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SMART GLASS RETILENZ - REVERSE LENS TECHNOLOGY FOR CAPTURING DEFECTS

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Abstract

Due to advancements in technology in the fields of Augmented Reality and Virtual Reality, things that seem nearly impossible have been made possible. Viewing the merge of real-life and digital data to get a real-time effect is beyond the expectation. Technologies are used in applications such as healthcare to ease the work of the people. Many health impairments are addressed with the help of these technologies. This paper aims to use the reverse lens, RetiLenz focus to view the different sections inside the eye. In particular, this paper addresses the need for this reversing effect to grade the most common eye disease over decades which is diabetic retinopathy. In the second phase the classification is done using capsule neural network for the captured images and the accuracy of 97.54% is achieved which is better than the previous methods.

Keywords: **Augmented reality; Virtual reality; diabetic retinopathy; capsule neural networks; RetiLenz**

1. Introduction

Diabetic Retinopathy is a defect in the eye, if not treated then it can lead in vision loss. At first, there is no symptoms of diabetic retinopathy or only mild vision problems but it can result in loss of vision. Anyone suffering from type 1 or type 2 diabetics can develop this condition. The longer you have diabetes and the less controlled your blood sugar is the more likely you are to develop it. Diabetic retinopathy has two different categories one being PDR (Poliferative Retinopathy) and NPDR (Non Poliferative Retinopathy).

There are four stages of diabetic retinopathy:

Stage 1: Mild nonpoliferative diabetic retinopathy

Primitive stage of diabetic retinopathy, characterized by small areas of inflammation in the blood vessels of the retina. These portion of inflammation and minor swelling are called micro aneurysms.Low amounts of liquid can discharge in the retina at this stage, activating swelling of the macula. This is the portion near the middle of the retina.

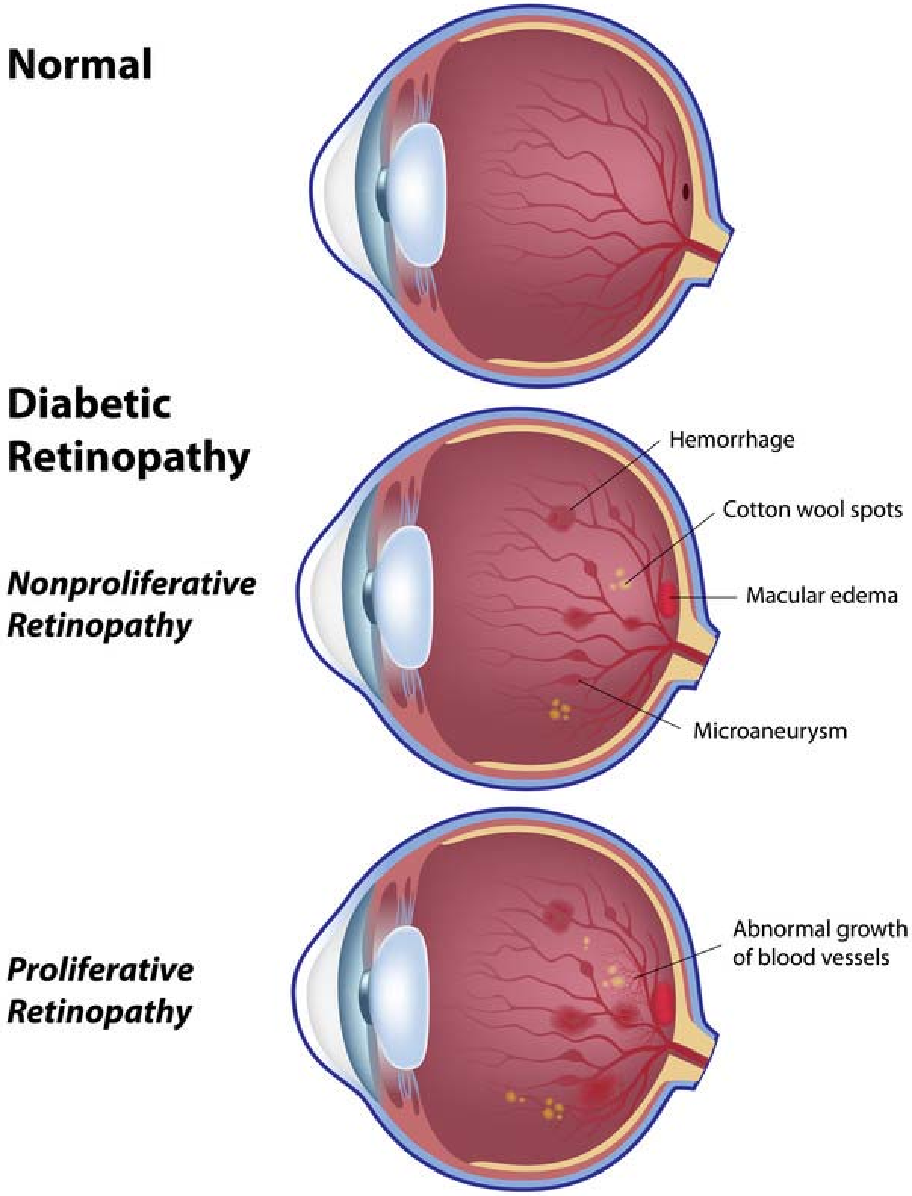

Fig. 1. Poliferative Retinopathy and Non Poliferative Retinopathy

Stage 2: Moderate nonproliferative diabetic retinopathy

Progression of inflammation of small blood vessels starts interfering with blood flowing into retina, averting proper supply of nutrition to the retina. This results in collection of blood and liquids inside the macula.

Stage 3: Severe nonproliferative diabetic retinopathy

A major portion of blood vessels in the retina chokes, resulting in reduction of blood flow in this area. At this juncture, the body gets signs to initiate the process of developing new blood vessels in the retina.

Stage 4: Proliferative diabetic retinopathy

This is the developed stage of the disease, in which the blood vessels are formed in the retina. Since these blood vessels are often breakable, there's a probable risk of liquid leakage. This starts different vision complications such as mistiness, diminished field of vision, and even loss of sight.

A. Wearable computing

Wearable computing comes as trend setters, based on the likelihood of the majority of crowd in terms of fashion. The combination of technology and fashion attracts customers to a greater extent. Wearable computers are borne on a person's cloth, they can be worn and with the help of the sensors and the small processors and the peripheral components like camera, display and power the information can be utilized for further processing

B. Smart glass

Smart glass is an application under this wearable computing[1], which uses the technologies like VR and AR.Smart glasses are glasses with a smart phone connected to it. They have power button, display, microphone, processor connected to it. The smart glasses allow you to answer a message, allows you to interact with the personal assistant. To provide connectivity to these smart glasses the use of either Wi-Fi or Bluetooth technology is required. These smart glasses looks very similar to that of the glasses that are regularly worn, except for the fact that the temple on the sides is little thicker which has the processing unit inside. Most of the operations such as answering the call, giving a voice command, to click a picture are at the sides of the goggles. The smart glasses' lens are smart they can adjust the lights for the convenience of the user by having features like blue light filters that does not hurt the eye for the long term usage of the system[2]. They have inbuilt cameras of 5MP which allows the user to click pictures so that the fun moments are not missed.

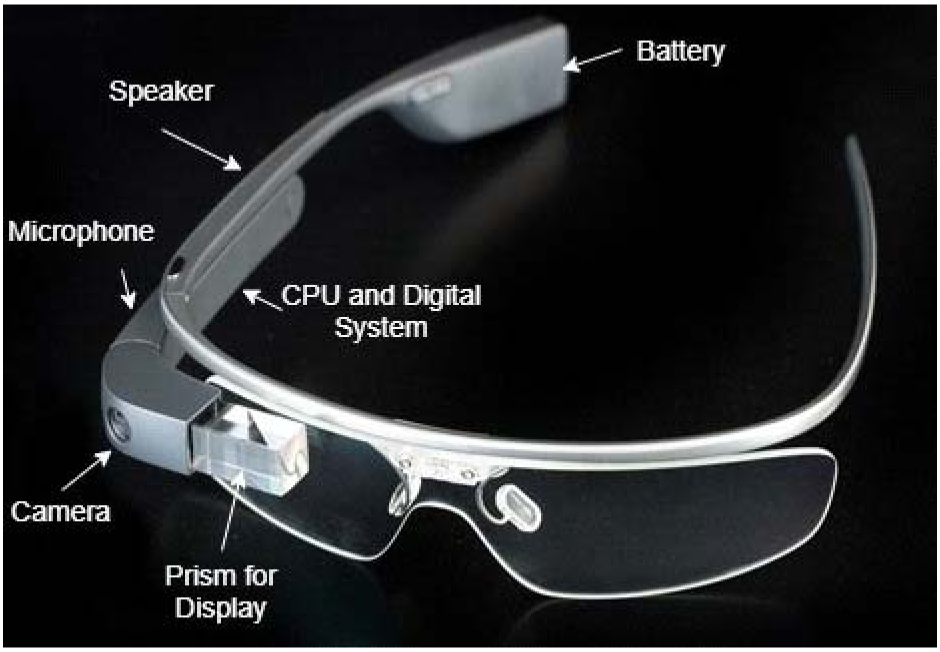

Fig. 2. Google glass

The main idea of the proposed work is to develop a Retilens that does the reverse technology of Google glass. This helps in analyzing the posterior portion of the eye and helps in taking the fundus image of retina, which helps in screening the data for the analysis of Diabetic Retinopathy and other vision related ailments. The rest of the paper is classified as Dataset, preprocessing steps, capsule neural networks and proposed architecture followed by results and conclusion.

2. Related Works

In place of the convolutional neural network, Sreelakshmi, K., et al. [6] suggest the capsule neural network for sorting garbage into plastic and non-plastic categories. Utilizing the capsule neural network, combining the two types of data sets, and real-time image collection from websites, the sorting out of waste, which is currently a major issue, is dealt with.

Deep learning (DL) frameworks have been reported to have the ability to learn characteristic features directly from fundus scans. [8] proposed detection of his RDR using InceptionV3 and achieved 99.1% and 97.5% respectively on two different datasets. [7] presented a modified AlexNet algorithm using the Mesidor dataset and achieved an average accuracy of 96.25%. A good detection of the Free-Response Receiver Operating Curve (FROC) of 95.4% was achieved using the Kaggle dataset. In a report in [8], we applied Inception-ResNet v2 to feature extraction by the optimized DNN method of moths using the Messidor data set, achieving 99.12 accuracy, 97.91% sensitivity and 99.47% specificity. The authors of [9] created a CNN architecture by extracting refined local features using the Accelerating Robust Properties and Bag of Visual Words techniques. In [10], a pre-trained attention and crop network CNN framework was used to detect patch sites, also called zoom for DR detection, using the MESSIDOR dataset.[11][19][20]From the article of author projected an algorithm oh automatic documentation which includes primarily two units: a combinational system focused at the fovea to assess the significance of stiff exudes, and a top-down strategy to split the exudes. On a dataset of 236 fundus photos, the author's test revealed 93.2% sensitivity. However, the likely course of action depends on the clinically relevant factors, such as the number of microaneurysms and the deviation from the representation of the normal retina in the examined retinal images annotated by human experts. The most voluminous segment of the works covered here either rely on physical parameters determined by professionals or take a lot of time and effort to decipher the necessary highlights utilising image processing techniques. Consequently, deep learning plans must be large enough to gain necessary highlights reasonably from the fundus pictures that have motivated the thought of researchers in the latest years.

[12][21] constructing a outline to identify diabetic retinopathy using a convolutional neural system (CNN) that categorises the wounds by creating heatmaps that have the potential to detect novel biomarkers in the fundus images. used a dataset with more than 128,000 images of the fundus to identify referable diabetic retinopathy using a CNN model called Inception-V3. The model successfully performs with AUC metric area under curve as 0.991 and 0.990 and 97.5% and 96.1% sensitivity on two different test sets simultaneously thanks to a large training dataset and very well-separated fundus images. A few metadata factors are added to the final fundus image results from the last pooling layer and used as input to the decision tree classifier, which distinguishes between normal fundus images and affected fundus images with diabetic retinopathy. By taking into account datasets from clinics and the general public, the proposed methodology was assessed for sensitivity and specificity. The authors of the research described a method that takes into account a number of characteristics, such as the area that is filled by veins, anomalies in the foveal zone, and microaneurysms. Based on the presence of microaneurysms, the authors of categorized DR images.39 photos are taken into account in the study, of which 4 are categorized as normal images and 35 as fundus images with exudates[13][22]. After studying fundus images, the authors of have demonstrated the application of SVM, Bayesian approach, and probabilistic neural network for differentiating the phases of DR as NPDR and PDR. For probabilistic neural network, SVM, and Bayes, the authors' accuracy was 87.69%, 95.5%, and 90.76%, respectively. Author Georgios has made a better method for the precise assessment of retinal highlights available in the article. The authors have utilized the Kaggle database for validation and obtained a accuracy of 75%.In

[14][23][24] have established a strategy for CNN-style arrangement of fundus images. The authors of the publication [46] have devised an automatic method of classifying a predetermined collection of fundus images. The inspection revealed that the given model had improved thanks to the inspection's perfect precision. The authors of [15] have revealed a method for combination error-dependent networks for picture classification. The authors of [16][25] attempted to use a mixed convolutional neural network to recognize macular abnormalities in SD-OCT images. [17].

3. Dataset

We set up our experiment using the Kaggle1 dataset, which, to the best of our knowledge, is the largest dataset of fundus photos for diabetics, is managed by Eye Pacs. Retinopathy. There are 88,702 photos in the EyePACS collection, of which 35126 are annotated images and the remaining. There are 53,576 unlabeled photos. Our goal, which is a supervised project, is to categories various phases of diabetic retinopathy. We only used the tagged photos from this dataset because there was a learning problem. Future semi-supervised learning techniques can make use of the entire dataset. Based on the kind of DR severity, the dataset is divided into five different classifications. Distribution of various DR classes in this dataset.

4. Preprocessing

We resize the photographs while keeping the aspect ratio in mind to pre-process the data before supplying it to the model. To 1349 × 1024. It aids in preventing feature loss in photos. Images are then arbitrarily cropped to a predetermined size of 1024x1024.The dataset is splitted into three setswhich are training, validation, and test, with respective ratios of 64%, 20%, and 16%. To verify that the model has improved, the validation dataset is employed.

5. Research Method

***Capsule neural network* -** The machine learning system includes artificial neural networks of the capsule network neural architectures type. The most popular application of it is in modelling hierarchical relationships and closely resembling biological brain networks. The significance of the capsules network is based on the idea of growing the convolution network and then reusing the findings to find more reliable and sophisticated exemplifications of the evolving capsules. The capsule network, a innovative architecture in neural networks and an improved method of the prevalent neural network model specifically for computer vision tasks, has been developed as a substitute for convolutional neural networks because the CNN exhibits few limitations in completing the applications of computer vision despite its efforts to manage accuracy in the areas where it is applied. Convolutional neural networks were initially created with the goal of classifying the images using the subsequent convolution layers and pooling layers, which are referred to as the base of the image processing in a deep learning aspect [3]. Although the convolution neural network was capable of achieving accuracy in the process, there was some performance deprivation as a result of the decline in the data dimension for gaining the spatial invariance, leading to a loss in the information (rotation, location, various features related to position and scale) that may be necessary in the process of segmentation, object detection, and proper localization of the objects [26]. The segmentation and detection processes are now worse. Developing advanced training and designing techniques for the convolutional neural network [4] to reduce the complications in the process of segmentation and detection, to gain accuracy in the classification of the images, was laborious but did not result in any enhancements, which led to the creation of the new architecture of convolution neural network. Geoffrey Hinton suggested this method as a workaround for the convolutional neural network's drawbacks. The architecture of a capsule neural network is depicted in fig. 3 below.

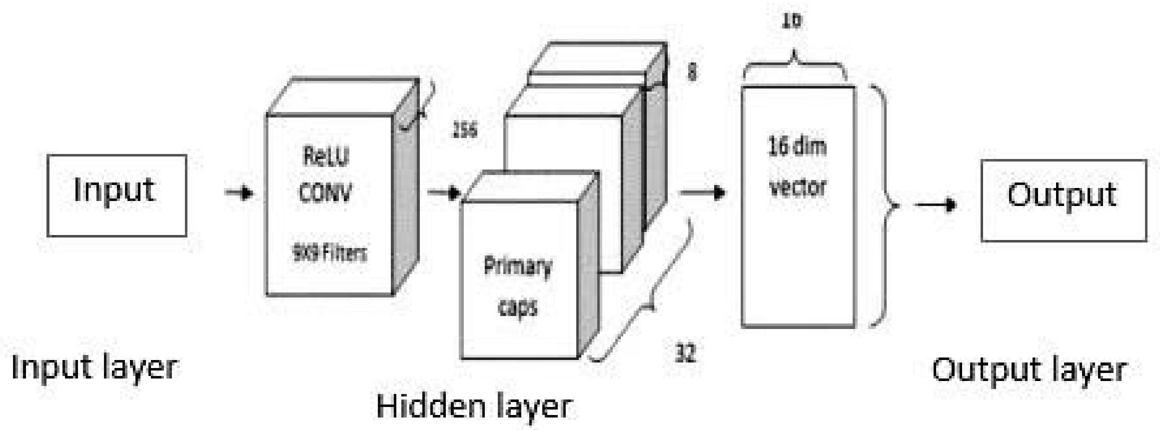

Fig 3.Capsule Neural Network Architecture

Architecture of capsule neural network **-** Encoders and decoders are the two main parts of a capsule network. They have a total of six layers. The first three layers of the encoder are in charge of taking the input image and turning it into a vector (16-dimensional). Convolutional neural network, the initial layer of the encoder, extracts the fundamental features of the image.The Primary Caps Network, which makes up the second layer, uses these fundamental components to uncover more intricate patterns[5][18]. It might be able to discern the spatial link between specific strokes, for instance. The Primary Caps Network contains a variety of capsule counts for various datasets; the MNIST dataset, for instance, comprises 32 capsules. The Digit Caps Network, the third layer, contains a variable number of capsules. The encoder outputs a 16-dimensional vector to the decoder after these layers.

Fig 4. shows the classification task by the capsule neural network as PDR,Severe PDR,Moderate NPDR ,Mild NPDR after capturing the information from the RetiLenz

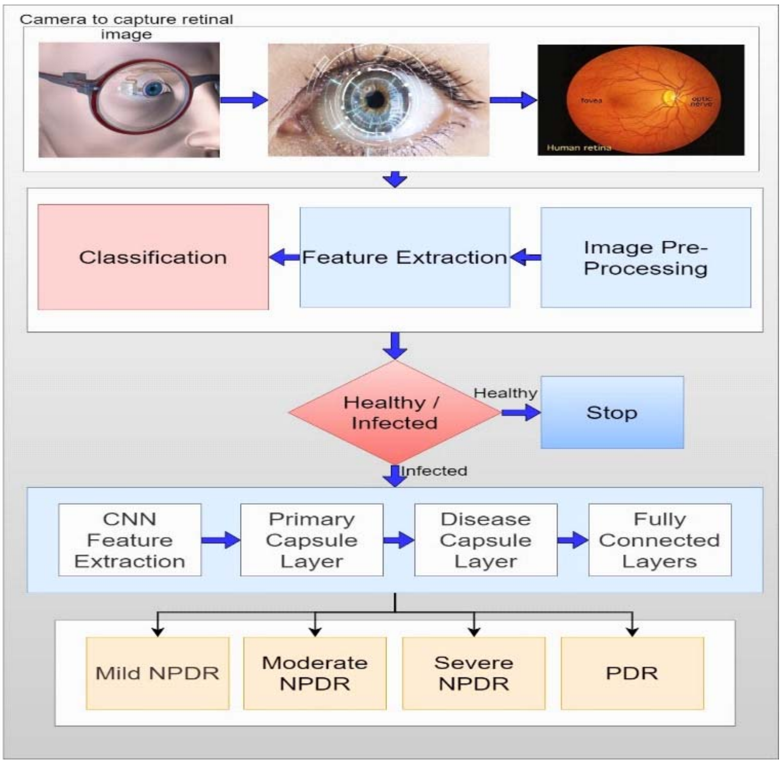

Fig. 4. The severity classification using capsules

6. Results and Discussion

While the dataset is trained with Healthy, Mild NPDR, Moderate, NPDR, Severe NPDR, PDR in 60:40 ratio that is 60% data for training the model and 40% for testing the model the precision, recall and F-1 Scores achieved are as follows:

Table 1. Precision, Recall, F1-Score with 60:40 ratio

Category / QOS	**Precision**	**Recall**	**F-1 Score**
Healthy	0.87	0.85	0.86
Mild NPDR	0.75	0.71	0.76
Moderate NPDR	0.52	0.63	0.57
Severe NPDR	0.44	0.37	0.40
PDR	0.60	0.59	0.59

On training these healthy retinal images, mild NPDR retina images, moderate NPDR retinal, severe NPDR and PDR using benchmark models like AlexNet, VGG16, VGG19, Resnet-50, DensNet 53 and Proposed Method gave the results as follows on training. The proposed method achived 93.5% accuracy with 60:40 ratio.

Table 2. Accuracy achieved in ALEXNET, VGG16, VGG19, RESNET-50, DENSENET53 and Proposed Method with 60:40 ratio

Models	**Accuracy**
AlexNet	73.14 %
VGG16	84.45%
VGG19	85.61%
Resnet-50	90.50%
DenseNet 53	88.50%
Proposed Method	93.55%

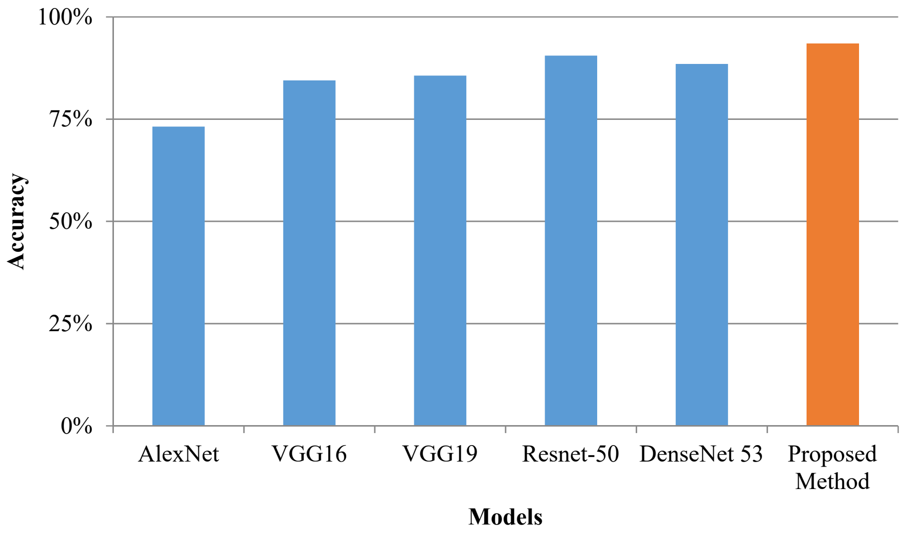

Fig. 5. Accuracy achieved in ALEXNET VGG16 VGG19 RESNET-50 DENSENET53 and Proposed Method with 60:40 ratio

While the dataset is trained with Healthy, Mild NPDR, Moderate, NPDR, Severe NPDR, PDR in 75:25 ratio that is 75% data for training the model and25% for testing the model the precision, recall and F-1 Scores achieved are as follows:

Table 3. Precision, Recall, F1-Score with 75:25 ratio

Category / QOS	**Precision**	**Recall**	**F-1 Score**
Healthy	0.97	0.95	0.96
Mild NPDR	0.85	0.81	0.86
Moderate NPDR	0.62	0.73	0.67
Severe NPDR	0.54	0.47	0.50
PDR	0.70	0.69	0.69

On training these healthy retinal images, mild NPDR retina images, moderate NPDR retinal, severe NPDR and PDR using benchmark models like AlexNet, VGG16, VGG19, Resnet-50, DensNet 53 and Proposed Method gave the results as follows on training. The proposed method achived 97.54% accuracy with 75:25 ratio.

Table 4. Accuracy achieved in ALEXNET, VGG16, VGG19, RESNET-50, DENSENET53 and Proposed Method with 75:25 ratio

Models	**Accuracy**
AlexNet	78.26%
VGG16	87.45%
VGG19	89.61%
Resnet-50	92.32%
DenseNet 53	90.45%
Proposed Method	97.54%

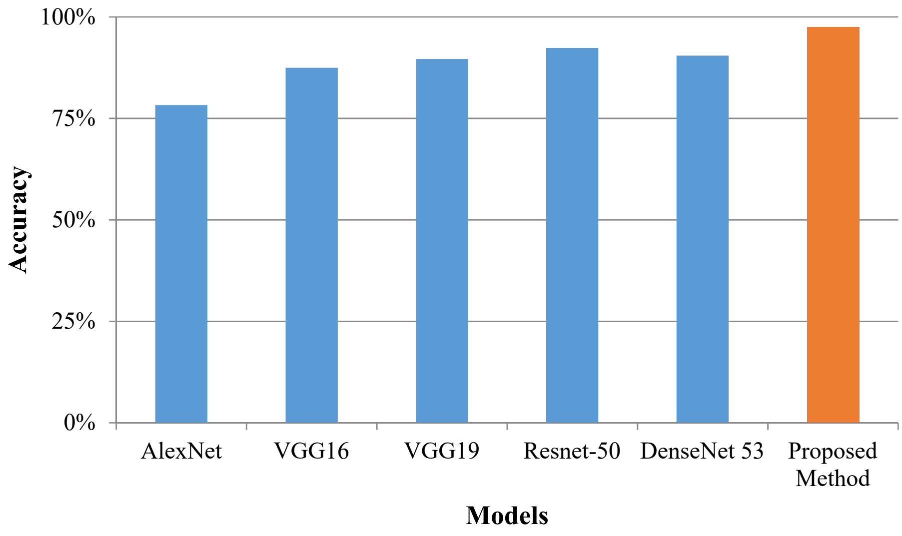

Fig. 5. Accuracy achieved in ALEXNET VGG16 VGG19 RESNET-50 DENSENET53 and Proposed Method with 75:25 ratio

5. Conclusion

The proposed idea of RetiLenz is a relatively new idea,which is taken from the inverse technology of google lens.This in combination with the capsules have generated good results when classified using the standard pretrained models like AlexNet,VGG16,VGG19 ,Resnet-50,DenseNet 53 and has given an accuracy of 97.54%. for the capsule neural network.This can be further enhanced by including the severity of the disease classification.

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Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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