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Human Eye Disease Detection And Classification Of Retinal Imagery Using Mobilenet Cnn

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ABSTRACT:
Eye diseases are crucial to be diagnosed at the initial stage. The physical diagnosis is inaccurate, expensive, slow, and could not be available to people in inaccessible or underdeveloped locations. High-resolution photographs of the eye's internal components can be obtained using imaging techniques like OCT and fundus photography, but these methods also necessitate expensive equipment, trained operators, and may not be able to spot early-stage illnesses. Additionally, these techniques provide a lot of data that can be challenging to analyse and interpret, delaying both diagnosis and therapy. Due to the shortcomings of present techniques, a more precise and effective strategy for finding eye illnesses is required (Rafay A et al., 2023). Machine-learning algorithms provide faster responses and are more accurate. However, the inherent limitations of machine learning algorithms result in compromised accuracy, which can be improved using the latest deep learning algorithms. In this context, the proposed study uses a MobileNet convolutional neural network, which has superior performance in detecting cataracts, glaucoma, and diabetic retinopathy compared to normal eyes. The results indicate that the proposed algorithm results in 95% accuracy in detecting the mentioned diseases, which is the highest in contrast to recent state-of-the-art algorithms observed in the existing literature.

I.INTRODUCTION:

The number of eye diseases is increasing day by day, and their manual detection involves multiple challenges. The image classification techniques are used to classify various diseases and healthy ones (Sarki et al., 2021; Raza et al, 2016; Khaskheli et al, 2024). The image classification algorithms are capable of classifying input labelled data, keeping in view the relevant features. The diseases are characterized by their fundamental characteristics. The first stage is to get an image of an eye. Several detection methods can be used to get a clear picture of an eye. The algorithms learn from various images (Sarki et al., 2020). The fetched images are pre-processed before being passed to the detection algorithm (Data Cleaning in Eye Image Dataset, n.d.). The preprocessing of image data includes a variety of tasks, including setting the values of pixels, photo scaling to optimal resolution, and minimizing unwanted data or outliers that may jeopardise accurate analysis. The diseases in the dataset must be labeled. The input data set works as fuel for the training algorithm; the algorithm cannot be trained without understanding the numerical depths in the dataset. Once the dataset is obtained, the selection of the classification algorithm is a very crucial stage. Since modern neural networks are capable enough to learn the depths of images, they are widely used to detect eye diseases. Deep neural networks learn the depths from a given dataset of images. The deep neural networks fetch the input data and train the model, keeping in view the depths in the dataset. In the later stages, the dataset is tested, and the performance is tested based on a variety of evaluation parameters, which include the calculation of prediction errors, accuracy, precision, etc. (Emmert-Streib et al., 2020; Koondhar et al, 2021).
Modern deep learning techniques are capable enough to detect eye disease with higher accuracy compared to physical treatment (Bali & Mansotra, 2024). The deep learning techniques have the added benefit of reducing human error, which is more often found in physical treatment, thereby increasing accuracy in interpreting the eye disease. Machine learning algorithms train themselves based on the datasets, predict eye diseases well before the appearance of symptoms, and direct treatment based on the urgency of treatment. The patients' needs are also met with the customization of the algorithms and direct the patients, which is analogous to health care operators. A machine learning algorithm also helps the health care operator diagnose the disease well in advance, which saves money and reduces the risk of extreme severity. In this way, the resources needed by eye technicians can also be reduced, which further minimizes the expenditure. The people in the remote areas are also privileged with the help of modern techniques; treatment in remote areas becomes possible without the physical presence of a health care operator. The correlations in the eye disease dataset and the detection of patterns are possible only with the help of machine learning algorithms, since health care providers cannot easily interpret the correlations with higher accuracy compared to machine learning algorithms. In summary, the machine learning algorithms have made detection and treatment much easier compared to conventional techniques, which require huge amounts of effort, labour, resources, and cost and are prone to low accuracy in detecting eye diseases.

In this context, a variety of works are presented in the existing literature. The existing studies indicate that a lot of work has been carried out to classify eye diseases with higher accuracy. A recent review of the literature is presented below. Prittopaul et al. (2023) observed that many people have diabetes, and if it is not well treated, it can result in eyesight loss. The diagnostic processes used today can be laborious and imprecise. A deep learning technique, namely recurrent convolutional neural networks, is used in this study to classify the severity of eye disorders in diabetics (Rafay et al., 2023a). An article published by Khan et al. (2022) highlighted the difficulties physicians encounter when diagnosing eye disorders using fundus photographs. The authors proposed a computer-aided method for the detection of a variety of eye disorders by using fundus photographs. This method classifies ocular disorders based on photos from the ODIR dataset by combining deep learning techniques with cutting-edge image classification algorithms like VGG-19. A study conducted by Berbar (2022) identified and classified diabetic retinopathy severity without segmenting lesions in fundus photographs. To retrieve and encode uniform local binary patterns (LBPs) from the images, a sequence of preprocessing procedures was carried out to standardize brightness. As a result of the proposed CNN model and Support Vector Machine (SVM), the binary classifier achieved the highest accuracy rate of 98.84% (Berbar, 2022). Kumar et al. (2022) highlighted technological constraints that impede medical specialists. However, with technological developments, a significant impact on diagnosing medical conditions, especially in ophthalmology, has been observed. The outcomes of the study indicated that the proposed method classifies different eye illnesses using Coherence coherence tomography pictures showing neovascularisation, diabetic macular oedema, and drusen. 95.6% of the testing data and 97.79% of the training data were accurately predicted by this autonomous model. Using advanced machine learning algorithms, Pahuja et al. in 2022 significantly improved the efficacy of early cataract detection by using 85.42 percent and 87.08 percent accuracy, respectively. He, J. et al. (2021) highlighted the importance of fundus images; however, the algorithms used to analyze these photos are still limited to recognizing a specific type of disease and frequently only look at one eye at a time. The dense correlation network (DCNet), a novel approach utilizing convolutional neural networks, has been developed to precisely diagnose patients and identify numerous potential problems. A publicly accessible dataset was used to evaluate the model, and the results were noticeably better than those of other approaches. To prevent vision loss, it is critical to identify and treat eye illnesses as soon as possible. To this end, improved diagnostic instruments are required He, J. et al., (2021). Nazir et al. (2021) highlighted that individuals with diabetes are at risk of developing eye conditions like diabetic retinopathy (DR) and diabetic macular oedema (DME) (Koondhar et al, 2015).

Serte et al. (2021) highlighted important findings and major conclusions from current research on the use of deep learning to identify disorders of the skin, thorax, and eyes. The article highlights the limits of these studies in providing a comprehensive summary of the topic and aids in identifying potential avenues for future research (Serte et al., 2022; Mukhtiar et al, 2021). He, J. et al. (2021) proposed that blindness can result from eye illnesses, and fundus imaging is a useful and economical early screening tool to stop this from further diffusion. Although some eye disorders have been successfully identified using deep learning, most research has only looked at one condition. Using the dataset, the efficacy of several state-of-the-art deep learning networks was evaluated. It was found that enlarging the network was insufficient to accurately classify several diseases. Rather, a systematic feature-fusion approach combining features from several diseases was required. Recently, Topaloglu et al. (2023) proposed convolutional neural networks (CNNs). The suggested model resulted in a recall of 83 percent and a training accuracy of 87 percent.

In the recent state of the art, it has been investigated that the available literature suffers from a few drawbacks. Since physical diagnosis is expensive, time-consuming, prone to errors, and not available in certain conditions, the viable option is to use modern diagnosis mechanisms for detecting eye diseases, which is one of the important aspects of telemedicine. OCT and fundus photography can be used to fetch the image of an eye; however, the mentioned methods are costly, unavailable in certain conditions, and require skilled trainees (Grace, n.d., Rafay et al., 2023a). Furthermore, the mentioned methods require the collection of large amounts of data, which is challenging to interpret, which further impedes the treatment procedure. Therefore, an alternative mechanism needs to be investigated that is more accurate and detects eye disease more easily. Furthermore, the system should diagnose the disease well before the symptoms appear and be available in remote areas. Summarizing, the required system mitigates the drawbacks of the existing diagnosis and improvises the treatment procedure. The existing studies have two limitations. In a few studies, the algorithms were not efficient enough to detect eye diseases with higher accuracies. The performance declines with large datasets, or in some cases, the model overfits and results in biased classifications, which jeopardise the model's performance. In a few studies, fewer eye diseases are considered, which limits the scope of the studies. An alternative approach involving huge datasets and detecting eye diseases with higher accuracies needs to be investigated. In light of the limitations observed in the existing state of the art, the presented study has the following contributions:

1.To develop methodology for accurate identification of eye diseases using MobileNet CNN- based algorithm

2.To simultaneously detect cataract, diabetic retinopathy, and glaucoma with large dataset

3.To validate the effectiveness of developed algorithm against some recently used algorithms.

The organization of the research article is discussed. The research methodology is presented in Section II. The results obtained using the presented research methodology are presented in Section III. In the end, conclusions are drawn based on the obtained results and are presented in Section IV.

II. RESEARCH METHODOLOGY

According to the present research, convolutional neural networks (CNNs) have been highlighted as an innovative approach to precisely detect a range of ocular dysfunction via conventional, expensive to execute, and labour-intensive diagnostic strategies. Convolutional neural networks (CNNs) have been implemented in the experiment to achieve a secure a segment on healthy eyes, retinopathy, and glaucoma. The entire number of samples in the dataset reached 4217.

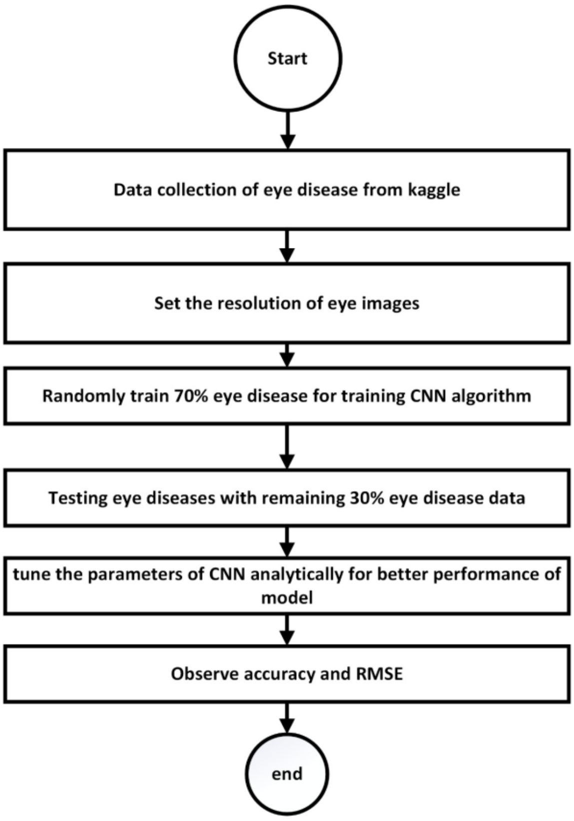

Figure1: Proposed Methodology

As mentioned earlier, there were 4217 samples altogether in the dataset. The dataset requires being segmented into training and testing subsets prior to training a convolutional neural network (CNN) model. The optimal split ratio in a harmonious dataset is 70/30. The 70% dataset, featuring 2949 samples, will be viewed as the training dataset. Yet, the remainder of 30% of the dataset which demonstrates and encompasses 1268 testing samples will be qualified as the testing dataset. A Python module entitled split-folders[1] has been employed to organize the dataset. Once the dataset was submitted to the model for training, it underwent pre-processing.

The standard preparation approaches, including scaling and adjusting the image, were implemented. The Convolutional Neural Network generated the image with dimensions of 224 × 224. The visual representation of the input that has been provided to the convolutional neural network for training. The model gained plenty from the resizing and normalizing operations.

2.1 Proposed MobileNet Architecture

MobileNet was established specifically to permit efficient processing of mobile and built-in gadget systems with disciplined computational measures. Developed and submitted by Google researchers in an article entitled as "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications." The distinctive features of the MobileNet architecture encompass:

2.1.1 Depth wise separable convolution:

Depth wise separable convolutions, powered by two discrete functions: depth wise convolution and pointwise convolution-inverses standard convolutional layers in MobileNet. The segmentation results in retaining the network's representativeness by considerably reducing number of parameters and statistical expenditure.

2.1.2 Depth wise convolution

An assorted dynamic of feature models is generated by particularly complexing specific input channel via its complementing filter. The algorithmic cost is reduced by figuring out the convolutional functionality accompanied by the channel dimension.

2.1.3 Pointwise convolution

The resultant feature maps obtained by depth wise convolutional layer are blended with a pointwise convolution following depth wise convolution. Pointwise convolution minimizes the complications of the feature space by executing a linear combination of input channels through 1x1 filters.

[1] https://pypi.org/project/split-folders/

2.1.4 Width multiplier and resolution multiplier

To compensate the commutative expenditure and authenticity of the model, two meta parameters of the MobileNet are initiated. Specifically named as, width multiplier and resolution multiplier. Considering that the resolution multiplier modifies the image resolution. Whereas the width multiplier multiplies the channel's number per layer.

2.1.5 Efficient architecture design

Contrary to standard CNNs, MobileNet incorporates a minimalistic architectural framework with minor constraints and commutative methods. MobileNet architecture attains an equilibrium among model size, accuracy, and efficiency. Thereby making it ideal for installation on gadgets with inadequate resources.

Inclusively, MobileNet architecture allows an alternative trade-off among computing power and model accuracy and is specifically optimized for mobile and integrated vision systems. Because of its powerful architecture, the programmed operates proficiently on systems with finite computational capability for operations like, semantic division, object identification and image categorization.

2.2 Metrics evaluation methods

The proposed study employed a selection of widely recognized performance criteria, notably accuracy, precision, recall, F1-score, and support, to figure out the utility of the model. As suggested by Eq. 1, precision quantifies the model's accuracy in identifying essential data fragments and is computed by dividing the number of true positives by the entire number of true positives and false positives.

Precision = $\frac{TP}{TP+FP}$ (Eq 1) reference?

The potential of a classification model is to track down all significant occurrences within a dataset that can be evaluated by its recall. As shown in Eq. 2, it is estimated by dividing the number of true positives by the total of true positives and false negatives.

Recall = $\frac{TP}{TP+FN}$ (Eq 2)

In line with Equation 3, the F_1 score is a standard deviation of the accuracy and recall after both metrics are measured.

F1-Score = $\frac{2 \times (\text{Precision} \times \text{Recall})}{Precision+Recall}$ (Eq 3)

In a nut, assessment parameters including accuracy, recall, and F1 score have critical significance as they enable an approach of analyzing a classification model's performance by weighing both true positives and false positives. The metrics drive the procedure of choosing and optimizing models and aid in evaluating the quality and dependability of a model. Since the assessment standards are prominent in the scientific community, they were decided on based on their popularity.

3. EXPIEREMENTAL RESULTS AND DISCUSSIONS

MobileNet, a form of convolutional neural network (CNN), was adopted in the conducted research. Considering the assistance of formerly assembled dataset, 12 discrete CNN models were tested. Each model encountered 10 instructing cycles or Epochs. In accordance with the construction of a particular model, learning frequency and weight decline were modified during the learning process. Some additional ratios were also explored to figure out how the parameters impacted the outcome.

Amid all the ones we tested, the MobileNet CNN emerged to be the most efficient system. Its precision was consistently elevated after 10 Epochs of training. The training was maintained unless it ceased evolving, a point regarded as convergence. The secondary training boosted the model's precision by 95%, when experimented with latest information. It validates the MobileNet CNN exceptional functionality in detecting and diagnosing abundant optical disorders composed in our dataset. Table I illustrates the model training outcomes.

Table I: Trained models and their parameters

Model	Weight decay	Learning rate	model	Weight decay	Learning rate
Xception	1e−6	6e−4	EfficientNet B2	1e−6	5e−4
ResNet 50	1e−6	3e−4	EfficientNet B3	1e−6	5e−4
ResNet 101	1e−6	6e−4	EfficientNet B4	1e−6	5e−4
ResNet 152	1e−6	6e−4	EfficientNet B5	1e−6	5e−4
EfficientNet B0	1e−6	5e−4	EfficientNet B6	1e−6	5e−4
EfficientNet B1	1e−6	5e−4	EfficientNet B7	1e−6	5e−4
Proposed MobileNet	**1e−6**	**5e−4**			

Several important metrics were analyzed to assess the model's efficiency. Specifically, accuracy and precision. It specifies the extent to which the model detects the elements of concern. In such scenario, for instance, the area of concern is how efficiently the model can precisely diagnose ophthalmic conditions.

To evaluate the accuracy, the degree of cases labeled as positive (true positives) are divided by the total estimate of (true positives false positives). This resulted a ratio that represents the level of precision of the model's positive expectations. Greater the accuracy, the more authentic the model is at precisely identifying the appropriate information. In this scenario, optical disorders.

Recall is a separate significant measure weighed while analyzing the efficacy of the model. Recall denotes the rate at which the model can figure out each significant instance among the entire datasets. As an example, in the current situation, the matter concerns how effectively the computation manages to pinpoint every instance of optical disorders.

To estimate the recall, the degree of cases labeled as positive (true positives) are divided by the total estimate of (true positives false positives). This resulted a ratio that represents the degree of precision of the model's positive deductions. Greater the recall, the more authentic the system is at precisely identifying the appropriate information. In the present case, optical disorders.

While considering both the metrics, the F_1 score is the standard deviation of recall and precision. Simplifying it, the pivotal measures demanded to determine the functionality of the classification model are accuracy, recall and F_1 score. They issue us with a strategy to evaluate its potency by reviewing both true positives and events that were effectively acknowledged and false positives or cases that were inaccurately identified.

With the objective to choose the most suitable model and amplify its productiveness, the measures permit us to assist the precision and trustworthiness of the model. They provide an accurate and reliable method of monitoring the effectiveness of classification models, that's the reason they are widespread in the field of research and technology. Thus, it can be evaluated how effectively the model is functioning and how to enhance it by measuring the precision, recall and F_1 score. Table 2 summarizes the analysis.

Table 2: Benchmarking the proposed algorithm

Model	**Testing accuracy**	**Training accuracy**	**Recall**	**Precision**	**F_1 score**	**Suppose**	**Epochs**
EfficientNet B3	0.9424	0.9841	0.94	0.94	0.94	1268	15
EfficientNet B0	0.9369	0.9644	0.94	0.94	0.93	1268	10
EfficientNet B2	0.9330	0.9790	0.93	0.93	0.93	1268	10
EfficientNet B1	0.9298	0.9807	0.93	0.93	0.93	1268	10
Xception	0.09267	0.9780	0.93	0.94	0.93	1268	10
EfficientNet B5	0.9259	0.9807	0.93	0.93	0.93	1268	10
EfficientNet B6	0.9243	0.9800	0.92	0.92	0.92	1268	10
EfficientNet B7	0.9188	0.9664	0.92	0.92	0.92	1268	10
EfficientNet B4	0.9085	0.9769	0.91	0.91	0.91	1268	10
ResNet-50	0.9014	0.9196	0.90	0.90	0.90	1268	10
ResNet-152	0.8935	0.9122	0.90	0.90	0.90	1268	10
ResNet-101	0.8667	0.9383	0.87	0.87	0.87	1268	10
Proposed MobileNet	**0.95**	**0.987**	**0.95**	**0.95**	**0.95**	**1268**	**10**

A crucial tool for assessing the classification model's effectiveness is a confusion matrix, offering an in-depth evaluation of the model's assumptions contrasted to the genuine labels identified in the dataset. It reveals critical details with respect to the algorithm's capability to appropriately diagnose retinal conditions as cataract, diabetic retinopathy, and glaucoma along with potential error hotspots. It comprises of four major key aspects: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). True negatives highlight précised predictions of the absence of any ophthalmic disorder, whereas true negatives indicate the accuracy of the model by detecting the occurrence of an eye infection. On the contrary, false positives are arises when the model inaccurately predicts an infection that's unlikely to exist and the false negatives results when the model couldn't identify an illness that exists.

The development of confusion matrix requires incorporating these authentic labels and assumptions within a grid like framework, including rows which represent the original labeling and columns suggesting the projected outcomes of the model. For example, the confusion matrix might demonstrate the number of true positives, true negatives, false positives, and false negatives for each disease type. Especially when it comes to recognize glaucoma, diabetic retinopathy, and cataract. Researchers may figure out a few metrics. Comprising accuracy, recall and F1 score for each illness category via reviewing the confusion matrix. The evaluations conveyed relevant data concerning the broad efficiency of the model besides its capacity to precisely identify specific optical illnesses. Likewise, they facilitated in diagnosing trouble areas and targeting various standardization attempts to strengthen the model's accuracy and reliance in discovering cataract, diabetic retinopathy, glaucoma, and other ocular illnesses. Figure 4.2 depicts the confusion matrix for MobileNet CNN.

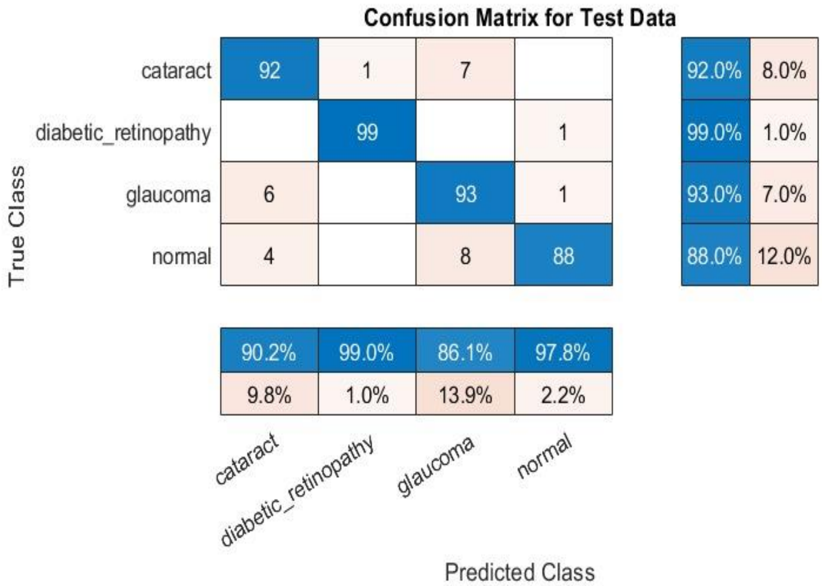

Figure 2: Confusion matrix of MobileNet CNN

Convergence curves provide significant details on the training mechanism and improved functionality of MobileNet CNNs that serves as tools for the detection of glaucoma, diabetic retinopathy, and cataracts. The diagrams indicate how various performance metrics fluctuate during the span of multiple, precision, recall, or F_1 score, that allows scholars to closely monitor the mode simulation training Epochs. Convergence curves frequently offers criteria like accuracy, lol's evolution while determining how effectively it might get smarter with additional training rounds. Researchers seek for modifications in convergence curve inquiry, that involves reducing damage, expanding precision, and evidence of stabilization, which proposes the model reaching at an equilibrium where improved efficiency yields reduced benefits. Furthermore, convergence curves assist in identification of overfitting, an occurrence in which the model operates exceptionally well on training data but fails to predict new data. Researchers may figure out the optimum amount of training Epochs, target areas for upgrading the model and measuring the statistical outcome of the system by evaluating convergence curves. In broad terms, they serve a purpose for leading the development of accurate and trusted testing devices for diagnosing ocular conditions which eventually modifies and upgrades the treatment of patients in ophthalmology. Figure 3 demonstrates the MobileNet CNN RoC curves.

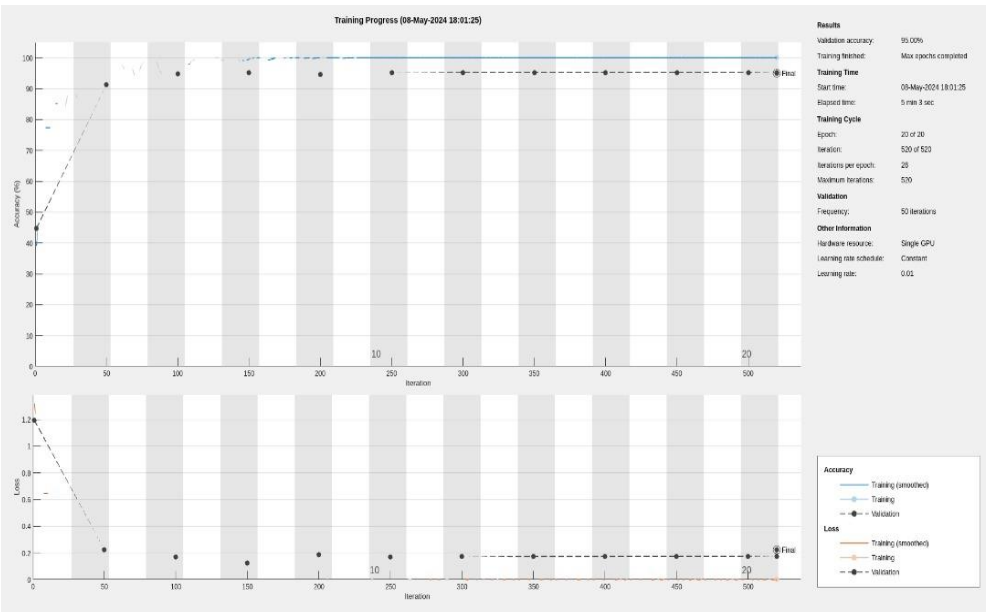

Figure 3: RoC curves of proposed MobileNet CNN

IV. Conclusion: To sum up, the analysis demonstrates how efficiently MobileNet CNNs function once applied in ophthalmology data to detect retinal disorders including glaucoma, diabetic retinopathy, and cataracts. The demonstration is performed via extensive experimentation and evaluation to prove that MobileNet CNNs operates far superior to previously developed versions of CNNs in the areas of recall, accuracy, and precision. In accordance with the results, MobileNet CNNs outscored alternative CNN designs with respect to accuracy and precision levels. In healthcare settings, the capability to accurately recognize vision ailments is critical since an error may result in a profound effect on patient outcomes. It's high accuracy and precision indicates its efficacy as potent ocular diagnostic instruments.

Additionally, MobileNet CNNs revealed outstanding recall rates, indicating their efficiency in minimizing false negatives and reliably acknowledging actual positive cases of vision problems. Ensuring complete illness diagnosis, particularly throughout the initial phases when swift treatment might prevent devastating damage to eyesight, demands rapid recall rates. MobileNet CNNs are advantageous due to their sophisticated layout, facilitating for effective feature extraction and classification with a restricted number of computational resources. MobileNet CNNs incorporate depth wise separable convolutions alongside other optimizations to guarantee an appropriate harmony between computational capacity and model complexity. This makes them perfect for employing in medical fields on platforms with restricted resources. In general, the outcomes emphasize the potential of MobileNet CNNs as beneficial equipment's to improve ophthalmology diagnostic effectiveness and precision. The research can be extended by integrating additional clinical data modalities beyond traditional fundus photographs, such as optical coherence tomography (OCT) scans and angiography images, real-world validation, and clinical translation of MobileNet CNNs for eye disease diagnosis and improving the existing algorithm to get improved testing accuracies.

REFERNCES

1. A Raza, M.Y. Koondhar, S Sindhu, M Hyder, GD Menghwar, B Baloch, Asadullah Shah "Application service delivery in the modern virtualized data center-improving reliability and scalability", Sindh University Research Journal-SURJ (Science Series) 48 (3), 2016.
2. Bali, A., & Mansotra, V. (2024). Analysis of Deep Learning Techniques for Prediction of Eye Diseases: A Systematic Review. In Archives *of Computational Methods in Engineering* (Vol. 31, Issue 1, pp. 487–520). Springer Science and Business Media B.V. https://doi.org/10.1007/s11831-023-09989-8
3. Berbar, M. A. (2022). Features extraction using encoded local binary pattern for detection and grading diabetic retinopathy. *Health Information Science and Systems*, *10*(1). https://doi.org/10.1007/s13755-022-00181-z
4. Harshit Sing, Archit Dogra, and Praveen Modi (2023). *Data Cleaning in Eye Image Dataset*. (n.d.).
5. Emmert-Streib, F., Yang, Z., Feng, H., Tripathi, S., & Dehmer, M. (2020). An Introductory Review of Deep Learning for Prediction Models With Big Data. In *Frontiers in Artificial Intelligence* (Vol. 3). Frontiers Media S.A. https://doi.org/10.3389/frai.2020.00004
6. Grace, P. (n.d.). *Investigation of the efficacy of an online diagnostic tool for improving the diagnosis of ocular fundus lesions imaged by Optical Coherence Tomography (OCT)*. J Optom. 2021 Apr-Jun;14(2):206-214.
7. He, J., Li, C., Ye, J., Qiao, Y., & Gu, L. (2021). Multi-label ocular disease classification with a dense correlation deep neural network. *Biomedical Signal Processing and Control*, *63*. https://doi.org/10.1016/j.bspc.2020.102167
8. Khaskheli, S. A., Koondhar, M. Y., Maher, Z. A., Khaskheli, G. B., & Khaskheli, A. A. (2024). A Model for Early Detection of Lumpy Skin Disease in Cattle Using Ensemble Technique. Pakistan J. Zool., pp 1-5, 2024.
9. Mukhtiar Memon, Muhammad Yaqoob Koondhar, Zulfikar Ahmed Maher, Mansoor Hyder Depar, Pinial Khan Butt, Healthcare Hub Platform: A Sustainable Healthcare Information Architecture For Health Monitoring, International Journal of Scientific & Technology Research, Volume 10 (05), 2021 Page # 305-308.
10. Muhammad Yaqoob Koondhar, Muniba Memon, Ali Raza Rang, Asadullah Shah, Pervasive Learning Environment For Educational Makerspaces With Emerging Technologies And Teaching And Learning Transformation, International Journal of Advanced Trends in Computer Science and Engineering (IJATCSE), Volume 10 (03), 2021 Page # 2272- 2277.
11. M.Y. Koondhar, N.N.B.A Molok, F.H. Chandio, M.M. Rind, A. Raza, A. Shah, A conceptual framework for measuring the acceptance of Pervasive Learning, International conference on Computing and Informatics 2015 at Istanbul, Turkey Dated: 11-13 August 2015. Pages: 97-103.
12. Nazir, T., Nawaz, M., Rashid, J., Mahum, R., Masood, M., Mehmood, A., Ali, F., Kim, J., Kwon, H. Y., & Hussain, A. (2021). Detection of diabetic eye disease from retinal images using a deep learning based centernet model. Sensors, 21(16). https://doi.org/10.3390/s21165283
13. Rafay, A., Asghar, Z., Manzoor, H., & Hussain, W. (2023a). EyeCNN: exploring the potential of convolutional neural networks for identification of multiple eye diseases through retinal imagery. International Ophthalmology, 43(10), 3569–3586. https://doi.org/10.1007/s10792-023-02764-5
14. Rafay, A., Asghar, Z., Manzoor, H., & Hussain, W. (2023b). EyeCNN: exploring the potential of convolutional neural networks for identification of multiple eye diseases through retinal imagery. International Ophthalmology, 43(10), 3569–3586. https://doi.org/10.1007/s10792-023-02764-5
15. Sarki, R., Ahmed, K., Wang, H., & Zhang, Y. (2020). Automatic Detection of Diabetic Eye Disease through Deep Learning Using Fundus Images: A Survey. In IEEE Access (Vol. 8, pp. 151133–151149). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/ACCESS.2020.3015258
16. Sarki, R., Ahmed, K., Wang, H., Zhang, Y., Ma, J., & Wang, K. (2021). Image Preprocessing in Classification and Identification of Diabetic Eye Diseases. Data Science and Engineering, 6(4), 455–471. https://doi.org/10.1007/s41019-021-00167-z
17. Serte, S., Serener, A., & Al-Turjman, F. (2022). Deep learning in medical imaging: A brief review. Transactions on Emerging Telecommunications Technologies, 33(10). https://doi.org/10.1002/ett.4080
18. Topaloglu, I. (2023). Deep learning-based convolutional neural network structured new image classi cation approach for eye disease identi cation. Scientia Iranica, 30(5D), 1731–1742. https://doi.org/10.24200/sci.2022.58049.5537