*Advances in Intelligent Systems Research, volume 175*
**2nd International Conference on Industry 4.0 and Artificial Intelligence (ICIAI 2021)**

# Detection of Dry and Wet Age-Related Macular Degeneration Using Deep Learning

Muhammad Muhammad Abdullahi[1], Sudeshna Chakraborty[2], Preeti Kaushik[3], Ben Slama Sami[4]

[1]*Department of Computer Science and Engineering, Sharda University, Greater Noida, India.*
[2]*Department of Computer Science and Engineering, Lloyd Institute of Engineering and Technology, Greater Noida, India.*
[3]*Department of Computer Science and Engineering, Sharda University , Greater Noida, India.*
[4]*Department of Computer Information and Technologies, King Abdulaziz University, Jeddah, Saudi Arabia.*
mmabdullahi10@gmail.com, sudeshna.chakraborty@sharda.ac.in, preeti.kaushik@sharda.ac.in, benslama.sami@gmail.com

**ABSTRACT**
Age-related macular degeneration (AMD) is a retinal disease in elderly people which deteriorate the central part of the retina. It is one of the leading causes of vision loss in the ageing persons. Every day, massive retinal images of patients with AMD are generated using the Optical Coherence Tomography (OCT) and other retinal imaging modalities. It is critical that these images are automatically analysed, so as to reduce the time consumption and over reliance on clinical professionals. The advance stage of AMD which usually causes loss of sight occurs in either dry or wet form. Most of the models developed in previous studies focuses on the classification of AMD infected and normal retinal images. However, in the later stages of AMD it is necessary to determine whether the AMD is dry or wet. Ability to classify between dry and wet Age-Related Macular Degeneration is very crucial to ophthalmologists in therapeutic indication. It determines whether a patient receives Anti-VEGF injection therapy treatment. The objective of this study is to develop a convolutional neural network model that will classify between dry and wet AMD. A pretrained Deep Residual Neural Network with 50-layers (ResNet50) was used to train the model using the KERMANY dataset consisting of 32,931 OCT images of dry and wet AMD. The model was evaluated and it performed with an accuracy of 96.56%, 98.20% Specificity and 89.45% sensitivity respectively.

***Keywords:*** *Age-Related Macular Degeneration, Deep Learning, Convolutional Neural Network, Optical Coherence Tomography, Residual Neural Network.*

## I. INTRODUCTION

Age-related macular degeneration (AMD) is a retinal infection in ageing people which affects the retinal central portion. It is among the major reasons of vision loss in aging individuals. Around 5% of blindness worldwide, is due to AMD [1]. It was predicted that 196 million people worldwide will be infected with AMD by 2020, increasing to 288 million by 2040 in spite of novel treatments to prevent and monitor AMD, which is partly due to rapidly ageing populations [1].

Age-related macular degeneration (AMD) is a set of related diseases that are commonly linked to a progressive loss of vision as a result of the weakening of the center of the retina and its supporting components in elderly people [4]. The macula which central part of the retina, is the component of the retina that is affected by AMD. It is the retina's functional core, measuring around 5mm in diameter, and when it is damaged and not handled, vision loss occurs [2]. During the course of the disease, lipid appears to collect in particles under the retinal pigment epithelium. These particles, which appear as light yellow spots on the retina, are known as drusen [3].

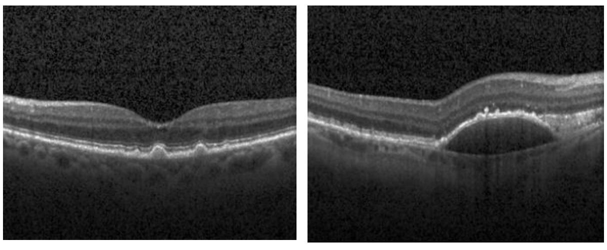
AMD is classified into four stages, which are normal, early AMD, Intermediate AMD, and advanced AMD. The normal or No AMD class has no or little small drusen. The Early AMD has many small drusen, handful intermediate drusen, or retinal pigment epithelium defects, Intermediate AMD class exhibit the presence of substantial intermediate drusen, at least one large drusen. Lastly, the Advanced AMD class further characterized in to either dry AMD or wet AMD.[4] The dry form of AMD occurs at the macular level due to the loss of the retinal pigment epithelium which gradually moves towards center of the retina and can cause a permanent blindness. In the wet form of advanced AMD, abnormal blood vessels formed under the retina leaks blood which causes a severe decrease in vision [5]. It is regarded as Choroidal Neovascularization or the Neovascular AMD.

Conventional methods of diagnosing retinal images are time-consuming, rely heavily on clinical professional experience, and can result in a high rate of misdiagnosis and a significant loss of medical data[6]. As a result, developing an automated image analysis tool that can detect the presence of infection in retinal images is very critical in the modern era. Manual segmentation was involved in previous approaches, but it was tiresome and needs a lot of time. In contrast, computer-aided diagnosis of retinal diseases is feasible, economical, and does not need highly qualified physicians to assess the images [7].

Identifying AMD is a pivotal task. Its passive nature during the early and intermediate stages might show little or no symptoms, which later leads to the advanced form of the disease resulting in total irreversible loss of sight. In accordance with its classification stage, AMD's clinical appearance can differ. Only medium drusen is detectable as there is only a slight retinal alteration in early AMD. While it may not be entirely healed, it might be possible to slow down the deterioration of AMD if diagnosed and treated early. It is necessary to devise the ability to analyze the enormous images from the escalating number of patients [8].

In the screening of AMD, several imaging modalities are used today [4]. The two main modalities used in the automatic detection of AMD are the optical coherence tomography (OCT) and fundus photography. Fundus photography is a non-invasive imaging procedure that involves the procedure of capturing a 2-D image of the 3-D fundus of the eye on an imaging plane, by projecting a reflected light on the plane. Fundus photographs are useful for early screening and detection of main causes of vision loss in the developed world, among which are AMD, glaucoma and Diabetic Retinopathy. The 2-D depiction of the retina obtained by fundus images is lacking the ability to apprehend so much depth, which led to an incorrect diagnosis of some retinal infections [10].

On the other hand, the OCT is a non-invasive imaging procedure which displays informative cross-section images of the retina in ophthalmology clinics. In the assessment and treatment of AMD, OCT is a very useful imaging modality. It helps in revealing region of epithelial thinning of the retinal pigment [11]. It also helps in identifying region of fluid beneath or within the retina and also the retinal pigment epithelium as it gives an in depth view of the retina [9]. This is why a dataset with OCT images was chosen for this study.



(a) (b)

Figure 1: Retinal OCT images of an AMD infected retina[11]. (a) Retinal OCT image of a dry AMD (b) Retinal OCT image of a wet AMD

## II. RELATED WORK

Many studies have been done in the image analysis and detection of AMD, however, not many researchers have focus in the detection of the two different forms of AMD. T. Y. Heo et al [11] developed a deep convolutional neural network model to detect the presence of AMD using 399 fundus retinal images. The images were augmented using the Keras Image Data Generator so as to increase the size of the data and reduce overfitting of the model. The model uses the architecture of VGG16 (Visual Geometry Group with 16 layers) model. Cross-validation of the model was done using the leave-one-out technique so as to assess the performance of the model. This study went on further to classify between Dry and Wet forms of AMD, where an accuracy of 91.32% was achieved in this regard [11].

N. Motozawa et al [12] developed two DL models which classifies normal and AMD OCT images, and then classifies the AMD images based on presence of exudative changes, that is either dry or wet. Class activation mapping (CAM) was used as a heat map to observe important locations on the OCT images that the CNN model will use for the classification. A dataset of 185 images of no-AMD category and 1049 images with AMD were used for training the model, and 49 images of no-AMD and 333 AMD images were used to test the model. Three 224x224 pixel sized images were cropped from each OCT image so as to increase the quantity of the dataset. 18-layer DCNN consisting of convolution layers, max-pooling layers, and fully connected layers was developed. The network used layer-15 as the global average pooling layer and layer-16 as the dropout layer, with layer-18 as the output softmax layer. However, this CNN model was used for both tasks. The first model which classifies no-AMD and AMD OCT images achieved accuracy of 99.5%, whereas the second model which screen whether exudative changes are present achieved an accuracy of 93.9% [12].

Guangzhou An et al [13] developed a DL model that classifies normal and AMD infected OCT images, and also separate AMD OCT images showing fluid changes and images with no fluid changes. Data augmentation techniques such as cropping, horizontal flip, random rotation and random shift were performed the OCT images so as to increment the size of the dataset and improve performance. In this study, a VGG-16 model pre-trained on ImageNet data was transfer learned to classify normal and AMD images. This model was again transfer learned with AMD OCT images to classify AMD images showing fluid changes and AMD with no fluid changes. Grad-CAM method was applied to monitor the important areas on the image for the model to judge. The first model which classifies normal and AMD infected OCT images achieved an accuracy of 99.2%, while the second model which classifies AMD images based on presence of fluid achieves an accuracy of 95.1% [13].

## III. METHODS

The dataset that was used to train the proposed model of this study is the Kermany[10] dataset available on Kaggle. Two classes of the dataset that is DRUSEN and CNV (Choroidal Neovascularisation), having 32,931 images were used to classify between dry and wet AMD. The training dataset consist of 23,792 images, 4,199 images for validation dataset, and 4940 images for test dataset. This study used the architecture of ResNet50 convolutional neural networks that have been pre-trained on the ImageNet dataset to classify between dry and wet AMD. The ImageNet dataset is an online dataset having more than one million images and one thousand classes which makes the parameters of the network well estimated.

Transfer Learning is a deep learning technique that uses weights of pre-trained CNN model. In this study, a pretrained ResNet50 model without fully connected layer was used. Custom fully connected layers were added and the pretrained model weights except last 3 layers were freeze while training. The final three layers as well as the fully connected layers were the fine-tuned.

The model was trained using Adam optimization algorithm and the learning rate was set to 0.001. Adam algorithms works well with noisy data and it helps to train the model faster with a better performance. A batch size of 64, and an epoch of 20 were used to train the model. The inputs to a layer were standardized using the Batch Normalization layer for each batch size so as to reduce the generalization error and also speed the training. EarlyStopping method of regularization was used to stop the training where the validation loss starts to increase so as to reduce overfitting of the model. ReduceLROnPlateau was used to decrease the learning rate when validation loss has not improved in an epoch. Dropout layer was also added so as to reduce overfitting of the model. The Softmax function was used as the activation function of the fully connected layers and ModelCheckpoint was used to save the weights of the model when the validation loss is minimum.

## IV. RESULTS

The proposed model in this study for the classification of dry (Drusen) and wet (CNV) AMD achieved a train accuracy of 98.74%, validation accuracy of 96.71%, and a test accuracy of 96.56%. Table 1 shows the confusion matrix of the test data having a true positive of 3939 images, false positives of 72 images, false negatives of 98 images, and true negatives of 831 images. These are then used to compute the sensitivity of 89.45%, and a specificity of 98.20%.

**Table 1**: Confusion matrix of the test data for classification dry and wet AMD

| | Actually CNV | Actually Drusen |
|---|---|---|
| Predicted CNV | 3939 | 72 |
| Predicted Drusen | 98 | 831 |

## V. DISCUSSION

Many models have been developed for the classification of AMD and normal retinal images using different datasets of varying imaging modalities. However, not many models were developed to detect between the two forms of advance AMD, that is the dry and the wet form. Knowing whether an AMD is dry or wet is crucial to physicians so as to assess if the patient will need an Anti VEGF therapy. This a therapy that is given to those that are suffering from wet AMD, also called choroid neovascularization. After thorough review of literatures, the studies that performed the detection of dry and wet AMD were noted. The table below shows four different model with the authors, the deep learning technique they used, and the corresponding accuracy achieved by each model. T. Y. Heo et al [11] deep learning model used VGG16 architecture to classify between dry and wet AMD. This model performed with 91.3% accuracy. N. Motozawa et al.[12] also developed an 18-layer CNN to classify the two classes of AMD and the model performed with 93.9% accuracy. Then An Guangzhou et al [13] later developed VGG16 using the Kermany dataset and was able to achieve 95.1% accuracy.

**Table 2:** Analysis of studies and techniques used by previous researchers and the performance of the studies in the classification of dry and wet AMD.

| Author | Technique | Accuracy |
|---|---|---|
| T.Y. Heo et al.[11] | VGG16 | 91.32% |
| N. Motozawa et al.[12] | DCNN | 93.90% |
| Guangzhou An et al.[13] | VGG16 | 95.10% |
| Proposed model | RESNET50 | 96.56% |

As can be seen from the Table 2 above, the last model which is the proposed model in this study, is the best performing model in the table, with an accuracy of 96.56%. The model was developed using an architecture of 50-layer Deep Residual network (RESNET50) pretrained on ImageNet dataset.

Further studies can explore the possibility of developing deep learning models that can classify between normal and AMD images, as well as the various forms of AMD using a combine dataset of OCT and fundus imaging modalities. To the best our knowledge, there's no study that detect AMD using more than one imaging modality.

## VI. Conclusion

In conclusion, a high performing 50-layer ResNet model was built to classify between dry and wet AMD. Ability to classify between dry and wet AMD is very crucial to ophthalmologists so as to determine whether a patient receives Anti-VEGF injection therapy treatment, which slows the progression of wet AMD. The performance of the model was evaluated and it achieved an accuracy of 96.56% surpassing the benchmark set by previous researchers. The model also achieved 98.20% Specificity and 89.45% sensitivity respectively. The objective of this study which was to improve the performance of previous models is achieved. The accuracy has significantly improved compared to the other models. The sensitivity of the model was low compared to the specificity due to the unbalanced nature of the dataset, as there are more images of CNV (wet AMD) than there are images of DRUSEN (dry AMD).

## References

[1] B. M. Williams, P. I. Burgess, and Y. Zheng, Drusen and macular degeneration. Elsevier Ltd., 2019.

[2] E. Pead et al., "Automated detection of age-related macular degeneration in color fundus photography: a systematic review," Surv. Ophthalmol., vol. 64, no. 4, pp. 498–511, 2019, doi: 10.1016/j.survophthal.2019.02.003.

[3] P. M. Arabi and G. Joshi, Computer-aided diagnosis of age-related macular degeneration by OCT, fundus image analysis. Elsevier Inc., 2020.

[4] S. Mehta, "Age-Related Macular Degeneration," Prim. Care - Clin. Off. Pract., vol. 42, no. 3, pp. 377–391, 2015, doi: 10.1016/j.pop.2015.05.009.

[5] J. H. Tan et al., "Age-related Macular Degeneration detection using deep convolutional neural network," Futur. Gener. Comput. Syst., vol. 87, pp. 127–135, 2018, doi: 10.1016/j.future.2018.05.001.

[6] W. Lu, Y. Tong, Y. Yu, Y. Xing, C. Chen, and Y. Shen, "Applications of Artificial Intelligence in Ophthalmology: General Overview," J. Ophthalmol., vol. 2018, no. Cml, 2018, doi: 10.1155/2018/5278196.

[7] M. Badar, M. Haris, and A. Fatima, "Application of deep learning for retinal image analysis: A review," Comput. Sci. Rev., vol. 35, p. 100203, 2020, doi: 10.1016/j.cosrev.2019.100203.

[8] M. Treder, J. L. Lauermann, and N. Eter, "Automated detection of exudative age-related macular degeneration in spectral domain optical coherence tomography using deep learning," Graefe's Arch. Clin. Exp. Ophthalmol., vol. 256, no. 2, pp. 259–265, 2018, doi: 10.1007/s00417-017-3850-3.

[9] U. Schmidt-Erfurth, A. Sadeghipour, B. S. Gerendas, S. M. Waldstein, and H. Bogunović, "Artificial intelligence in retina," Prog. Retin. Eye Res., vol. 67, no. May, pp. 1–29, 2018, doi: 10.1016/j.preteyeres.2018.07.004.

[10] D. S. Kermany et al., "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning," Cell, vol. 172, no. 5, pp. 1122-1131.e9, 2018, doi: 10.1016/j.cell.2018.02.010.

[11] T. Y. Heo et al., "Development of a deep-learning-based artificial intelligence tool for differential diagnosis between dry and neovascular age-related macular degeneration," Diagnostics, vol. 10, no. 5, 2020, doi: 10.3390/diagnostics10050261.

[12] N. Motozawa et al., "Optical Coherence Tomography-Based Deep-Learning Models for Classifying Normal and Age-Related Macular Degeneration and Exudative and Non-Exudative Age-Related Macular Degeneration Changes," Ophthalmol. Ther., vol. 8, no. 4, pp. 527–539, 2019, doi: 10.1007/s40123-019-00207-y.

[13] G. An et al., "Deep Learning Classification Models Built with Two-step Transfer Learning for Age Related Macular Degeneration Diagnosis," Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS, pp. 2049–2052, 2019, doi: 10.1109/EMBC.2019.8857468.