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Optical Coherence Tomography based Diabetic – Ophthalmic Disease Classification using Bilateral Filter and Transfer Learning approach

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Abstract
Eye is the most sensitive organ in human body; eye captures the images and sends signals to brain via optical nerve. In most of the developing countries after certain age people are affected by diabetic. Due to this primarily human eyes are affected most. To get protection from this problem Optical Coherence Tomography (OCT) technique helps a lot. This OCT is a diagnosis device. In OCT, high air resolution and highly sensitive heterodyne detection technology are used to measure tomographic images of living organisms. Using Tomographic Images different eye problems can be detected earlier. But this OCT captured images are corrupted by noise, because of this problem identification little bit complex. This paper presents Noise removing technique using Bilateral filter and classification of ophthalmic diseases caused by diabetes. Decreased OCT image quality can be attributable to cataracts which block light, patient motion artifact, or any other media opacity. A study is being conducted on Chorodial Neovascularization (CNV), Diabetic Macular Edema (DME), Drusenism, and Normal. Bilateral filter is used for image pre-processing and noise removal. In order to classify the images, Deep Convolutional Neural Network and Support vector machine (SVM) are used as transfer learning techniques. Images are analyzed using AlexNet model and classified using SVM model based on the extracted features. In comparison to other deep learning approaches, the proposed approach achieved higher classification accuracies.
Keywords— Optical Coherence Tomography, Deep Convolutional Neural Network, Support vector machine and Bilateral Filter.

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I. INTRODUCTION

Optical Coherence Tomography (OCT) is one of the most famous Non-inventive Eye measurement technique. This OCT gives a cross-sectional view of the retina, using these OCT images pre-diagnosis of eye disease is possible. The OCT gives the inner cross-sectional view; by using this ophthalmologists easily identify the problem that is present in the side-eye. In most of developing countries, middle-aged people are suffering with diabetes, this diabetes cause harm to eyes. In OCT, high air resolution and highly sensitive heterodyne detection technology are used to measure tomographic images of living organisms. Using Tomographic Images different eye problems can be detected earlier. But this OCT captured images are corrupted by noise, because of this problem identification little bit complex. This Noise Decreases image quality and it can be attributable to cataracts which block light, patient motion artifact, or any other media opacity. So primary goal is to remove Noise from captured images then afterwards classifying images based on their characteristics. This paper presents a classification of ophthalmic diseases caused by diabetes. Decreased OCT image quality can be attributable to cataracts which block light, patient motion artifact, or any other media opacity. A study is being conducted on Chorodial Neovascularization (CNV), Diabetic Macular Edema (DME), Drusenism, and Normal. Bilateral filter is used for image pre-processing and noise removal. In order to classify the images, AlexNet and Support vector machine (SVM) are used as transfer learning techniques. Images are analysed using AlexNet model and classified using SVM model based on the extracted features. In comparison to other deep learning approaches, the proposed approach achieved higher classification accuracies.

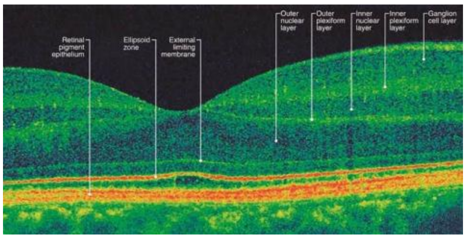

Fig. 1Optical Coherence Tomographic Image

An optical coherence tomography (OCT) is a non-invasive inspection technique that generates tomographic images of the fundus. They use light waves to take cross-section pictures of your retina. With OCT, ophthalmologist can see each of the retina's distinctive layers. This allows your ophthalmologist to map and measure their thickness based on the difference. Based on the various light penetration depth captured image layer thickness going to change, this is one way. Because of diabetic in patient's eyes blood vessel thickness also change. This also identified using OCT images. Using OCT images macular hole, macular pucker, macular edema, age-related macular degeneration, glaucoma, central serous retinopathy, diabetic retinopathy, vitreous traction, abnormal blood vessels, and blood vessel blockage are identified. There is a small variation one problematic image to another and healthy eye images. To classify these images requires sufficient knowledge and experience.

II. LITERATURE SURVEY

Due to the scarcity of labelled images, transfer learning approaches for deep learning have become popular in medical image classification [11], [12]. One of the initial works in this area was discussed in Bar et al. [13] where they introduced the transformation of the DeCAF deep learning model, which was originally trained with a large number of natural images, as a transfer learning model to classify normal and pathology classes (normal chest and pathology chest) in chest X-ray images [14]. Since then, transfer learning has been applied in many medical image classification tasks. A survey of transfer learning based medical image diagnosis can be found in Litjens et al. [15]

Milivoje Aleksic[1], proposed that The classical bilateral filter smoothes images and preserves edges using a nonlinear combination of surrounding pixels. Our modified bilateral filter advances this approach by sharpening edges as well. This method uses geometrical and photometric distance to select pixels for combined low and high pass filtering. It also uses a simple window filter to reduce computational complexity.

Sugmk, Jathurong[2] et al. proposed that step of image segmentation to be divided the optical coherence tomography (OCT) to find the retinal pigment epithelium (RPE) layer and to detect a shape of drusen in RPE layer. Then, the RPE layer is used for finding retinal nerve fiber layer (RNFL) and for detecting a bubble of blood area in RNFL complex. Finally, this method uses a binary classification to classify two diseases characteristic between AMD and DME.

Kh Tohidul Islam[3] et al. proposed that,explore how to use deep transfer learning for the diagnosis of diabetic retinopathy using OCT images. We retrain existing deep learning models for this task and investigate how a retrained model can be optimized. We demonstrate that using an optimized pre-trained model as a feature extractor and training a conventional classifier on these features is an effective way to diagnose diabetic retinopathy using OCT images. We show through experiments that the proposed method outperforms similar existing methods with respect to accuracy and training time.

Identifying diabetic retinopathy from oct images using deep transfer learning with artificial neural networks

Depeng Wang and Liejun wang (2019) [2], an automatic method based on deep learning is proposed to detect AME and AMD lesions, in which two publicly available OCT datasets of retina were adopted and a network model with effective feature of reuse feature was applied to solve the problem of small datasets and enhance the adaptation to the difference of different datasets of the approach. Several network models with effective feature of reusable feature were compared and the transfer learning on networks with pre-trained models was realized.

Akshat Tulsani[4-10](2024) et al. proposed in his paper A novel convolutional neural network for identification of retinal layers using sliced optical coherence tomography images. Propose a novel convolutional neural network for identifying retinal layers using sliced optical coherence tomography images.

III. METHODOLOGY

The OCT captured images give information related to internal structure of eye. Generally human eye is combination of several layers, due to diabetic or many reasons layer thickness, structure going change. These differences identified by observing OCT images. An optical coherence tomography (OCT) is a non-invasive inspection technique that generates tomographic images of the fundus. They use light waves to take cross-section pictures of your retina. With OCT, ophthalmologist can see each of the retina's distinctive layers. This allows your ophthalmologist to map and measure their thickness based on the difference. Based on the various light penetration depth captured image layer thickness going to change, this is one way. Because of diabetic in patient's eyes blood vessel thickness also change. This also identified using OCT images. Using OCT images macular hole, macular pucker, macular edema, age-related macular degeneration, glaucoma, central serous retinopathy, diabetic retinopathy, vitreous traction, abnormal blood vessels, and blood vessel blockage are identified. There is a small variation one problematic image to another and healthy eye images. To classify these images requires sufficient knowledge and experience.

Due to above mentioned problems Blurred vision occurs when the macula fills with fluid and swells, impairing the ability of these cells to function Blindness can be prevented and medical expenses can be reduced through early detection of ophthalmic diseases, which is important for patients and society.

In the proposed method first the captured images are de noised net from collected data few sample images were trained under experts observation. Next test data is applied to algorithm and image is classified using trained algorithm. To perform this Deep Convolutional Algorithm is used. The novelty present in this is removing noise from captured image by preserving the edges next extracting features, compare the features with trained data set then to classification.

3.1. Noise removing: In the present approach Noise is removed by using Bilateral Filter, Filters such as the Gaussian filter have the disadvantage that the contours are also blurred when trying to remove noise as much as possible. Processing algorithm that attempts to resolve this drawback is bilateral filter is a (bilateral filter). Bilateral filter array of the image data before processing f (i, j) , the sequence of the processed image data g (i, j) to the

$$g(i,j) = \frac{\sum_{n=-w}^{w}\sum_{m=-w}^{w} f(i+m,j+n)\exp\left(-\frac{m^2+n^2}{2\sigma_1{}^2}\right)\exp\left(-\frac{(f(i,j)-f(i+m,j+n))^2}{2\sigma_2{}^2}\right)}{\sum_{n=-w}^{w}\sum_{m=-w}^{w} \exp\left(-\frac{m^2+n^2}{2\sigma_1{}^2}\right)\exp\left(-\frac{(f(i,j)-f(i+m,j+n))^2}{2\sigma_2{}^2}\right)}$$

However, **w** controls the kernel size, $\boldsymbol{\sigma}_1$ controls the Gaussian filter, and $\boldsymbol{\sigma}_2$ controls the brightness difference.

3.2. AlexNet : AlexNet is a convolutional neural network for large-scale image class classification. When CNN model is used, features are automatically extracted as a multi-resolution hierarchical convolutional kernel layer group even for a dataset. It can be said that it was possible, and on top of that, it was shown that the accuracy was considerably higher than that of conventional image recognition.

AlexNet's research has established for the first time a CNN learning framework for successfully learning large networks for multi-class identification from large datasets, which have taken for granted in recent years. In this sense, AlexNet is the original network structure of modern image recognition CNNs in recent years.

The key to AlexNet's achievement of high accuracy was the suppression of deep CNN overfitting. In other words, it can be said that AlexNet's research was the first to build a basic collection of tips that can train CNN models for large-scale image datasets as well as possible without overfitting. In addition, high-speed learning of large-scale CNN was achieved by introducing ReLu. In this way, the advent of AlexNet had a great impact on the computer vision industry, and caused a paradigm shift that "the computer vision industry will shift to CNN-based image recognition methods at once."

3.2.1. AlexNet structure

AlexNet has a network structure as shown in Figure 2 below:

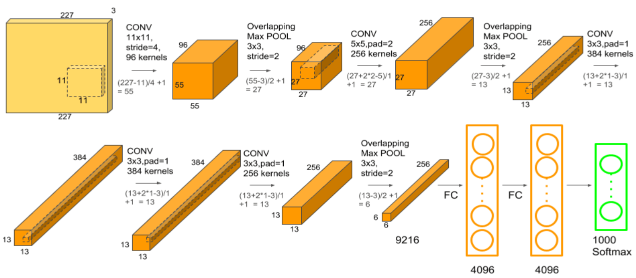

Figure 2: AlexNet structure.

AlexNet is a class identification CNN with a structure in which each layer is connected in series in the following table 1:

Table 1: Network layers

Layers	Performance
Input:	3-channel color image normalized to 224 x 224 (color whitened)
Conv1:	Convolution layer – [11 x 11] kernel x 96 channels, stride = 4, padding = 2
Activation function:	ReLU + local response normalization
P1	Pooling layer – Overlapping maximum pooling, [3 x 3] kernel, stride = 2
Conv2	Convolution layer – [5 x 5] kernel x 256 channels, stride = 1, padding = 2
Activation function:	ReLU + local response normalization (Section 3.2.2)
P2	Pooling Layer – Overlapping Maximum Pooling, [3 x 3] Kernel, stride = 2
Conv3	Convolution Layer – [3 x 3] Kernel x 96 channels, stride = 1, padding = 1
Conv4	Convolution Layer – [3 x 3] Kernel x 96 channels, stride = 1, padding = 1
Conv5	Convolution Layer – [3 x 3] Kernel x 96 channels, stride = 1, padding = 1
P3	Pooling Layer – Overlapping Maximum Pooling, [3 x 3] Kernel, stride = 2 (Only when learning: Dropout)
FC6	Fully coupled layer – 9216 (= 256 x 6 x 6) vs 4096
Activation function	ReLU (Only when learning: Dropout)
FC7	Fully coupled layer – 4096 vs 4096 Activation function: ReLU
FC8	Fully coupled layer – 4096 vs 1000
Output	1000-dimensional vector probabilized by softmax function (output probability of each dimension).

LeNet has 60K (60,000) learning parameters, while AlexNet has 60 million parameters. AlexNet was a fairly huge model not only in comparison with LeNet but also in comparison with machine learning up to that point.

3.2.2. AlexNet Features / Ingenuity

In AlexNet, in order to ensure image recognition accuracy in ImageNet, it is necessary to learn well while suppressing overfitting because it is a network with a huge number of parameters compared to LeNet, which is the representative of CNN until then. rice field. Therefore, various ideas were newly introduced into CNN.

3.3 Introduction of ReLU

AlexNet used ReLU (Rectified Linear Unit) as the activation function:

$$f(x) = \max(0, x)$$

The sigmoid function and tanh (also used in LeNet) were used as activation functions in traditional neural networks. However, in these saturated functions, the differential value becomes smaller as the number of insertions is increased, so the deeper the CNN layer, the more likely it is that the gradient disappears.

Therefore, AlexNet decided to use only the unsaturated type ReLu for the deactivation function. As a result, the disappearance of the gradient was avoided and the learning speed was increased (by increasing the gradient value). By replacing it with ReLu, the accuracy can be maintained while achieving about 5 times faster speed in each layer than other activation functions such as sigmoid function and tanh function. Since then, it has become standard for CNNs to use the ReLU-based activation function.

3.4 Reduction of overfitting

As mentioned in the first section, how to suppress and reduce overfitting for AlexNet, which is an overparametrised model, was the key to scaling Deep CNN to support ImageNet learning.

Therefore, AlexNet has adopted the following three measures against overfitting:

1. Data expansion
2. Local Response Normalization
3. Drop Out

3.5 Using data extensions

Data Augmentation, which is very important in the current CNN, is used in AlexNet for the purpose of reducing overfitting.

ImageNet used for learning is a large-scale class identification data set for image identification problems. ImageNet image data is annotated with a class label (one of 1000 classes) corresponding to the image (256 x 256) in which only one central object is shown. ing. In ImageNet, the number of images for each class is not so large (at most 500 images / class). Therefore, if possible, we would like to artificially increase the number of images to improve the generalization performance of learning. The easiest way to increase data and improve generalization performance is to use "data expansion" to edit the image slightly by arbitrary affine transformation or change the color value while keeping the label value fixed. I can think of using it.

Therefore, AlexNet first expands the original image into the following two data, and as a result, learns AlexNet from the expanded ImageNet dataset whose total number of samples has increased:

3.6. Geometric extension

Create a flip image that is flipped horizontally from the image (256 x 256). Expansion of object position by translation: From the original image and flip image, a 224 x 224 area is randomly cropped, and these are used as data-expanded input images. These steps 1 and 2 increase the size of the dataset by 2048 times.

3.7. Local response normalization (LRN)

Another regularization is the neighborhood with respect to the pixel values in the feature map. Same spatial location on the feature map of channels (5 channels before and after by default) Local response normalization (LRN), which normalizes from the luminance value group in, was proposed. Since ReLU is an unbound function, it is a trick used to adjust the function form by performing local response normalization on the output after ReLU. In AlexNet, local response normalization was performed after each ReLU layer.

3.8. Regularization by Dropout (suppression of overfitting)

The dropout, which was the standard method for deep neural network regularization at the time, was also used on AlexNet. AlexNet significantly reduced overfitting by using dropouts with a drop probability of 0.5 for neurons in the final two fully connected layers (FC6 and FC7).

3.9. Overlapping Maximum value pooling

The "average value pooling" used in previous CNNs such as LeNet acts like an average filter, so there was a problem that the image of the feature map after pooling was blurred. Therefore, AlexNet adopted Max Pooling as the pooling layer. AlexNet also used overlapped max pooling with a kernel size of 3 x 3 and a stride size of 2. In previous CNNs such as LeNet, tile-type operations such as kernel size 2 x 2 and stride size 2 were common so that pooling areas did not overlap.

3.3 Support vector machine (SVM)

SVM is a supervised machine learning algorithm. It's basically available for both classification and regression tasks, but it's actually more used for classification tasks. It is a fast and reliable classification algorithm, and it can expect good performance even with a small amount of data. It comes with an example code.

For simplicity, consider a dataset of 2D data with only two features. Then, in SVM, the basic idea is to find the straight line that divides the target data set most appropriately according to the class (the figure below is for two-class classification).

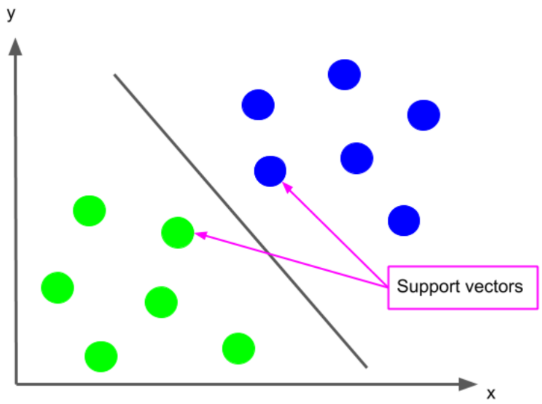

Figure 2: support vectors

3.9. The Support Vector, which is also mentioned in the name of the Support vector algorithm, is the data point closest to the straight line that divides the dataset. In SVMs, this Support Vector plays a major role in determining the straight lines that divide the dataset. More on this in the next section.

Once this dividing straight line is determined, the class is determined based on which side of this straight line the data to be determined is located. In the graph above, if there is data to the left of the straight line, it is a yellow-green class, and if it is to the right, it is a blue class.

3.9.1. Woking of SVM

Let's use a simple example. Suppose it want to create a classifier that classifies whether the data is in the blue or yellow-green class based on the two features x and y. First, consider the training data that has already been classified on the xy plane.

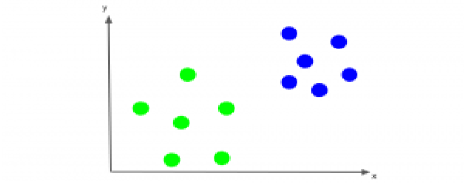

Figure 3: Feature of SVM

As mentioned earlier, SVM finds a straight line that best separates this training data, taking into account the class of each data. Then, with this straight line as the boundary, all the data located on one side is classified as blue, and all the data located on the other side are classified as yellow-green. For this reason, this straight line is sometimes called the decision boundary.

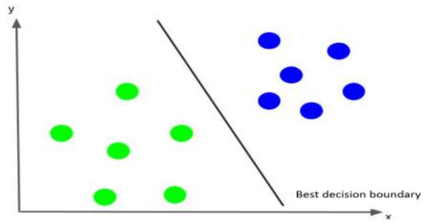

Figure 4: Decision boundaries of SVM

In SVM, in each class, the data point (Support Vector) closest to the straight line is considered, and the straight line is determined so that the distance (margin) between the data point and the straight line is as large as possible.

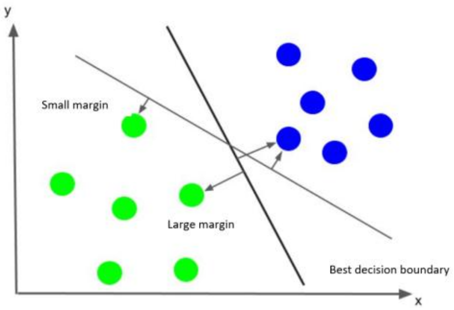

Figure 5: Determined the classes

The above is how to determine the decision boundary in SVM.

IV. Results

This section presents the experimental results carried out eye dataset. The number of images in the dataset are 1200. The total dataset is divided into 4 categories which are Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), DRUSEN, and NORMAL. Each category has 30 images from the total dataset. From these images, 120 images are used for training and 40 images are used for testing. The figure 6, figure 7, figure 8 and figure 9 shows the input images.

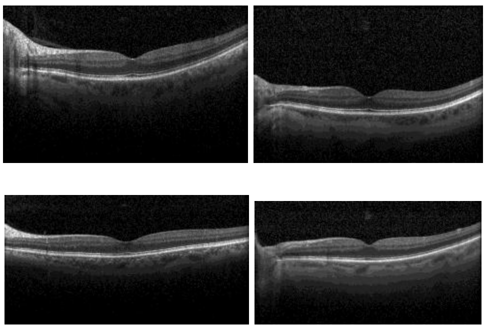

Figure 6: Nomal Images

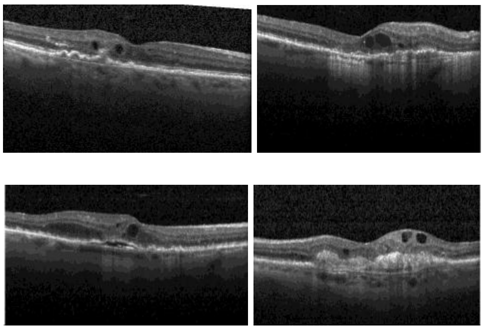

Figure 7: CNV Images

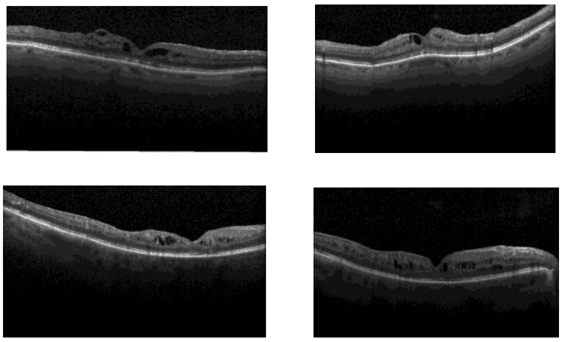

Figure 8: DME Images

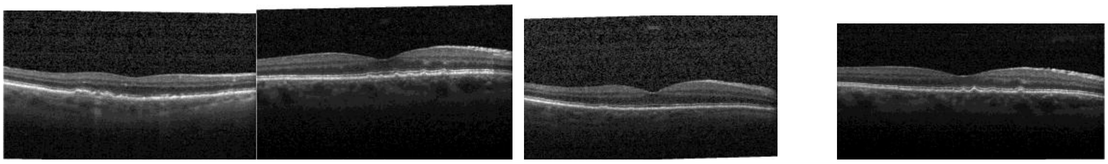

Figure 9: DRUSEN Images

Above are the sample images used to train the Deep Nrural Network, based on that following are calculated.
True positive (TP) = the number of cases correctly identified
False positive (FP) = the number of cases incorrectly identified
True negative (TN) = the number of cases correctly identified
False negative (FN) = the number of cases incorrectly identified
Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Sensitivity: The sensitivity of a test is its ability to determine the patient cases correctly. To estimate it, one should calculate the proportion of true positive in-patient cases. Mathematically, this can be stated as:

$$Sensitivity = \frac{TP}{TP + FN}$$

Specificity: The specificity of a test is its ability to determine the healthy cases correctly. To estimate it, one should calculate the proportion of true negative in healthy cases. Mathematically, this can be stated as:

$$Specificity = \frac{TN}{TN + FP}$$

Transfer Learning:
Table 2 shows the confusion matrix of training dataset. Training completed using transfer learning and produces results with the accuracy of 100% and almost 0% loss.

Table 2: Trainig confusion matrix

		Predicted Class			
		CNV	DME	DRUSEN	NORMAL
Actual Class	CNV	30	0	0	0
	DME	0	30	0	0
	DRUSEN	0	0	30	0
	NORMAL	0	0	0	30

Table 3 shows the results of confusion matrix for test data set. In testing 40 images are categorized into 4 class with each class have 10 images. For test data set the results produces with the accuracy 97%.

Table 3: Test confusion matrix

		Predicted Class			
		CNV	DME	DRUSEN	NORMAL
Actual Class	CNV	10	0	0	0
	DME	0	10	0	0
	DRUSEN	0	0	10	1
	NORMAL	0	0	0	9

Table 4 shows the results of parameters comparison comparision for train dataset with existing methods. Pameters used for comparison are precision, sensitivity, specificity and accuracy. Precision for CNN and alexnet are 0.69, 0.95. Sensitivity for CNN and alexnet are 0.68, 0.95. Specifity for CNN, alexnet are 0.68, 0.95. Accuracy for CNN, alexnet are 0.68, 0.95. Precision, sensitivity, specificity, and accuracy for proposed method are 1.0, 1.0, 1.0 and 1.0.

Table 4: Parameters comparison for Train dataset

Method	**Precision**	**Sensitivity**	**Specificity**	**Accuracy**
CNN	0.69	0.68	0.68	0.68
AlexNet	0.95	0.95	0.95	0.95
Proposed	1.00	1.00	1.00	1.00

Table 5 shows the results of parameters comparison for test dataset with existing methods. Pameters used for comparison are precision, sensitivity, specificity and accuracy. Precision for CNN, alexnet are 0.36, 0.93. Sensitivity for CNN, alexnet are 0.35, 0.92. Specifity for CNN, alexnet are 0.33, 0.93. Accuracy for CNN, alexnet are 0.35, 0.93 and 0.95. Precision, sensitivity, specificity, and accuracy for proposed method are 0.98, 0.97, 0.99 and 0.97.

Table 5: Parameters comparison for Test dataset

Method	**Precision**	**Sensitivity**	**Specificity**	**Accuracy**
CNN	0.36	0.35	0.33	0.35
AlexNet	0.93	0.92	0.93	0.93
GoogleNet	0.96	0.95	0.95	0.95
Proposed	0.98	0.97	0.99	0.97

V. Conclusion

OCT called optical coherence tomography (OCT) is based on a low coherence interferometer. Initially, this low coherence interferometer was applied to the evaluation of optical waveguides, etc., and its sensitivity was examined. In the field, it was applied to the measurement of axial length and angular film thickness. The proposed approach consisted of a transfer learning model using AlexNet for feature extraction, for the proposed model achieved an accuracy of 97%, while other deep learning models, CNN, AlexNet are lower. The precision sensitivity and specificity are also considerably higher.

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