinson, Y. H., Kaliappan, M., Vijayalakshmi, K., &Seo, S. (2021). A method of progression detection for glaucoma using K-means and the GLCM algorithm toward smart medical prediction. The Journal of Supercomputing, 77(1), 1–17. https://doi.org/10.1007/s11227-020-03268-0

35. Kaliappan M, Guruprakash B, Rajalakshmi, J. Blessing Karunya T, Mariappan E, Ramnath M and Angel Hepzibah R, Analyzing Public