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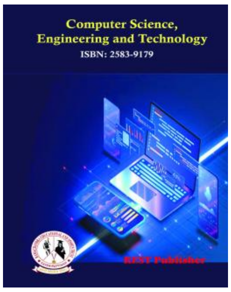

Improving Detection of Eye Cataract Disease by Transfer Learning Technique with Convolutional Neural Network

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Abstract: *One of the most usual eye diseases is cataracts and individuals get during their aged and it happens whenever the eye lens forms a fog. Major symptoms and signs of the disorder include blurry vision, difficulty in looking bright light and fading colors. These symptoms are commonly associated with difficulty accomplishing a variety of tasks. Thus, early cataract detection and treatment may help to reduce the incidence of blindness. The present research employs Convolutional Neural Networks (CNN) to classify cataract illness using a publicly accessible image dataset. The suggested CNN combines the MobileNet as Transfer Learning (TL) benefits with CNN as pre-trained for obtaining better feature understanding of data that correlate among the patches. When compared to traditional diagnosis techniques, image classification using CNN is a potentially high-performing and cost-effective solution. Thus, the current research aims to develop a technique for cataracts prediction. Normal human being may have difficulty in detecting early and slight modifications in the optic disc. This research work has access in identifying the cataract using fundus images are identified with respect to a complete ophthalmologic examination. Hence, the encoder of Deep Learning (DL) may be trained basic features in fundus images for individuals with early stage cataracts.*

Keywords: *Fundus images, Cataract detection, Transfer Learning, Convolution Neural Network, MobileNet*

1. INTRODUCTION

Cataracts occur if the lens within the eye becomes clouded. This condition develops progressively with age and might result in blurred or glare vision. Cataracts render it harder to see distance things and read small fonts. Cataracts are the major cause of blindness for aging population, imposing a significant financial burden on both countries and people. The lens with circular and transparent portion of the eye which continues ahead of the iris, refracts light towards the retina [1]. Eventually, it may hinder vision as well as cause vision loss for persons over the age 40 years. Based on the cataract severity, early detection has save people from painful as well as expensive surgeries and mitigates blindness. According to the World Health Organization (WHO), over 285 million individuals in worldwide are visually impaired. There are 39 million peoples are blind, whereas the rest encompass damaged eyesight. Cataracts are considered with 33% visual impairment as well as 51% blindness. In 2020, there are several individuals are suffer from moderately to severe vision impairment (MSVI) as well as the blindness would rise to 237.1 million and 38.5 million correspondingly. Cataracts will impact with 24% (57.1 million) as well as 35% (13.4 million). In 2025, the world's blind population will reach nearly 40 million [2]. Analyzing the findings of these surveys reveals that the eye care scheme and the prevention of vision loss have merely improved slightly over past 10 years. Cataracts are the greatest frequent blindness cause tracked by glaucoma [3], corneal opacity, trachoma, as well as diabetic retinopathy [4] which is considered as the most primary blindness causes [5]. Early identification of cataracts is critical for effective treatment as well as may drastically minimize the blindness risks. Providing an autonomous method for cataract identification is a difficult task for three major reasons are

1. Gender, age and the eye type
2. Scales, location and the form of cataracts
3. Cataract lesions with large spectrum as well as the eye tones

Recently, the possibility of autonomous cataract detection using several different types of imaging is being researched. In general, automatic cataract diagnosis and classification techniques use four distinct image types are retro-illumination, slit lamp, fundus images and ultrasound. Despite these methods of imaging, fundus images are getting a lot of attention in the field because technologists as well as individuals may readily use the fundus camera. In other hand, Slit-lamp cameras are employed only trained ophthalmologists. Finally the findings determines the professional ophthalmologists scarcity specifically for developing countries, prevents timely diagnosis and treatment. In order to streamline the procedure of cataract screening earlier with automated cataract detection method has utilized fundus image are majorly focused. AI-based cataract diagnosis systems rely primarily upon global attributes, while local features and deep feature-based approaches have demonstrated greater accuracy. However, there are many DL based automatic cataract detection techniques are currently published in the literature, most still have disadvantages like less detection accuracy with several model parameters are higher in computational costing. Recent developments in surgical procedures have significantly enhanced cataract surgery, resulting in a less invasive operation with quick vision recovery as well as good visual prognosis. The posterior capsule rupture (PCR) have causes a breach in the posterior capsule of the crystalline lens is captured as being present in only a minority of cataract procedures, ranging from 0.2% to 1.8%. This issue has substantial consequences, involving the difficulty of properly placing an intraocular lens (IOL), the danger of endophthalmitis, as well as the development of cystoid macular edema. Surgeons generally assess the PCR probability prior to surgery for mitigating the dangers related to this impediment. Their comprehension provides this evaluation that frequently includes a grading system [6]. Computer-aided design (CAD) tools may improve the accuracy as well as objective associated with these risk evaluations through offering an automated and controlled method for minimizing the occurrence of PCR [7]. These computerized approaches might decrease the PCR incidence, reduce the limits of traditional methods of evaluation, and improve caregivers as well as PCR detection in healthcare using CAD tool [8]. The glaucoma diagnosis is an initial step toward discovering the etiology of the retinal disorder that can increase damage to the optic nerve and result in progressive, permanent vision loss. Several DL architectures are being designed for the classification issue, each with a unique process of methodology and classification outcome. To obtain comparable accuracy, certain DL methods have been used, including pre-trained CNN models including AlexNet, ResNet-50 and VGG-16 [9-11]. This is crucial to highlight and these architectures are deep and complicated which require extensive training and testing. This research describes a CNN-based technique to perform automatic catract identification from fundus images using MobileNet as TL. The suggested solution was tested using the ODIR dataset, and it outperformed earlier approaches using the same dataset in a variety of criteria. Hence, the proposed MobileNet as TL with CNN generate better catract detection using both eyes fundus images.

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2. LITERATURE REVIEW

The fundus images make it feasible to identify and classify the cataracts. A significant portion of traditional cataract diagnostic procedures rely on optical coherence tomography as well as human-engineered features. Hossain et al. have provided significant advances to the cataract diagnosis field by developing an advanced strategy that employs Deep CNN (DCNN) as well as Residual Networks (ResNets). This research involves getting high accuracy in cataract severity classification [12]. Similarly, Zhang et al. have revealed detection of cataract technique employed ensemble method and incorporates ultrasound images for enhancing accuracy, outperforming other DL methods with an impressive 97.5% precision [13]. The system that's suggested involves 3 major components namely object detection network, model fusion module and multiple categorization networks. The model's performance evaluation yielded adequate outcomes, especially in circumstances with little training data. Moreover, it is critical to recognize a major weakness of technique whereas the image clarity reliance as per guideline for determining cataract seriousness, which can be impacted by various ocular, disorders namely corneal opacities as well as diabetic retinopathy. Thus, the approach might be ineffective in discriminating among various ocular disorders types. Shimazaki et al. have identified CNN and RNN approaches significantly enhanced the diagnosis of nodular as well as malignant tumors with radiology [14]. The challenges in finding nodules stems because of similarity in tumor structure with ordinary structures. There are two ways for finding lesions employing DL detection as well as segmentation, with the traditional method offering more comprehensive data. Employing structured data with training as well as validation, the DL-based models was built to detect lung cancer over radiographs. Hosseini et al. have offered comprehensive evaluation of the advancements gained in applying DL approaches for predicting small-sized as well as non-small cell lung tumors [15]. The summary covers all five DL models step for development in input image, IP, designing architecture, hybrid model generation, and TL. The tiny dimensions of nodules needs sensitive detection approaches, making earlier lung cancer prognosis as challenging. Zhang et al., have recently proposed attention-based Multi-Model Ensemble technique for automated cataract identification using ultrasound images with proposed method have achieved the highest accuracy as 97.5% among the other DL methods [16]. In this technique, the entire system has been constructed up of three major components namely object detection method, tree classification method, and finally with model ensemble method. The performance remained poor yet adequate, particularly in situations of insufficient training samples. The fundamental shortcoming of this method was it assessed the degree of cataract depending on the blurring of retinal images that can be a result of cataracts as well as other eye disorders like corneal edema as well as diabetes mellitus. Evaluation results determine the proposed approach may be ineffective for distinguishing between different forms of eye disease. Khan et al. have accomplished nearly same accuracy as 97.47% for fundus images using the VGG-19 model and a TL strategy on a previously published dataset [17]. In a further investigation by Pratap and Kokil, the diagnosis of cataract was studied in a noisy setting. For feature extraction, a pre-trained CNN was employed, that was made up of both globally and locally trained separate with support vector machine model [18]. The observed findings demonstrated its resistance to noise and it was the first study to look into the resilience of cataract detection methods. Moreover, this study established a trained classification model employing the ResNet model presented an autonomous cataract detection technique using DCNNs [19]. The suggested methodology provides a mechanism for automatically classifying colposcopy image using MobileNetV2 method. The input consists of 3 separate image models are a green lens, VIA, and VILI. MobileNetV2 is an inverse residual as well as module of linear bottleneck layer that drastically decreases the memory needed to perform processing [20]. In an associated investigation, an efficient framework was suggested that used as TL with MobileNetV2. This type has been designed to consume less power devices with very few resources. It improved the fundamental MobileNetV2 design by adding a new convolution as well as dropout layer. Thus, the feature extraction used target with five classes of fruit dataset using 3213 trained images which is then fine-tuned using Softmax layer in MobileNetV2 with training dataset. The validation dataset included 457 fruit images that generate an output with accuracy as 85.13% [21].

3. RESEARCH METHODOLOGY

Research work concentrates on recognizing cataract patients by IP of both eyes fundus images. Retina images are gathered is preprocessed using MobileNetV2 as TL, in which the images are carefully processed and classed to provide better detection of cataract, which is a hazardous eye illness that can cause blindness. There are numerous CNN architectures accessible, but further data is gathered through channels from other aspects that were not present in the pre-training original channel. Figure 1 illustrates the architecture of MobileNetV2 with CNN method for diagnosing the cataract detection by fundus images shown in figure 1. In this experimental research, the MobileNetV2 act as TL used to avoid bias by pre-trained images using MobileNet V2 with stride as 2 for the image has comprised with convolutional layer with Relu and output with linear layer process.

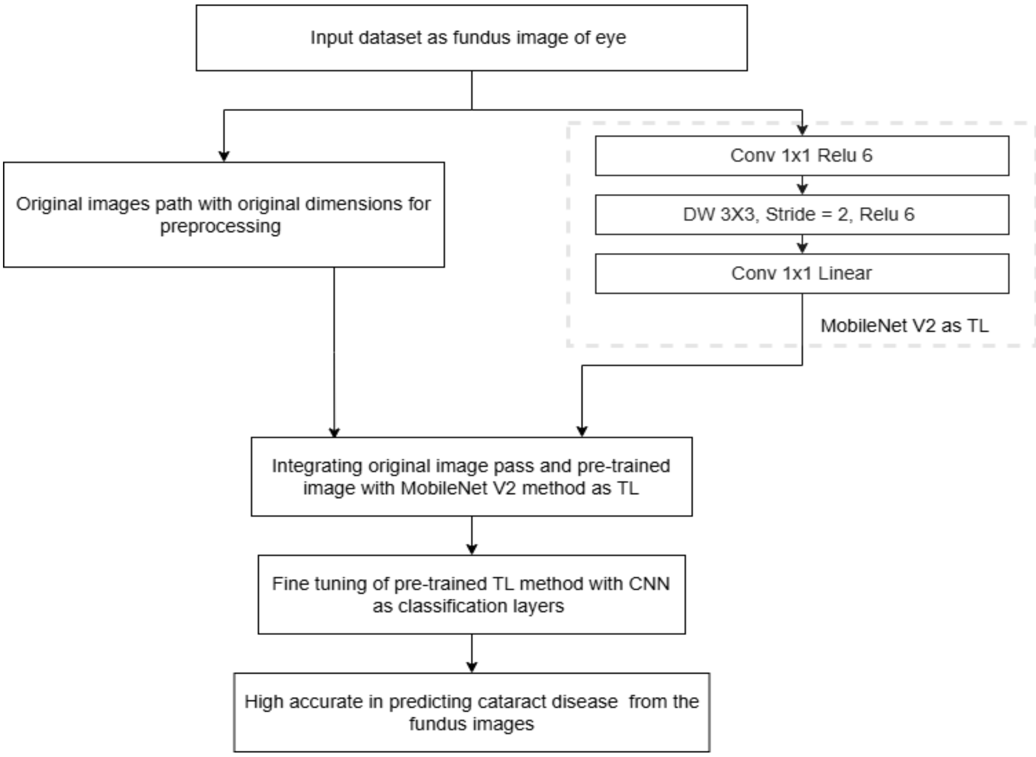

FIGURE 1. MobileNet V2 with CNN in predicting cataract diagnosis

Data collection

Dataset collected are fundus images include 5000 individuals with 6392 images accessible, including both eye fundus images, and details about the patient such as patient ID, gender, and age. Involved dataset contains variety images from ocular disease images and this experiment involves cataract disease. The dataset acquired by M/S. Shanggong Medical Technology Co., Ltd. from several hospitals/medical facilities in China. There are different forms of ocular disease in fundus images whereas this experimental work focuses on cataracts as well as cataract-related diseases. Figures 2a and 2b depict images of normal individuals as well as cataract patients who may be affected by cataract owing to natural aging, which is the most important criteria for early diagnosis of cataract.

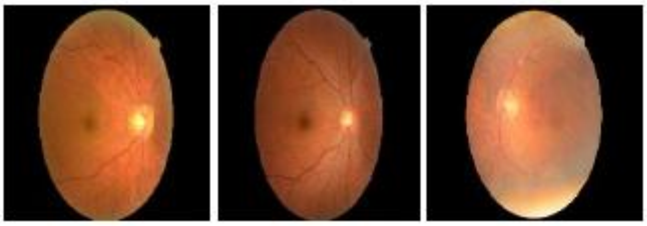

FIGURE 2 a. Sample fundus images of normal eye from image dataset

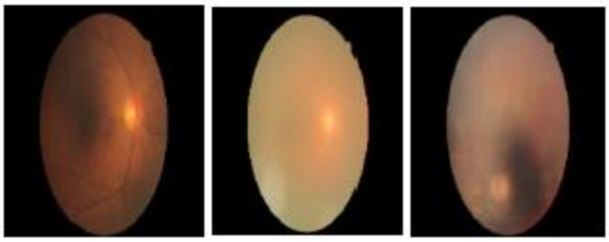

FIGURE 2 b. Sample fundus images of cataract eye from image dataset

The suggested technique involves MobileNetV2 that improved on mobileNetv1 by including modules of linear bottleneck as well as inverted residuals. The MobileNet architecture was built around depth-wise separable convolution. Typical 2D convolution generates output channel through each input channel get processed individually and also convolve in the depth size. The convolution of depth-wise has divided the input image as well as filter towards independent channels prior to convergence of each input channel with associated filter channel. Once it generated, the output channels obtained from filtered are joined. The segregated convolution depth-based is then applied for aggregating the mounded output channels towards a single channel and get filtered with 11-fold cone is said to be point-worst cone. The segregated convolution depth-based has produces the identical result as the typical convolute since it employs less parameters which generate high efficiency. Major advantages of MobileNet models are smaller size in nature that results in robust inference times with less power consumption. MobileNetV2 offers improvements like linear bottlenecks as well as inverted residuals to improve the model's capability while remaining efficient. Thus, the results with high accuracy that is comparable to several methods. It determines that MobileNetV2 an excellent selection for diagnosing applications in real-time performance. Furthermore, MobileNet methods provide versatility by configurable parameters such as the width multiplier as well as resolution multiplier that allow practitioners in customizing the model in meeting its individual requirements. This experiment utilized Keras as well as TensorFlow for training a classifier that can recognize whether or not a person has cataract disease or not. Moreover, this work by fine-tuning the MobileNetV2 with CNN has resulted an exceptionally efficiently design has deployed to embedded devices because to its lightweight nature, while drastically lowering computation and model size during training. Hence, the capability of DL technique on personal mobile devices have enhance the individual experiences using threshold range in diagnosing cataract disease, as well as providing further remuneration for security, resilience and energy consumption. This research employed fine-tuning to construct a baseline model as CNN to generate better model understanding. Fine-tuning procedure steps are as follow.

Step 1: Loading the MobileNetV2 as pretrained weights that breaches head of network

Step 2: Construct a novel Fully Connected head as well as attached with base instead of old one.

Step 3: Freezing the network base layers and the weights of these base layers won't be updated at the backpropagation process. The head layer weights will be tuned.

4. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed CNN with MobileNetV2 method learning is potential for accessing in performance of eye disease dataset with and without TL. In this study, data from eye fundus image is considered as a potential input for learning in the target of cataract disease using CNN model of 2D convolution operators on information regarding eye disease dataset. Moreover, it focuses on early detection of cataract patients using fundus images. The brightness of each pixel in the image fluctuates depending on the patient's features. In the eye illness dataset, the MobileNetV2 technique as pre-trained weights has been fine-tuned at testing. The parameters of input is assigned equal to 224 pixels with respect to input image size (Length x width), the size of batch at training was set to 32 images, and the number of epochs was set to 45. The training mode is designed to iterate for 45 epochs for obtaining gain and better model knowledge understanding which aids in providing high accuracy in early prediction of cataract disorders. Figure 3 illustrates the training and validation of proposed model as CNN-MobileNet with TL in which training accuracy 86.17% and a validation accuracy of 88.08% after 25 epochs. The training accuracy began at 49.74% at the first epoch and gradually climbed to 93.67%, while the validation accuracy began at 16.82% and increased to 92.75%. As the period progresses, the CNN fine tuning aids in boosting validation accuracy to 92.75%.

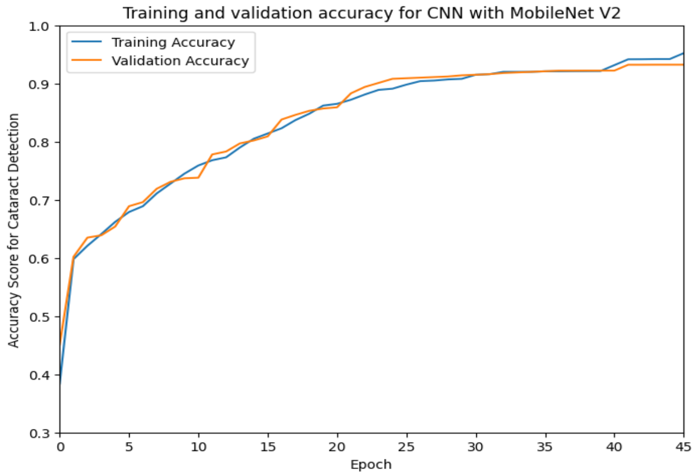

FIGURE 3. Accuracy for proposed CNN-MobilenetV2 model in cataract detection

Figure 4 illustrates the training and validation of proposed model as CNN-MobileNet with TL in which loss training and validation of the proposed CNN-AE model for cataract fundus images. The loss of the CNN-MobileNet with TL model began at 1.362 and gradually decreased as the epoch count increased, eventually reaching 0.068 at epoch 45. Similarly, the validation loss fell from 2.176 to 0.070 at epoch 45.

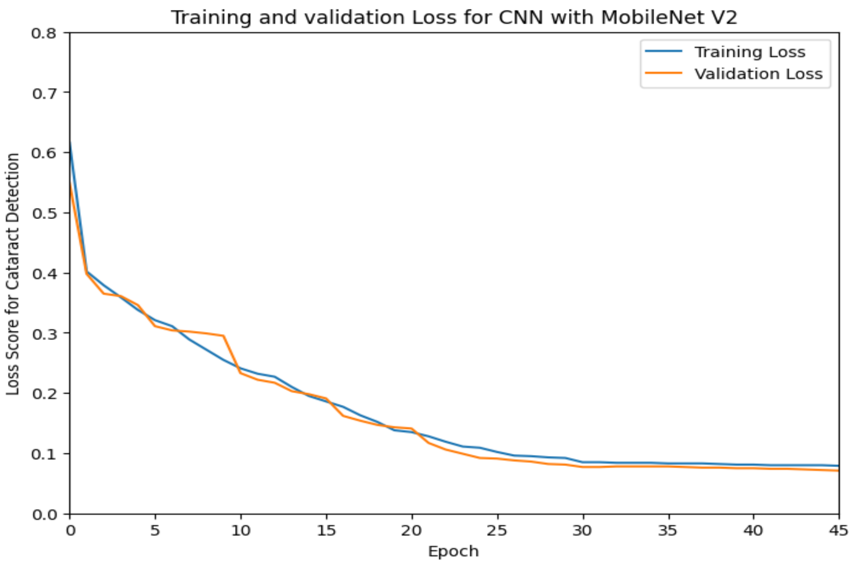

FIGURE 4. Loss for proposed CNN-MobilenetV2 in cataract detection

According to table 1 and figure 5, the accuracy of training and testing of CNN-MobilenetV2 model is 93.67% and 92.75% correspondingly is higher than CNN-AE and MobileNetV2 which is 92.16% and 92.09% as well as 90.84% and 90.61% respectively. The model has performed better result in of CNN-MobilenetV2 method.

TABLE 1. Comparison of accuracy performed for various classification methods

Evaluation Metrics for detecting cataract	CNN-Mobilenet V2 with VGG19	CNN-AE method	MobileNet V2
Training	93.67	92.16	90.84
Testing	92.75	92.09	90.61

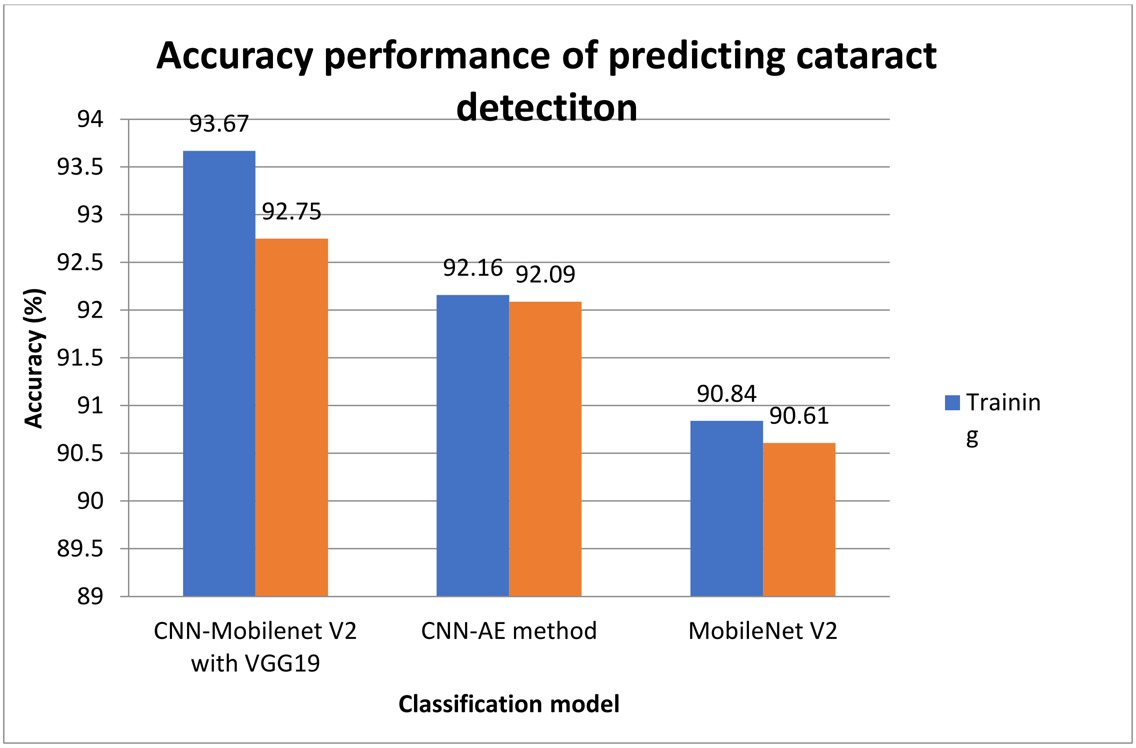

FIGURE 5. Accuracy performances for various classification methods in predicting cataract disease

TABLE 2. Comparison of loss performed for various classification methods

Evaluation Metrics for the DL models	CNN-Mobilenet V2	CNN-AE method	MobileNet V2
Training	0.068	0.965	0.985
Testing	0.075	1.175	1.965

According to table 2 and figure 6, the loss of training and testing CNN-MobilenetV2 model is 0.068 and 0.075 correspondingly is comarively lesser than CNN-AE and MobileNetV2 model in testing are 0.965 and 1.175 as well as 0.985 and 1.965 respectively. The model has performed better result in of CNN-MobilenetV2 method.

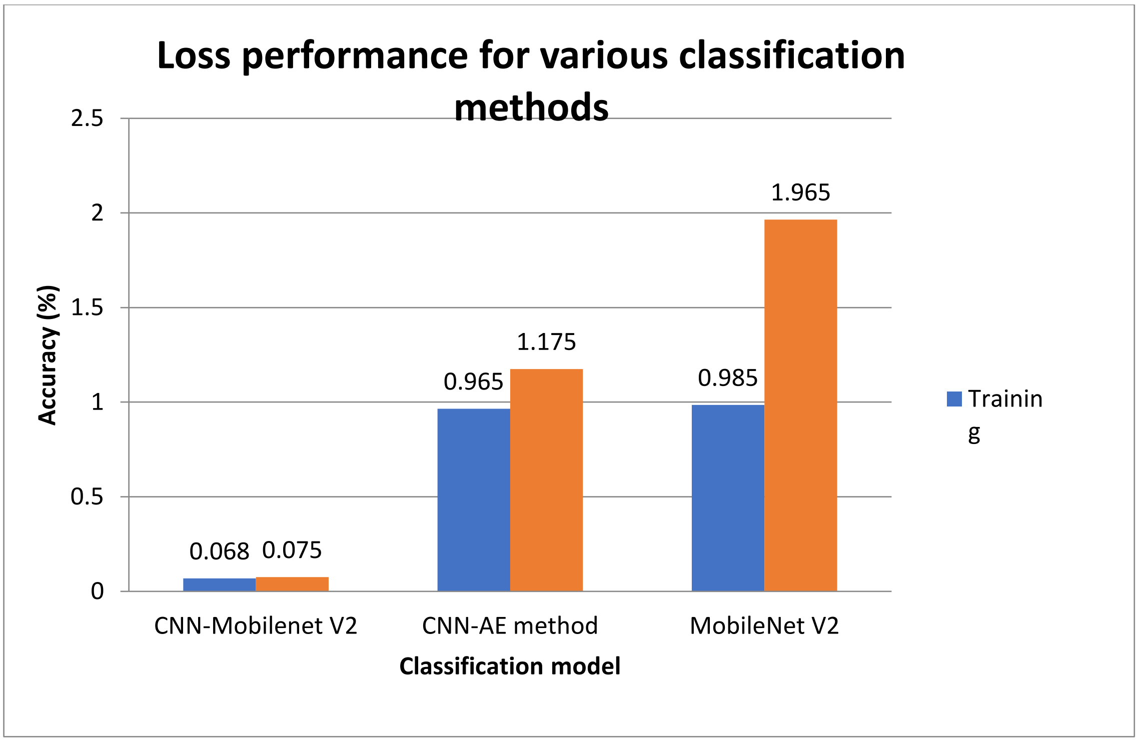

FIGURE 6. Loss performances for various classification methods in predicting cataract disease

Based on obtained result, the proposed CNN-MobilenetV2 model has produce high accuracy in predicting cataract disease. The validation accuracy CNN-MobilenetV2 is 92.75% higher than other TL method (CNN-AE) and no TL method (MobileNetV2).

5. CONCLUSION

This study introduced a novel approach called MobilenetV2 to improve the functional strength of CNN. CNN has performed much better as a result of the use of artificial intelligence. However, CNN's design incorporates the MobilenetV2 notion, and TL has an improved generative model that utilized in improving result in input representation. As a result, the MobilenetV2 technique functions as auxiliary learner, separating the dispersion as well as variation of an input data. The TL performance assist in producing channels from auxiliary learners that are accessible with the original CNN model's feature set, allowing for the establishment of a complicated feature hierarchy. To further reduce processing time, TL is used to fine-tuning the proposed model using CNN-MobilenetV2 training. Thus, the suggested model outperforms with high prediction results in detecting cataracts. The accuracy of training and testing are acquired for fundus image data samples collected from the right eye demonstrating a high accuracy in predicting cataract disorder as 92.75%, compared to other existing method. Furthermore, the objective is to deploy several auxiliary learners in both supervised as well as unsupervised settings.

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