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Survey on Diagnosing Retina Diseases in Optical Coherence Tomography Images Based on Deep Learning

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ABSTRACT

This study provides a comprehensive and extensive review of the use of deep learning techniques in diagnosing a variety of retinal diseases, such as Drusen, choroidal neovascularization (CNV), and diabetic macular edema (DME) using optical coherence tomography images (OCT). The research reviews the different models used in this field and evaluates their effectiveness, robustness, and reliability in distinguishing and diagnosing retinal diseases with high accuracy. The research analyzes the most effective and most widely used models in this field, focusing on the results achieved in terms of accuracy and reliability, highlighting the methods that showed the best performance in diagnosis, and improving and developing them in the future to achieve better results. The specialized data sets used to train and test these models are also reviewed, with an assessment of their role and importance in promoting and supporting scientific research in this field. Furthermore, the paper discusses recent advances in research that have been achieved in recent years. In addition, the research addresses current research gaps and challenges facing researchers and provides a comprehensive vision of future work that can contribute to the further development of this field. One of the topics that the research aims for is the importance of using deep learning techniques in the medical field to enhance the accuracy and speed of diagnosis. The research concludes by providing recommendations on future directions that research in this field can take, with the aim of achieving sustainable progress and improving the quality of healthcare for patients with retinal diseases using deep learning techniques.

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1. Introduction

The human eye, an organ of extreme complexity, holds the retina, a light-sensitive region crucial for vision. The retina is situated at the back of the eye, close to the optic nerve, and plays an essential role in converting the focused light into neural signals [1], [2]. The macula holds significance within the retina due to its central vision responsibility. Unfortunately, the macula's health can be jeopardized by several pathologies, such as DME, CNV, and Drusen [3] (as shown in Fig. 1).

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OCT, introduced in 1991, has been a transformative and non-invasive imaging technique in ophthalmology, enabling in-depth exploration of the retina and choroid at micron resolutions [4]. Its ability to record high-resolution cross-sectional tomographic data of biological tissues has played a crucial role in diagnosing several retinal and choroidal illnesses [3]. Diagnosing conditions requires using OCT, which allows for the sensitive detection and quantitative evaluation of macular lesions inside the retina's numerous cell layers [5]. It can distinctly reveal cystic and sub-retinal swellings in the preliminary phases, which typically remain invisible in retinal fundus photographs [2], [4].

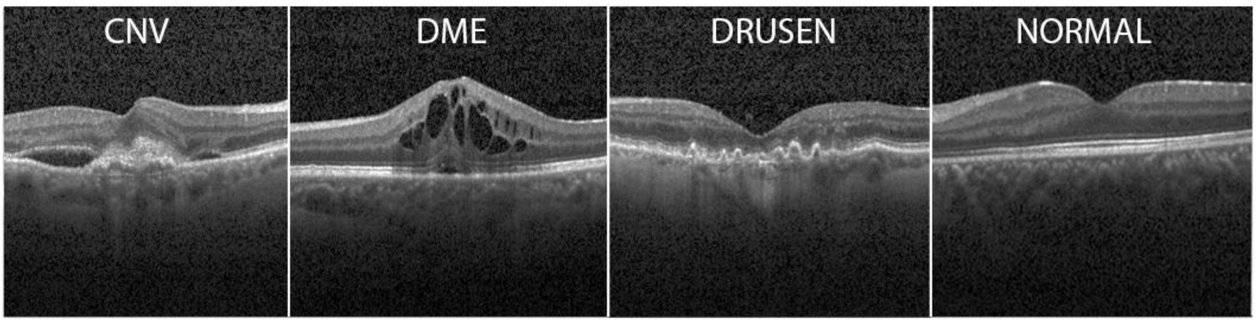

Fig. 1 - Illustrative OCT Images.

Introducing DL techniques in medical diagnostics has begun a new era in healthcare, especially Convolutional Neural Networks (CNNs) algorithms, where precise and quick decision-making is possible. These technologies are particularly transformative in ophthalmology, revolutionizing automated diagnosis systems with robust algorithms, leading to fast and accurate disease classification [2], [6]. The CNN framework has been extensively developed for retinal OCT image processing in several studies [7], enabling the automated learning of hierarchical abstract features from large datasets [3], focusing on aspects like segmentation of the retinal layers and classification of OCT images [8] and some employed multiple pre-trained models, rather than a single model [9]. The advanced capabilities of CNN models have made them preferable in many scenarios.

In biomedicine, pre-trained models often overcome models trained from scratch [10]. TL strategies have emerged as a competent solution (as in Fig. 2), proving efficient in giving good results even if there is limited available data. These strategies are instrumental in mitigating overfitting and processing constraints by leveraging pre-trained models on extensive datasets, ensuring superior performance in medical image classification tasks. The deployment of TL conserves time and resources and adeptly manages overfitting issues. By capitalizing on models trained in data-rich domains, TL allows the knowledge to be applied in fields where data might be little [7], [10]. Sometimes, pre-trained models may be used without their weights, meaning they are trained from scratch (i.e., without TL) and may give higher results, but in this case, you need extensive data.

1.1. Motivation

Every year, millions globally are diagnosed with varying retinal diseases, presenting themselves in numerous ways [7]. Multiple eye illnesses afflict more than 2.2 billion people globally, according to statistics for 2019, resulting in substantial vision impairment and, in severe instances, total blindness [11], [12]. Every year, around 2 million people in the USA are diagnosed with CNV [13]. According to studies, DME affects over 7.5 million people 40 years of age or older [14]. Drusen also affects more than 7 million people annually in the USA [12], [15]. The advent of artificial intelligence (AI) and its use in analyzing medical images like OCT images has significantly enhanced the accuracy and speed of diagnostic processes, allowing for the automatic detection of retinal diseases [16].

1.2. Organization Of Paper

The structure of the paper is as follows: The subsequent section will summarize previous scholarly works engaged with survey research within this specific scope, in addition to the datasets they have used and their specifications. The third section elucidates the research methodologies used in this paper. The fourth section is a discussion of the research papers that have been adopted. The last section encompasses the conclusion and the references cited.

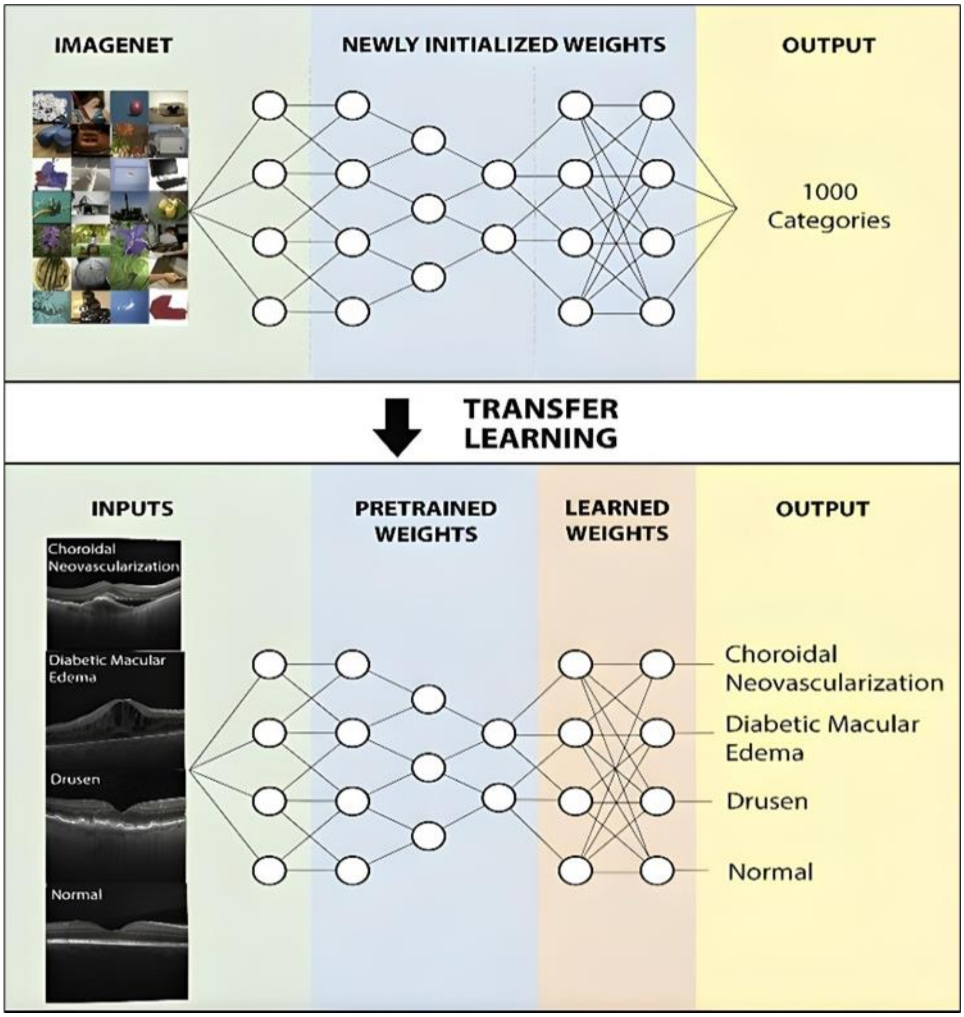

Fig. 2 - Outline of a CNN. The outline illustrates the adaptation of CNN, initially trained on the "ImageNet" dataset, which encompasses "1,000 classes", to enhance accuracy and reduce training time when retrained on a dataset of OCT images [6].

2. RELATED WORKS

A set of articles from 2018 to 2023 was reviewed to address this query. Previous studies focused on identifying retinal conditions by dividing OCT images, frequently into the DME, CNV, DRUSEN, and NORMAL classes. Using the UCSD dataset, the research papers differed in the number of images they used from this dataset depending on its version and whether they balanced the data. There is another dataset called Duke that is sometimes used with the first. Modern approaches increasingly employ DL techniques for pinpointing and categorizing retinal conditions. The details below provide an overview of the work conducted to date:

D. Kermany et al.[6] established an effective diagnostic tool for classifying DME, CNV, DRUSEN, and Normal from OCT images. They used TL with a pre-trained InceptionV3 model. They used the UCSD-V3 dataset, achieving an accuracy of 96.6%. However, the dataset is imbalanced, and the noise pixels are not removed.

J. Kim and L. Tran.[17] Used FCN algorithm to eliminate noise from the OCT images and cropping the retina. The UCSD-V2 dataset was used. Two practical DL approaches were proposed, three binary (CNN) classifiers and four binary CNN classifiers, then adapted with six different pre-trained models (InceptionV3, ResNet50, ResNet152, VGG16, VGG19, and DenseNet121). These two approaches have achieved a high classification performance of retinal diseases, especially the four-binary classifier model with (0.987) accuracy. However, the data used is a subset (35,464) of the entire dataset.

M. Reza et al.[18] Various steps of pre-processing for retinal diseases were applied to OCT images. Three pre-trained models were used (EfficientNetB0, Inception V3, and ResNet50). The XAI is applied to explain the reasons for misclassifications. UCSD-V3 dataset was used, achieving an accuracy of 96.9% from the ResNet50 model. However, the dataset is imbalanced; the noise pixels are not removed.

K. Islam et al.[19] Performed pre-processing steps for enhancement and cropping region of interest (ROI). Eleven pre-trained models (ResNet-50, VGG16, VGG19, ResNet-101, AlexNet, GoogLeNet, ResNet-18, InceptionV3, DenseNet-201, InceptionResNet-V2, and SqueezeNet) are retrained, and the best performance one is selected. The UCSD-V3 dataset was used to identify diabetic retinopathy. DenseNet-201 model achieved 0.986 accuracy.

V. Latha et al. [20] They are proposed combining two models and using TL to detect diseases in OCT images. Augmentation has been applied to the images as pre-processing. The proposed novel model fused multilayer feature vectors of InceptionV3 and VGG16 pre-trained models to create an effective model with global features and local. They used versions (2 & 3) of the UCSD dataset, with accuracies of 99.7% and 98.1% respectively.

A. Roy et al.[21] Performed some pre-processing steps to reduce noise, improve quality, and segmentation of OCT images. Then, a custom-made model (RetNet) that classified the retinal diseases with high accuracy and speed was proposed. Used UCSD-V2, which achieved an accuracy of 97.85%. However, the data used is a subset (30,904) of the overall dataset (84,484), unlike most other scientific research.

Z. Zhou et al.[22] The symmetrical cross-entropy loss function is used to prevent overfitting. They then took advantage of the Vision Transformer DL model, which is the latest from CNN and has good performance in classifying retina diseases. Used OCT images from the UCSD-V2 dataset in training with other images to test and validate, so the total number of images reached (126,193), achieving an accuracy of 95.76%. Although its accuracy is high, it does not live up to the results achieved by other researchers.

L. Mou et al. [23] Used a methodology involving Multi-scale Bayesian U-Net, a variant of Bayesian Neural Network, designed to assess the epistemic uncertainty inherent in retinal diseases OCT images. Besides leveraging the UCSD-V3 dataset, the private BFHJLU dataset was also incorporated. The methodology demonstrated an accuracy of 94.9% on the UCSD-V3 dataset and 92.1% on the BFHJLU dataset. However, deploying BNN necessitated extensive computational resources and time.

M. Do et al.[24] Performed fine-tuning on the Xception model. The last section of the model is replaced with a block of neural structures comprised of four labels of classification results from the input two versions (2 & 3) of UCSD datasets that have OCT retinal disease images. Over (81,000) were used for every dataset, and the accuracies achieved were 0.995 and 0.9725, respectively.

P. Elena-Anca.[25] Used five DL models (DenseNet121, 12-convolutional layers based, DenseNet169, DenseNet201, and InceptionResNet). The DenseNet-169 model was the best as it achieved an accuracy of 97% on the UCSD-V2 dataset with retinal diseases OCT images. However, there are no pre-processing procedures.

A. Adel et al.[9] Integrated both machine learning (ML) and DL, where Xception and inceptionV3 models are two adopted in the proposed DL models with the use of TL, and a categorical-hinge loss is also used with the Support Vector Machine (SVM) algorithm for classification of the retinal diseases from OCT images. The overall accuracy achieved was 93% for the inceptionV3 model and 98% for the Xception model. However, a subset (7,000) from the whole dataset was used.

D. Paul et al.[26] In the pre-processing, high-quality and enhanced images were obtained. Then, the authors introduced a new framework (called OCTx) that ensembled four pre-trained models (DenseNet, VGG16, Custom model, and InceptionV3). The outputs from these models were merged to establish an ensemble network, achieve good results on the retinal OCT images, and address the problem of over-fitting. High accuracy was achieved with 98.53% on the UCSD-V2 dataset. Although high classification results, the number of epochs is vast, which is 250.

P. Jayanthi et al.[27] Introduced a TL approach with three pre-trained models (Custom-built sequential model, ResNet50, and VGG19), achieving classification accuracies of 0.972, 0.958, and 0.996 on the UCSD-V2 dataset that contains retinal diseases OCT images. The accuracy of the custom model surpasses that of the other pre-trained models. However, the dataset used needed to be balanced.

O. Akinniyi et al.[28] developed a feature-rich pipeline using a pyramidal structure to draw features from multi-scale inputs through partially connected networks (PCNet). Furthermore, they extracted reflectivity features from the retinal OCT images to merge them with the pyramidal features and then used SVM for classification. The UCSD-V3 dataset was used for evaluation. They executed both binary and multi-class classifications. The binary approach determines if the retina in the image is normal or abnormal. At the same time, the multi-class method distinguishes the image as Normal or identifies specific conditions such as DME, CNV, or Drusen, achieving an accuracy of (96.9%) in multi-class classification and (98.51% ± 1.2) in binary classification.

R.S. Khedgaonkar et al.[29] Employed DL models, which they called Model-1, Model-2, and Model-3, were compiled in the Sequential model. Meanwhile, ResNet50, called Model-4, achieved the highest accuracy, reaching 97% on the UCSD-V2 dataset. However, pre-processing on the OCT images needs to be done, which can increase classification accuracy. The data used is a subset (that is, 12,000 images) of the overall dataset (which is 84,484).

B. Brasil et al.[30] Two methodologies were used; the first was the ML approach, which measured minimum, maximum, skewness, kurtosis, variance, and mean to feed to the KNN algorithm. The second is a DL approach that exploits two pre-trained architectures: a ResNet50 network and a network based on Cifar-10. By using the UCSD-V2 dataset, the accuracy values for the KNN, sequential network, and the Resnet50 network were 99.7%, 99.64%, and 98.44%, respectively.

M. Berrimi and A. Moussaoui.[31] Suggested a new classification framework based on TL with DL. The outcome of the proposed CNN architecture was compared with pre-trained models such as VGG16 and InceptionV3. By using the UCSD-V2 dataset that has retinal diseases OCT images, the Custom CNN structure yielded an accuracy of 98.5%. In contrast, the Inception-V3 model achieved as much as 99.27% accuracy. VGG-16, initially scoring just 53%, was enhanced by integrating additional convolution layers and regularization components, pushing its accuracy to 93.5%. However, the imbalanced nature of the dataset could reduce the accuracy. In addition, there are no image enhancement and noise removal operations.

P. Dutta et al.[12] Proposed a hybrid feature extraction method that fuses features of the three models: vision transformer (ViT), ResNet-50, and Inception-V3 in a model called (Conv-ViT). ResNet-50 and InceptionV3 models are for extracting texture features, while the ViT is for extracting shape features. Achieved an accuracy of 94.46% on the UCSD-V3 dataset and 92.37% on the OCTID dataset. However, its computing complexity may limit its usefulness in real-world applications.

N. Khalaf et al.[32] Performed some pre-processing steps, then a custom model and a pre-trained VGG16 model were used, and the latter's accuracy was the best. On the UCSD-V2 dataset that has retinal diseases OCT images, the accuracy of the proposed CNN architecture reached 98.3%, while the accuracy of the VGG16 model reached 99.28%. Despite the high accuracy, the number of images used in this study is a subset (that is 1,336) of the overall dataset (84,484), so it differs from studies that this model has been compared with.

O. Akinniyi et al.[33] A network of multi-stage classification is proposed for classifying retinal disease OCT images built on a pyramidal feature ensemble framework. Initially, a scale-adaptive neural network is utilized for feature extraction and ensemble learning. Subsequently, a pyramidal structure enriched with features is crafted to draw multi-scale features using the pre-trained DenseNet model as the foundational network. The average accuracy achieved was 97.78% for the binary classification, 96.83% for the three-class classification, and 94.26% for the comprehensive four-class classification, all using the UCSD-V3 dataset. Meanwhile, when tested on the Duke dataset, our system demonstrated an accuracy of 99.69%. The absence of eliminating noise in images could result in reduced accuracy.

R. Mohan et al.[34] Presented a new CNN design named MIDNet-18. It comprises 14 convolutional layers, seven Max Pooling layers, four dense layers, and a single classification layer. Used the UCSD-V2 dataset to train with other images to test and validate, so the total number of OCT images was (126,193), achieving an accuracy of 98.86%. However, the noise in the images has not been eliminated.

İ. Kayadibi and G. Güraksın.[35] Used dual pre-processing and then suggested a hybrid approach to identify retinal diseases using Frequency-Domain CNN (FD-CNN) for retinal disease identification; after training FD-CNN, features were extracted and reclassified using D-SVM and D-KNN and then tested on two retina diseases OCT datasets. D-SVM excelled both in the UCSD-V2 dataset and achieved an accuracy of 99.60%, whereas in the Duke dataset, the accuracy was 97.50%. However, it overlooked the imbalanced dataset issue.

P. Barua et al.[36] Developed a novel system for diagnosing retinal disorders in OCT images by leveraging TL and DL techniques. The approach involved extracting deep features from 18 pre-trained neural networks (ResNet18, ResNet50, ResNet101, DarkNet19, DarkNet53, MobileNetV2, Xception, EfficientNetB0, ShuffleNet, NasNetMobile, NasNetLarge, DenseNet201, InceptionV3, InceptionResNetV2, GoogLeNet, AlexNet, VGG16, VGG19) and optimizing classification with a Quadratic Support Vector Machine. The results demonstrated an accuracy of 97.40% and 100% on two datasets, UCSD-V3 & Duke, respectively, highlighting the system's effectiveness. The accuracy of the Duke dataset is perfect, and the data is complete, but not all of the data is used in the UCSD dataset.

X. Huang et al.[37] This research introduces a new and efficient global attention block (GAB) tailored for feed-forward CNNs. Based on the GAB, a streamlined classification network model called GABNet has been proposed for feature extraction. The Xception model with GAB and by using TL attained an accuracy of 0.99 on the UCSD-V3 dataset that has retina diseases OCT images, but it reached only 0.965 without TL. The GABNet algorithm faced longer testing durations because of its broader branch relative to other algorithms.

F. Li et al.[38] Utilized an approach of DL with TL by fine-tuning the pre-trained VGG-16 network to classify OCT images. They attained a prediction accuracy of 98.6% on the UCSD-V3 dataset. To further evaluate the model's efficacy, the 'limited model' was trained using a limited training that is a subset of the UCSD dataset (4000 to train), achieving a good accuracy of 96.1%. However, the dataset is imbalanced.

A. Alqudah et al.[39] Constructed a hybrid artificial intelligence system for classification using eight different ML algorithms (Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Naive Bayes (NB), SVM with Linear Kernel (LSVM), SVM with Radial Basis Function Kernel (RBF SVM), Artificial Neural Network (ANN), K Nearest Neighbour (KNN), and Random Forest (RF)), and deep features extracted based on Advanced OCT Network CNN (AOCTNet). They amassed a substantial dataset of SD-OCT images for retina diseases, incorporating the UCSD-V3 and Duke datasets (137,437 images). The RF and the KNN classifiers attained accuracies of 99.12%. However, the imbalance of the dataset and the noise in the images are not addressed.

S. Asif et al.[40] Employed TL with pre-trained ResNet50 to circumvent the vanishing gradient problem. By incorporating a new "fully connected" block into the model, the precision of the classification of retinal diseases OCT images has been improved. The proposed model produces an elevated overall accuracy on the UCSD-V2 dataset, reaching 99.48%. The imbalance in the dataset was ignored.

D. Rastogi et al.[1] employed an advanced Deep-learning pre-trained model, DenseNet, and displayed the results of the Class Activation Map on the retina diseases OCT images. Achieved an accuracy of 97.65%. The authors focused on addressing dataset partitioning and data dimensions. In contrast, they did not address the noise.

J. Kim and L. Tran.[41] Utilized FCN in pre-processing, then various pre-trained models (DenseNet201, ResNet50, ResNet152, VGG16, VGG19, InceptionResNetV2, InceptionV3) were tested to classify retinal diseases in OCT images, with and without TL. Subsequently, the Bootstrap Aggregating method was applied to enhance performance. Among the various models, ResNet152 yields the most superior outcomes, attaining 0.9810 in accuracy on the UCSD-V3 dataset. Furthermore, the ensemble learning approach displays 0.989 in accuracy.

H. A. Nugroho and R. Nurfauzi.[42] They have diagnosed retinal diseases in OCT images by many modern models (ResNet18, ResNet50, GoogleNet, MnasNet0.5, SuffleNet-v2, MobileNet-v2, Inception-V3, and DenseNet121) to verify which one the most effective. Among them, MobileNet-V2 had the best accuracy of 0.9964 on the UCSD-V2 dataset. Despite exhibiting a high degree of accuracy, the model did not address the imbalance in the dataset.

2.1. Review of the Retinal Disease Datasets

In retinal disease research, having access to varied datasets ensures the development of robust, accurate, and generalizable models. Here, publicly available datasets that have been significantly adopted in the field are mentioned.

A. Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification Dataset

This comprehensive dataset is designed to serve dual roles and is essential to research endeavors in ophthalmology and pulmonology. This dataset is crucial because it is the most comprehensive and contains the highest quality OCT images, making it one of the most widely used databases in this specialized field. Version 3 of this dataset comprised 109,309 images - 37,205 exhibiting CNV, 11,348 with DME, 8,616 with Druse, and 51,140 Normal - originating from 4,686 distinct patients. Additionally, a subset of 1,000 images, 250 from each class, typically derived from 633 patients, is designated for testing. As for the first and second versions of this dataset, they differ in the number of Normal images, as their number is 26,315, so the total number is 84,484. The Spectralis OCT from "Heidelberg

Engineering," Germany, was used to obtain the OCT images, which were taken of cohorts of adult patients connected to many illustrious institutions between July 1, 2013, and March 1, 2017. These institutions include the Shiley Eye Institute of the University of California San Diego et al. All imaging procedures were conducted as a component of the patient's routine clinical care [6].

This dataset is available in three different versions, with each version having variations in the number of images and divisions. Various names in scientific publications, such as UCSD, OCT2017, Mendeley, and Kermany dataset, refer to it. In this research paper, the term (UCSD dataset), which is the most commonly used name, was used. The datasets are publicly accessible and can be acquired by visiting the following link:

V1: https://doi.org/10.17632/rscbjbr9sj.1.

V2: https://doi.org/10.17632/rscbjbr9sj.2.

V3: https://doi.org/10.17632/rscbjbr9sj.3.

B. Duke Dataset

The Duke Dataset for Retinal OCT Images is crucial for the research and study of macular conditions, comprising a variety of samples and a significant quantity of images within each classification. It offers extensive pathological perspectives on diverse retinal ailments.

This dataset of SD-OCT incorporates volumetric scans collected from a total of 45 patients, subdivided into 15 normal individuals, 15 with dry AMD, and 15 diagnosed with DME. All the SD-OCT volumes were gathered by Institutional Review Board-approved protocols utilizing Spectralis SD-OCT (Heidelberg et al.) for imaging at esteemed institutions like Duke University et al. [43]. The dataset encompasses 3231 OCT images distributed across three distinct classes: 1407 - Normal, 723 (or 686) - AMD, and 1101 - DME. This dataset has no designated separation into training and testing subsets [35]. For access to this dataset, you can visit: http://www.duke.edu/~sf59/Srinivasan_BOE_2014_dataset.htm.

C. OCTID Dataset

It is a collection of OCT images, systematically organized into distinct disease categories, featuring high-resolution JPEG formatted images. Over 500 spectral-domain OCT volumetric scans make up the dataset, which is classified into different categories such as Normal (NO), Macular Hole (MH), Age-related Macular Degeneration (AMD), Central Serous Retinopathy (CSR), and Diabetic Retinopathy (DR). These pictures were taken using a Cirrus HD-OCT instrument at "Sankara Nethralaya (SN)" in India, using a raster scan protocol with a scan length of 2 mm and a resolution of 512 x 1024 pixels (Carl et al.). An expert clinical optometrist (MKP) carefully selects an image centered on the fovea within each volumetric scan. The dataset includes retinal images from 102 MH, 55 AMD, 107 DR, and 206 Normal [44]. This dataset is publicly accessible and can be retrieved from the following link: https://dataverse.scholarsportal.info/dataverse/OCTID.

3. Survey Methodology

This research review focused on retinal disease classification using OCT images. A thorough understanding of the capabilities of existing models in DL is crucial, so that was our primary objective. The primary source of literature was Google Scholar, where extensive searches were carried out using "CNN, retinal diseases, CNV, DME, Drusen, Age-related macular, Diabetic retinopathy, Deep Learning, and OCT images" as keywords. This process involved identifying relevant papers, initially reviewing their abstracts, and then downloading them for detailed analysis. The reviewed papers varied in their focus, so they were carefully selected.

To deepen the understanding of these retinal diseases, which form the core of the project, various online resources were consulted, visits to nearby eye hospitals were conducted, and informative videos on social media platforms were reviewed. This comprehensive approach was crucial in acquiring a detailed understanding of how retinal diseases are detected from OCT images instead of color fundus images.

The papers that formed the basis of this survey were recent and published in reputable publishers such as IEEE, Springer, MDPI, and Elsevier, ensuring that the project was grounded in current, credible research. This methodology, which seamlessly blended a review of academic literature with practical, real-world knowledge, laid a solid foundation for this survey.

Table 1. - Literature Survey

Ref	Methodology	Year	Dataset	Best accuracy
[6]	TL with pre-trained Inception-V3 model.	2018	UCSD-V3 (109,309)	96.6
[1]	Pre-trained DenseNet model.	2019	UCSD-V3 (109,309)	97.65
[19]	Pre-trained models (ResNet-50, VGG16, VGG19, ResNet-101, AlexNet, GoogLeNet, ResNet-18, InceptionV3, DenseNet-201, InceptionResNet-V2, and SqueezeNet) and the best performance one is selected	2019	UCSD-V3 (109,309)	98.6
[38]	TL with pre-trained VGG-16 model.	2019	UCSD-V3 (109,309)	98.6
			UCSD-V3 (5000)	96.1
[9]	TL with pre-trained inception-V3 & Xception models with SVM.	2020	UCSD-V2 (7000)	98
[26]	Ensemble model of pre-trained models: DenseNet, VGG16, Inception-V3, and a custom model.	2020	UCSD-V2 (84,484)	98.53
[31]	New framework using DL and TL, with five models: Two were proposed, two pre-trained (Inception-V3 & VGG-16) and modified VGG-16.	2020	UCSD-V2 (84,484)	99.27
[41]	Pre-trained models (DenseNet201, ResNet50, ResNet152, VGG16, VGG19, InceptionV3, and InceptionResNetV2), with and without TL.	2020	UCSD-V3 (109,309)	98.9
[17]	Three and four binary CNN classifiers, adapted with six pre-trained models, including Inception-V3, ResNet50, ResNet152, VGG16, VGG19, and DenseNet121.	2021	UCSD-V2 (35,464)	98.7
[18]	Pre-trained models, including ResNet50, EfficientNetB0, and InceptionV3.	2021	UCSD-V3 (109,309)	96.9
[36]	TL with 18 pre-trained models (ResNet18, ResNet50, ResNet101, DarkNet19, DarkNet53, MobileNetV2, Xception, EfficientNetB0, ShuffleNet, NasNetMobile, NasNetLarge, DenseNet201, InceptionV3, InceptionResNetV2, GoogLeNet, AlexNet, VGG16, VGG19) and utilizes IRF for feature selection and SVM for classification.	2021	UCSD-V3 (11,000), Duke (3194)	0.974, 1.0
[39]	Hybrid of ML algorithms: LSVM, RBF SVM, ANN, KNN, RF, LDA, QDA, and NB with AOCTNet CNN.	2021	UCSD-V3 & Duke (137,437)	99.12
[42]	Pre-trained models to verify the most effective one: (ResNet18, ResNet50, GoogleNet, MnasNet0.5, SuffleNet-v2, MobileNet-v2, Inception-V3, and DenseNet121).	2021	UCSD-V2 (84,484)	99.64
[23]	Multi-scale Bayesian U-Net (MBU-Net).	2022	UCSD-V3 (109,309), BFHJLU (1021)	94.9, 92.1

[29]	CNN with four DL models.	2022	UCSD-V2 (12000)	97
[30]	ML (by extracting minimum, maximum, skewness, kurtosis, variance, and mean to feed to KNN algorithm) and DL (Resnet50 network and a sequential network based on Cifar-10).	2022	UCSD-V2 (84,484)	99.7
[34]	CNN architecture: MIDNet18.	2022	UCSD-V2 & another (126,193)	98.86
[40]	TL and incorporate a new "fully connected" block into the pre-trained ResNet50 model.	2022	UCSD-V2 (84,484)	99.48
[12]	The hybrid feature extraction method fuses models, such as vision transformer (ViT), ResNet-50, and Inception-V3, in a model called "Conv-ViT".	2023	UCSD-V3 (109,309), OCTID (261)	94.46, 92.37
[20]	TL with fusing feature vectors of pre-trained VGG16 and InceptionV3 models.	2023	UCSD-V2 (84,484), UCSD-V3 (109,309)	99.7, 98.1
[21]	Custom-made model: RetNet.	2023	UCSD-V2 (30904)	97.85
[22]	Vision transformer (ViT) based DL model.	2023	UCSD-V2 & another (126,193)	95.76
[24]	TL with pre-trained Xception model.	2023	UCSD-V2 (81,000), UCSD-V3 (81,000)	99.5, 97.25
[25]	Five DL models, 12 convolutional layers based, InceptionResNet, DenseNet201, DenseNet121, and DenseNet169, were used.	2023	UCSD-V2 (84,484)	97
[27]	TL with pre-trained models: VGG19, ResNet50, and the custom-built sequential model.	2023	UCSD-V2 (84,484)	99.6
[28]	Pyramidal structure to draw features from partially connected networks (PCNet) with binary and multi-class classifications by SVM.	2023	UCSD-V3 (109,309)	0.969
[32]	Pre-trained VGG16 model with a four-layer CNN model.	2023	UCSD-V2 (1,336)	99.28
[33]	Multi-stage networks with binary (normal or abnormal) and multi-class (3- classes) classification approaches are founded on an ensemble structure of pyramidal features.	2023	UCSD-V3 (109,309), Duke (3231)	Binary 97.79 Multi 96.83, 99.69
[35]	FD-CNN and dual pre-processing, followed by features reclassified using D-SVM and D-KNN.	2023	UCSD-V2 (84,484), Duke (3231)	99.6, 97.5

[37]	Built GABNet utilizing a global attention block (GAB) and CNN and employed the pre-trained Xception model + GAB model with TL.	2023	UCSD-V3 (109,309)	99

4. Discussion

This study includes thirty models. The efficiency of each model was assessed by analysis using the accuracy metric across all papers. Based on the findings of these papers on diagnosing retinal diseases using deep learning in OCT images, this study reveals the high efficacy of deep learning models and the high accuracy obtained in classifying retinal diseases. The most frequently used pre-trained models were (InceptionV3, ResNet50, and VGG16) as demonstrated in Table 2, which shows all the models, how many times they were used, and in which papers. Models like MobileNet-V2, Xception, ResNet50, VGG-16, and InceptionV3 show remarkable accuracy in [78, 56, 39, 35], as shown in Table 1, and often when adapted with TL techniques, their accuracy is higher. In addition to the pre-trained models, the Vision Transformer model was also used, as in [12], [22], [28], or building a Custom model, as in [21], [26], [27], [31], [32]. However, a notable drawback of these deep learning models is their reliance on large datasets for optimal performance in addition to the long time required. These requirements can be a significant limitation in scenarios where extensive data is not readily available or feasible to gather.

Table 2. - Literature Survey

No.	Models	Count	References
1	InceptionV3	12	[6], [9], [12], [17], [18], [19], [20], [26], [31], [36], [41], [42]
2	ResNet50	11	[12], [17], [18], [19], [27], [29], [30], [36], [40], [41], [42]
3	VGG16	9	[17], [19], [20], [26], [31], [32], [36], [38], [41]
4	VGG19	5	[17], [19], [27], [36], [41]
5	DenseNet201	4	[19], [25], [36], [41]
6	Xception	4	[9], [24], [36], [37]
7	DenseNet	3	[1], [26], [33]
8	DenseNet121	3	[17], [25], [42]
9	InceptionResNetV2	3	[19], [36], [41]
10	GoogleNet	3	[19], [36], [42]
11	ResNet18	3	[19], [36], [42]
12	ResNet101	2	[19], [36]
13	ResNet152	2	[17], [41]
14	EfficientNetB0	2	[18], [36]
15	MobileNet-v2	2	[36], [42]
16	AlexNet	2	[19], [36]
17	DenseNet169	1	[25]
18	InceptionResNet	1	[25]
19	NasNetMobile	1	[36]
20	MnasNet0.5	1	[42]
21	NasNetLarge	1	[36]
22	ShuffleNet	1	[36]
23	DarkNet19	1	[36]
24	DarkNet53	1	[36]
25	SqueezeNet	1	[19]

As for the promising methods that gave the highest accuracy and let us take the UCSD-V2 dataset as a basis for comparison, they are as in the following Table 3:

Table 3. - Methods with the highest accuracy

Ref	Promising method	Accuracy
[20]	Fusing feature vectors of multi-model.	0.997
[27]	Building new custom models.	0.996
[35]	Integrating machine learning techniques with deep learning algorithms.	0.996
[40]	Modify the pre-trained models by adding new layers.	0.9948
[32]	Using transfer learning methodology with pre-trained models.	0.995
[17]	Segmentation of multi-class classification into several binary classifications.	0.987
[26]	Use an ensemble approach instead of a single model.	0.9853

Regarding future work, several areas require further solutions to overcome gaps in previous research:

1- Develop pre-processing techniques that can more effectively address noise issues, including Inconsistency in (size, quality, rotation, translation, and zoom ratio), salt and pepper noise, and white background noise since many studies neglected pre-processing as in [33], which may cause less accuracy.
2- Exploring methods to address data imbalance because some researchers neglect this point, as in [38], which affects the model's accuracy.
3- Improving the efficiency of DL algorithms to reduce the time and computational resources needed for training and classification, making these models more accessible to use and apply in diverse clinical environments.
4- Finding better ways in the ensemble methods to build a robust model that benefits from the advantages of each model and eliminates the disadvantages in each model to produce a model with the highest accuracy.
5- Develop methods for integrating ML techniques with DL models to provide more accurate retinal disease classification. This method is very promising and has achieved outstanding results, as in [9].
6- Develop techniques that reduce the reliance on large datasets, such as advanced data augmentation methods, which can be beneficial in medical imaging fields where data availability is often limited.
7- Develop Explainable AI (XAI) methods to provide insights into their decision-making processes, which is crucial for clinical acceptance and trust.

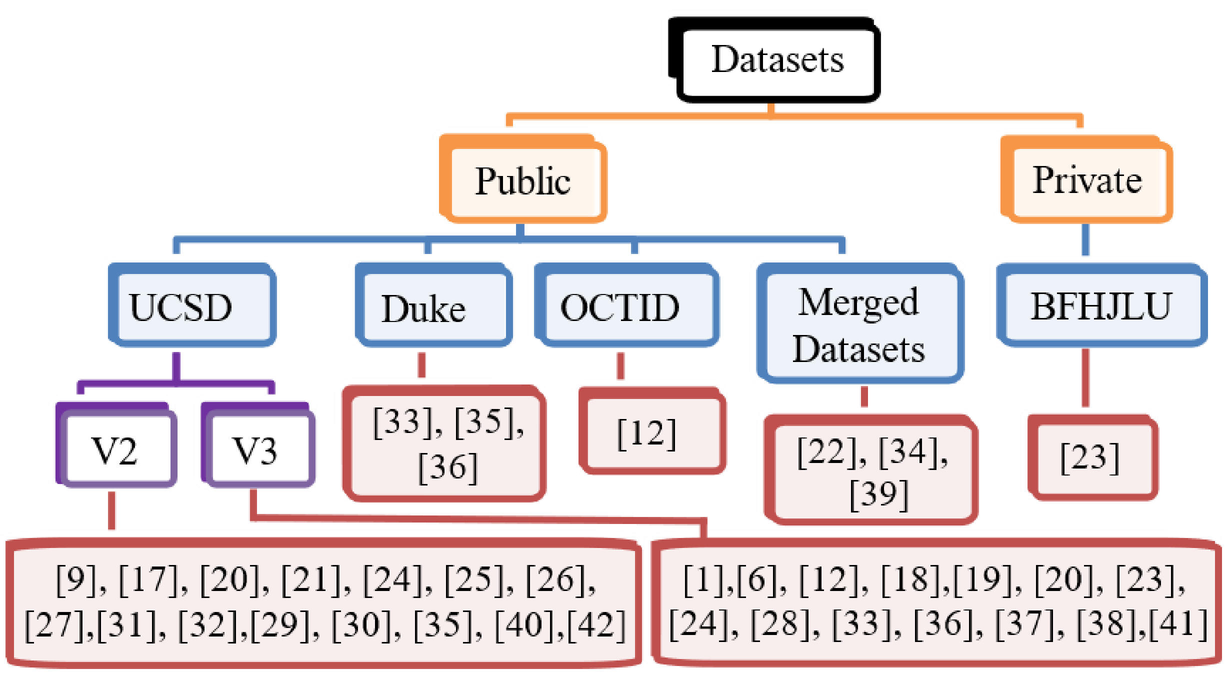

Fig. 3 - Datasets of OCT Images.

The datasets used in this research are divided into two types: public and private (as shown in Fig. 3):

1- Public, which are:

- UCSD V2 (84,484): It obtained the highest accuracy (0.997) in the paper [20] and the lowest accuracy (0.97) in the paper [25] and was used 17 times.
- UCSD V3 (109,309): It obtained the highest accuracy (0.99) in the paper [37] and the lowest accuracy (0.9446) in the paper [12] and was used 15 times.
- Duke (3194 or 3231): It obtained the highest accuracy (1.0) in the paper [36] and the lowest accuracy (0.975) in the paper [35] and was used 4 times.
- OCTID (261): It obtained the highest accuracy (0.9237) in the paper [12] and was used once.
- Merged Datasets:
  - Merging of UCSD-V3 & Duke (137,437): It obtained the highest accuracy (0.9912) in the paper [39] and was used once.
  - UCSD-V2 with another (126,193): It obtained the accuracies (0.9576 & 0.9886) in the papers [22] & [34], respectively, and was used twice.

2- Private, which are:

- BFHJLU (1021): It obtained the highest accuracy (0.921) in the paper [23] and was used once.

5. Conclusion

This survey has meticulously evaluated the advancements in diagnosing retinal diseases using OCT images. The exhaustive analysis of various research studies reveals that DL, particularly CNNs and their variants, plays a pivotal role in enhancing the accuracy and efficiency of diagnosing retinal diseases like DME, CNV, and Drusen, which has shown impressive progress and may significantly advance the field of ophthalmology.

TL has become a prominent approach for leveraging existing datasets, even if they are limited in number, using it with pre-trained models, such as InceptionV3, ResNet50, VGG16, and Xception, which have shown remarkable effectiveness, as evidenced by its frequent adoption and high accuracy rates achieved.

Combining ML techniques with distance learning algorithms, integrating multiple model vectors, and using different clustering methods have shown high effectiveness, as shown by the outstanding results in this survey. In addition, the creation of new models tailored to specific requirements for the diagnosis of retinal diseases in OCT images also holds great potential.

We mentioned that most of the methods used require large and diverse datasets to achieve optimal performance, and this poses a drawback, especially in scenarios with limited data available. We should point out the importance of pre-processing OCT images, and paying attention to it is a crucial step in enhancing the accuracy of the model. Furthermore, the computational complexities and time required to train sophisticated models can be considered practical limitations. These were the most critical challenges we noticed.

Developing more efficient DL algorithms with fewer computational resources, devising ways to mitigate the impact of data imbalance, enhancing pre-processing techniques, and exploring advanced data augmentation methods are critical areas that need attention and focus in future directions. The development of XAI is also essential to gain insights into decision-making processes.

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