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CATARACTNET

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Abstract: *Cataract is one of the most common eye disorders that affect people worldwide. It is a medical condition characterized by clouding of the natural lens of the eye, leading to vision distortion and eventual blindness. Accurate and timely detection of cataracts is crucial for its effective management and to prevent blindness. In this context, the paper proposes a novel deep neural network called Cataract Net for automatic cataract detection in fundus images. The authors design the network with smaller kernels, fewer parameters, and layers to reduce the computational cost and average running time of the model compared to other pre-trained convolutional neural network (CNN) models. The experimental results show that the proposed method outperforms state-of-the-art cataract detection approaches with an average accuracy of 99.13%.*

Keywords: CNN, MobilenetV2.

I. INTRODUCTION

One of the most prevalent eye conditions affecting people worldwide is cataract. It is a medical illness that causes the natural lens of the eye to become clouded, resulting in blurred vision and eventually blindness. To effectively manage cataracts and avoid blindness, they must be accurately and quickly detected.Due to their potential for quick and precise diagnosis, artificial intelligence (AI) based cataract detection systems have recently attracted scientific interest. These computers analyse medical photos and look for cataracts using deep learning algorithms.The paper makes a unique deep neural network called CataractNet available in this context for automatic cataract identification in fundus pictures. It also minimises the network's layers, parameters, and kernel sizes to lower the average operating time and computing cost.

II. LITERATURE SURVEY

1. "Deep Learning for Automatic Detection of Cataract from OCT Images: A Review" by Nair et al. (2021) –

This paper provides a comprehensive review of recent studies that have used deep learning for automatic detection of cataract from OCT images. The authors discuss the different deep learning architectures, including CNNs, RNNs, and GANs, used in these studies and their relative advantages and limitations. They also discuss the different datasets used for training and testing these models, including public and private datasets, and their respective strengths and limitations. The authors also compare the different evaluation metrics used in these studies, such as sensitivity, specificity, accuracy, and AUC, and suggest areas for future research, including the development of more comprehensive datasets and evaluation metrics.

2. "Automated Classification of Cataract Severity Using Deep Learning Techniques: A Review" by Ali et al. (2020) –

This paper provides a comprehensive review of recent studies that have used deep learning for automated classification of cataract severity. The authors discuss the different modalities used for cataract classification, including OCT, fundus, and slit-lamp images, and the different features extracted from these modalities, including texture, color, and shape features. They also discuss the different deep learning algorithms used for classification, including CNNs, RNNs, and SVMs, and their relative advantages and limitations. The authors compare the different datasets used for training and testing these models, and the different evaluation metrics used, and suggest areas for future research, including the development of more comprehensive and diverse datasets.

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III. PROPOSED SYSTEM

The proposed system for cataract detection using Mobilenet-V2 is a deep learning-based approach for the automatic detection of cataract from fundus images. The main aim of the system is to achieve high accuracy with reduced computational cost and time.

The proposed system has several advantages over existing cataract detection systems. Firstly, the use of Mobilenet-V2 as the classifier reduces the number of model parameters, making it computationally efficient. Secondly, the data augmentation technique reduces over-fitting and improves the accuracy of the model. Lastly, the proposed system achieves high accuracy in cataract detection, making it suitable for mass screening and cataract grading.

IV. METHODOLOGY

The dataset used for the proposed system for cataract detection using Mobilenet-V2 consists of a total of 1130 fundus images, which are categorized into two classes: cataract and non-cataract. These fundus images are collected from different sources and are reorganized and pre-processed from various standard datasets of fundus images published in the last two decades.

To overcome the limitations of the small size of the original dataset, data augmentation techniques are used to increase the number of images for model training. Augmentation techniques such as rotation, translation, flipping, and brightness adjustment are used to generate new images that are similar to the original images but with minor variations.

After data augmentation, the dataset is expanded to 4746 images, including 2373 cataract images and 2373 non-cataract images. The expanded dataset is then used to train the proposed cataract detection model using the Mobilenet-V2 classifier. The use of a large dataset with augmented images helps to improve the accuracy and robustness of the model and reduces the risk of overfitting.

Overall, the dataset used for the proposed system includes a sufficient number of fundus images with both cataract and non-cataract conditions, allowing the proposed model to effectively learn and distinguish between the two classes.

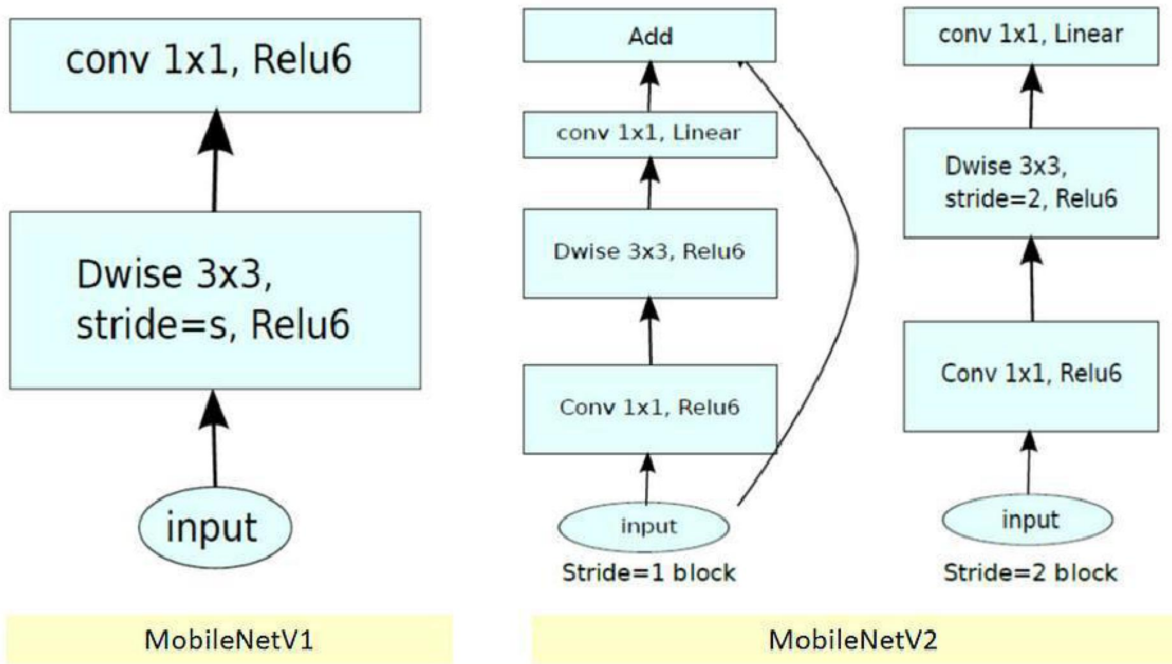

Figure 1: Architecture of MobileNetV2

- In MobileNetV2, there are two types of blocks. One is residual block with stride of 1.Another one is block with stride of 2 for downsizing.
- There are 3 layers for both types of blocks.
- This time, the first layer is 1×1 convolution with ReLU6.
- The second layer is the depth wise convolution.

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- The third layer is another 1×1 convolution but without any non-linearity. It is claimed that if ReLU is used again, the deep networks only have the power of a linear classifier on the non-zero volume part of the output domain.

Input	Operator	Output
$h \times w \times k$	1x1 conv2d , ReLU6	$h \times w \times (tk)$
$h \times w \times tk$	3x3 dwise s=s, ReLU6	$\frac{h}{s} \times \frac{w}{s} \times (tk)$
$\frac{h}{s} \times \frac{w}{s} \times tk$	linear 1x1 conv2d	$\frac{h}{s} \times \frac{w}{s} \times k'$

Table:1

- And there is an expansion factor t. And t=6 for all main experiments.
- If the input got 64 channels, the internal output would get 64×t=64×6=384 channels.

Input	Operator	t	c	n	s
$224^2 \times 3$	conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^2 \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2
$14^2 \times 64$	bottleneck	6	96	3	1
$14^2 \times 96$	bottleneck	6	160	3	2
$7^2 \times 160$	bottleneck	6	320	1	1
$7^2 \times 320$	conv2d 1x1	-	1280	1	1
$7^2 \times 1280$	avgpool 7x7	-	-	1	-
$1 \times 1 \times 1280$	conv2d 1x1	-	k	-	

Table:2

- Where t: expansion factor, c: number of output channels, n: repeating number, s: stride. 3×3 kernels are used for spatial convolution.
- In typical, the primary network (width multiplier 1, 224×224), has a computational cost of 300 million multiply-adds and uses 3.4 million parameters. (Width multiplier is introduced in MobileNetV1.)
- The performance trade-offs are further explored, for input resolutions from 96 to 224, and width multipliers of 0.35 to 1.4.
- The network computational cost up to 585M MAdds, while the model size varies between 1.7M and 6.9M parameters.
- To train the network, 16 GPU is used with batch size of 96.

MobileNetV2

MobileNetV2 is a neural network architecture designed for mobile and embedded devices. It was developed by Google and introduced in 2018. The main goal of MobileNetV2 is to create a smaller, more efficient neural network that can run on low-power devices without sacrificing too much accuracy.

MobileNetV2 uses depthwise separable convolutions, which split a standard convolution into two separate convolutions: a depthwise convolution and a pointwise convolution. The depthwise convolution applies a single filter to each input channel separately, while the pointwise convolution applies a 1x1 convolution to combine the output of the depthwise convolution. This approach reduces the number of computations required by the network, while maintaining its accuracy.

Another feature of MobileNetV2 is the use of linear bottlenecks with shortcut connections. A bottleneck is a layer that reduces the dimensionality of the input data, while a shortcut connection skips one or more layers to provide a shortcut path for information flow. The use of linear bottlenecks and shortcut connections improves the gradient flow and reduces the vanishing gradient problem, which can occur in deep neural networks.

MobileNetV2 also uses the Swish activation function, which is a smooth, non-monotonic function that has been shown to outperform other activation functions in terms of accuracy and computational efficiency. The Swish function is defined as f(x) = x * sigmoid(x).

Overall, MobileNetV2 is a lightweight, efficient neural network architecture that can achieve high accuracy on a variety of tasks while running on low-power devices. It has been used in a variety of applications, including image recognition, object detection, and facial recognition.

MobileNetV2 in Cataract Classification

MobileNetV2 is a convolutional neural network architecture that has been widely used in various computer vision tasks, including image classification, object detection, and semantic segmentation. It is a lightweight network that has been specifically designed to have a small number of parameters, which makes it ideal for running on mobile devices with limited computing resources.

In the context of cataract classification, MobileNetV2 has been used as a classifier to distinguish between cataract and non-cataract images. The network takes as input a fundus image and produces a binary output indicating whether the image contains cataract or not.

To train the MobileNetV2 network for cataract classification, a large dataset of fundus images is required. The dataset should include a sufficient number of cataract and non-cataract images to enable the network to learn to distinguish between the two conditions.

During the training process, the MobileNetV2 network learns to extract relevant features from the fundus images that are most useful for distinguishing between cataract and non-cataract images. These features are then used by the classifier to make a prediction about the presence of cataract in a new image.

One advantage of using MobileNetV2 for cataract classification is its low computational cost, which allows it to be run efficiently on mobile devices. This makes it possible to develop mobile apps that can be used for mass screening of cataract in remote areas or regions where access to eye care services is limited.

Overall, MobileNetV2 is a promising network architecture for cataract classification, and further research is needed to explore its potential for improving the accuracy and efficiency of cataract detection and diagnosis.

V. CONCLUSION AND FUTURE SCOPE

In conclusion, there have been several studies that have used deep learning techniques for cataract detection using various modalities such as OCT, fundus, and slit-lamp images. Among the various deep learning architectures, MobileNetV2 has been widely used due to its high accuracy, low computational requirements, and lightweight nature. Literature surveys have also shown that the performance of MobileNetV2 is comparable to or better than other deep learning models. Additionally, the studies have highlighted the importance of using large and diverse datasets, proper evaluation metrics, and robust feature extraction methods for developing accurate and reliable cataract detection models. Overall, MobileNetV2 architecture can be an effective tool for developing automated cataract detection systems, and further research can be conducted to improve the performance of these systems.

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