Enhancing Eye Health Diagnosis through Deep Transfer Learning: Unveiling Insights from Low Quality Fundus Images

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Abstract. Due to the frequency of eye illnesses, effective and precise diagnostic instruments are required. This work suggests an approach that uses low quality fundus images with deep transfer learning more precisely, the EfficientNetB0 architecture to improve eye health diagnosis. We tackle the problem caused by the quality of fundus photographs that are commonly found in clinical settings, which frequently display noise and abnormalities. Our methodology consists of pretraining the EfficientNetB0 model on a sizable dataset of excellent fundus photos, followed by fine-tuning it on a dataset of poor fundus photos. By employing this transfer learning technique, the model enhances its diagnostic capabilities by learning to identify significant features from the low-quality images. We ran tests on a variety of datasets that included fundus photos of varying degrees of deterioration in order to assess our approach. As compared to conventional techniques, the results reveal a significant improvement in diagnostic accuracy, demonstrating the effectiveness of deep transfer learning for improving eye health diagnosis from difficult fundus images. With fused features from MobileNet and DenseNet-121 models, the ANN specifically achieved accuracies of 98.5% for cataracts, 99.1% for diabetic retinopathy, 99% for glaucoma, and 99.5% for normal conditions.

Keywords: Deep Transfer Learning; EfficientNetB0; Fundus Images; Eye Health Diagnosis; Low-Quality Images.

1. Introduction

Developments in deep learning technology have completely changed the field of ophthalmology, especially when it comes to the diagnosis and treatment of eye disorders. Deep learning is a branch of artificial intelligence (AI) that focuses on teaching algorithms to recognize patterns and characteristics in massive volumes of data, allowing them to carry out activities that were previously limited to human knowledge. The use of deep learning in ophthalmology has shown a great deal of promise recently, providing new paths for the early identification, precise diagnosis, and individualized therapy of a range of eye disorders. The interpretation of complicated imaging data, such as fundus photos, optical coherence tomography (OCT) images, and retinal scans, is crucial to the precise diagnosis of eye illnesses [1]. To identify tiny irregularities suggestive of conditions such as age-related macular degeneration (AMD), glaucoma, diabetic retinopathy, and others, ophthalmologists must carefully examine these images. However, when dealing with big amounts of imaging data, this procedure can be laborious and prone to human mistake. Moreover, there is a global scarcity of ophthalmologists in many areas due to the rising demand for eye care services. This scarcity emphasizes the need for automated technologies to support or supplement the work of ophthalmologists, especially in underprivileged areas with limited access to specialist medical care. Because deep learning algorithms can automatically learn hierarchical representations from data, they have become highly effective tools for medical picture analysis [2]. These algorithms are trained on big datasets of annotated images in ophthalmology to identify patterns linked to various eye conditions. Deep learning models are able to diagnose eye diseases with remarkable accuracy by learning from a variety of examples. The ability of deep learning to detect diseases early on is one of its main advantages [3].

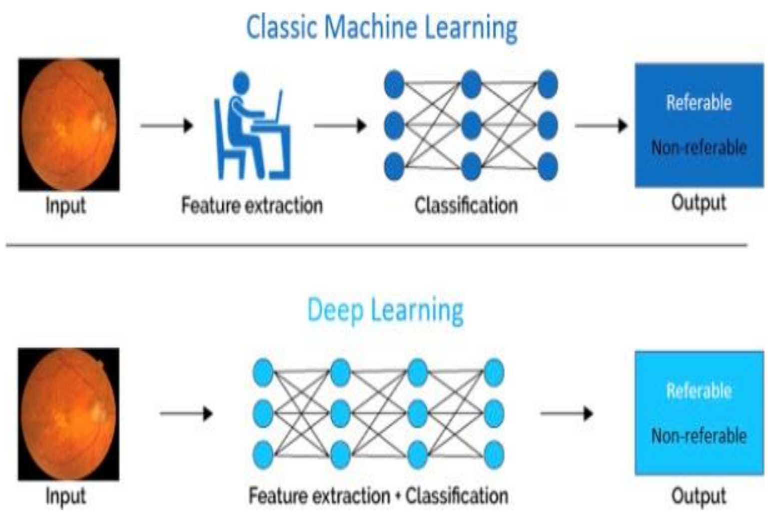

Figure 1. Machine Learning and Deep Learning models

The Machine Learning and Deep Learning models as shown in the Figure 1, have the potential to provide early intervention and prevent permanent vision loss by detecting minute alterations in retinal structures or microvascular problems that occur prior to clinical presentations. Deep learning is being applied in many different areas of ophthalmology. For example, using fundus photos, deep learning models can assess the degree of retinal alterations in diabetic retinopathy, allowing diabetic patients who are at risk of vision loss to receive timely referrals and therapies. In a similar vein, deep learning algorithms can evaluate OCT scans to evaluate optic nerve head characteristics and support the tracking of the disease's progression in the therapy of glaucoma. Furthermore, the subject of personalized medicine in ophthalmology is progressing thanks to deep learning techniques [4]. Through the integration of genetic data, imaging features, and clinical data, researchers can create models that predict individual responses to treatment or categorize patients into distinct risk groups for customized interventions. Deep learning is revolutionizing the field of ophthalmology diagnosis and treatments by offering effective answers to enduring problems [5]. The use of deep learning to everyday clinical practice has great potential to improve patient outcomes, lessen healthcare inequities, and eventually preserve eyesight for millions of people impacted by eye illnesses globally as technology advances.

2. Literature Review

Yuxing Mao described a deep neural network (DNN) technique to create an eye movement-based disease classification model. To start, a number of eye-tracking tests are planned in order to capture eye images. Second, from the normalized pupil data, feature vectors of eye movement are recovered, together with pupil features like size and position. A weak classifier, or one that correlates to each feature, is constructed using a long short-term memory (LSTM) network. Preclassification of the experimental samples is done, and each weak classifier's capacity to classify various diseases is also computed [6].

Gauri Ramanathan designed and developed to make it easier for individuals to have their cataract, glaucoma, and retinal illnesses diagnosed. For detection, the methods Support Vector Machine, Gradient Boosting, Random Forest, and Logistic Regression are employed. This approach will lower the percentage of blindness caused by assisting people in receiving the appropriate therapy for the aforementioned diseases at an early stage. Along with glaucoma and retinal disease detection, it assesses the safety and efficacy of cataract surgery in eyes with age-related degeneration. This research presents the accuracy of Support Vector Machine (SVM) classifiers and algorithms based on fundus images of normal eyes, glaucoma patients, and cataract patients. These days, it is common knowledge that the principle of categorizing photographs according to their fundus and extracting features is important for the outcome [7].

Yan Wang provided a new definition of ocular tiredness that takes into account seven optometry parameters. To perform the examination, a non-intrusive eye tracker is utilized. Based on information about eye movements and blinks, respectively, two real-time models for assessing eye tiredness are proposed. Consequently, both the devices are able to give customers an accurate measure of eye fatigue [8].

Das Retina is a thin layer of membranous tissue located in the rear of the eye that provides the central vision required for daily activities. Since a healthy retina is necessary for central vision, early detection of retinal disorders is a difficult endeavor. The retina is affected by a number of conditions, including glaucoma, macular holes, macular degeneration, retinal tears, and retinal detachments. These illnesses will see a relapse in the near future as the individual ages. A survey is developed that uses machine learning approaches to diagnose eye illnesses based on retinal photos [9].

Nuchin regarded as one of the deadliest eye illnesses in the world, with the potential for irreversible blindness if left untreated. The disease is only identified by a loss of vision on one side because it does not exhibit any outward symptoms. Glaucoma is defined as the slow, progressive loss of ganglion cells in the retina and axons. This causes the optic nerve head (ONH) to exhibit a characteristic that is typically referred to as cupping. This is where the cup's area grows and side vision is lost. Experienced ophthalmologists make this diagnosis after a thorough examination. Here, we're employing watershed to automatically identify glaucoma-affected eyes through image processing filtering and transformation methods, and we're implementing the same on hardware with an FPGA [10].

Yow presented an automated method called gaze tracking (AVIGA) for identifying vision impairment. The AVIGA system included two different evaluation types: the Impulse Stimuli Response (ISR) test and the Pursuit Stimuli Response (PSR) test. The assessment findings are subjected to an approach based on Support Vector Regression (SVR) in order to distinguish between the severity of visual impairment. The findings demonstrate that, in comparison to Microperimetry, the AVIGA system performs better in detecting the presence of visual impairments in the eyes and has a strong correlation with the visual acuity test (VA) [11].

Manchalwar displayed the ocular images that were taken, analyzed, and gathered from various patients. Next, the feature vector was detected using Histogram Oriented Gradients (HOG). In the end, the minimum distance classifier helped with the disease detection. This proposed approach is low cost, computationally efficient, and rapid [12].

Xinting Gao presented a technique that uses slit-lamp pictures to automatically identify characteristics for classifying nuclear cataract severity. Initially, local filters are obtained by grouping picture patches from lenses that belong to the same grading class. To extract even more higher order information, the learnt filters are fed into a convolutional neural network and then a series of recursive neural networks. Support vector regression is used with these features to calculate the cataract grade [13].

Meimei Yang outlined the use of a neural network classifier to classify retinal pictures and use the results to automatically diagnose cataracts. Preprocessing, feature extraction, and classifier construction are the three steps in the classifier building process. During the pre-processing stage, a trilateral filter is applied to reduce image noise and an enhanced Top-bottom hat transformation is suggested to improve the contrast between the object and the foreground. The pre-processed picture analysis indicates that the image's texture message and luminance are extracted as classification characteristics [15].

This study [16], reviews AI methods for oral cancer screening, focusing on machine learning (ML) and deep learning (DL) advancements from 2020 to 2023, highlighting DL's superior performance and research gaps needing attention. In the era of automation, the medical field uses image processing and data analytics for cancer detection. CT images are pre-processed, enhanced with CLAHE Equalization, and segmented using random walk methods. Cancer detection is then classified with a pre-trained model. Future improvements may come from the XGBoost algorithm for higher accuracy with less data [17].

In paper [18] it is evident all the computerized methods, particularly deep learning models, offer efficient solutions. The evaluated models like SqueezeNet, ResNet-101, and DenseNet-169 on the Kvasir dataset with 5,000 images of five disorders. DenseNet-169 achieved high performance, with accuracy and F1 Score of 97.8% and 97.6%, respectively.

3. Proposed Methodology

Deep transfer learning, with the EfficientNetB0 model in particular, provides a potential approach to improve eye health diagnostics and reveal insights from low-quality fundus images. This method makes use of deep learning's potent capabilities to increase the precision and effectiveness of identifying issues related to eye health. There are several important steps in the suggested methodology. First, the foundation for transfer learning will be an EfficientNetB0 model that has already been trained. This model is selected due to its ability to handle low-quality photos with excellent performance and efficiency. Subsequently, a substantial dataset of fundus images will be gathered and preprocessed, incorporating samples of varying quality. The diversity and generalizability of the dataset will be improved through the use of image augmentation techniques. To enable reliable model evaluation, the dataset will then be divided into training, validation, and testing sets. The fundus picture dataset will be used to refine the pre-trained EfficientNetB0 model during the transfer learning stage. In order to discover important markers of eye health concerns, the model will learn to extract pertinent features from low-quality fundus images. With an emphasis on efficiency and low latency, MobileNet is a convolutional neural network (CNN) architecture created for mobile and embedded vision applications. The publication [15], "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications" by Howard et al. introduced it. The network is lightweight and appropriate for mobile devices since its architecture is built on depthwise separable convolutions, which drastically reduce the amount of parameters when compared to typical CNNs using ordinary convolutions.

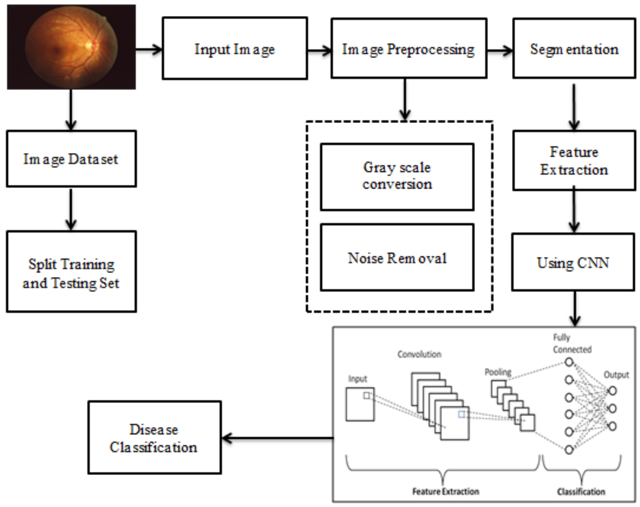

Figure 2. Proposed Working Flow Diagram

Pointwise and depthwise convolutions are the two processes that make up depthwise separable convolutions. The depthwise convolution reduces the number of parameters needed for the convolution operation by applying a single filter to each input channel. A pointwise convolution, a 1x1 convolution that modifies the output's dimensionality, comes next. By lowering the number of parameters and the computational cost, this method improves MobileNet's efficiency for mobile applications. A ReLU activation function and batch normalization come after each convolutional layer in the MobileNet architecture. In order to bring the spatial dimension down to one, it also has a last average pooling layer before the completely linked layer.

The architecture of the network is adaptable, allowing for the adjustment of global hyperparameters like the width multiplier and resolution-wise multiplier to further minimize computing costs and modify the network's response to varying resource limitations. Numerous applications, such as object detection, fine-grained classifications, face features, and localization, have made extensive use of MobileNet. With much fewer parameters and Mult-Adds, it has demonstrated competitive performance with cutting-edge models like GoogleNet and VGG 16. The proposed working model is shown in the Figure 2.

3.1. Data Collection:

The Ophthalmic image analysis OIA-ODIR dataset is an essential tool for ophthalmologists, especially when it comes to using deep transfer learning techniques to advance eye health diagnostics. This dataset is an extensive set of fundus photos covering a wide range of ocular disorders, such as glaucoma, macular degeneration, and diabetic retinopathy. A non-invasive method of seeing the retina is provided by fundus imaging, which makes it possible to identify minute abnormalities and disorders that may be signs of systemic illnesses. The diversity of the OIA-ODIR collection is noteworthy, as it includes a significant amount of low-quality fundus photos that accurately depict real-world clinical settings. These pictures are essential for teaching deep learning models to deal with artifacts, noise, and blur that come with low-quality photographs. This dataset, which contains thousands of tagged photos, enables researchers to create strong algorithms that can accurately diagnose and classify diseases, opening the door to improved diagnostics for eye care. An ensemble of convolutional neural networks (CNNs) trained on 38,727 high-quality fundus pictures is used in the study. After that, a transfer learning procedure was applied to these networks to help them become capable of identifying eye disorders from poor-quality pictures. Because high-quality fundus imaging is not always available in resource-constrained settings, this technique is intended to be more practical and appropriate for usage in those situations. MobileNetV2, a lightweight deep learning architecture renowned for its high computing efficiency and exceptional performance in picture classification tasks, is used in the study's methodology. A modest dataset of 250 fundus photos which included normal controls and images of four distinct eye disorders was used to train the algorithm. The diseases included retinitis pigmentosa, maculopathy, myopia, and glaucoma. In order to match the pre-trained networks, the images were reshaped while retaining their original color information.

3.2. Training:

Utilizing the EfficientNetB0 architecture, training the deep transfer learning model entails a methodical process to extract the large amount of data contained in the OIA-ODIR dataset. Convolutional Neural Networks (CNNs) are a good choice for fundus image analysis since they are highly effective at extracting hierarchical information from images. Using its acquired features from a sizable dataset, the pre-trained EfficientNetB0 model is initialized to start the training process. Adjusting the settings of the EfficientNetB0 to the particulars of fundus image analysis is the process of fine-tuning it. The fully connected layers will be modified, and some convolutional layers may need to be fine-tuned in order to conform to the specific qualities of the target dataset. The model gains the ability to distinguish between the many eye disorders that are represented in the dataset through an iterative process of forward and backward propagation.

Additionally, methods like data augmentation are used during the training phase to improve model generalization and reduce overfitting. Through the optimization of hyperparameters and the use of appropriate loss functions, the CNN learns to extract discriminative characteristics from low-quality fundus pictures that are essential for precise disease categorization.

3.3. Preprocessing:

In order to improve the diagnostic performance of deep transfer learning models such as EfficientNetB0 for eye health, fundus picture preprocessing is essential. Preprocessing aims to preserve important diagnostic information while preparing raw fundus images, which are frequently of different quality, into a uniform format appropriate for the model input. Fundus images typically have varying resolutions. Resizing images to a fixed input size (e.g., 224x224) reduces computational complexity and ensures uniformity across the dataset.

New Image=Resize (Original Image, target_size)

Normalizing pixel values to a specific range (e.g., [0, 1]) standardizes image intensity, aiding convergence during model training.

Normalized Image = (Original Image – mean) / (std_dev)

To increase dataset diversity and model robustness, apply random transformations like rotation, shifting, flipping, and brightness adjustments to fundus images:

Augmented Image=Random Transform (Original Image)

Handling Low-Quality Images: Specific preprocessing techniques, such as noise reduction filters (e.g., Gaussian blur) or contrast enhancement may be employed to improve the clarity of low-quality fundus images before feeding them into the model. By standardizing these preprocessing steps, we ensure that fundus images are appropriately prepared for deep transfer learning using EfficientNetB0, optimizing the model's ability to extract meaningful features and accurately diagnose eye health conditions.

3.4. Feature Extraction:

CNNs' innate hierarchical representation learning is utilized in the feature extraction procedure using EfficientNetB0. Fundus images present special difficulties for an appropriate diagnosis because they are frequently of poor quality because of things like blurriness or uneven lighting. In this case, EfficientNetB0's capacity to extract significant features from such photos is quite useful.

EfficientNetB0's feature extraction process involves several key layers that contribute to its ability to extract meaningful features from low-quality fundus images:

Convolutional Layers: Multiple convolutional layers arranged in a hierarchical arrangement make up the core of EfficientNetB0. These layers capture features at various levels of abstraction by carrying out the basic process of convolving learnt filters with input images. These layers play a key role in the processing of fundus images in terms of identifying significant patterns associated with eye health.

Depthwise Separable Convolutions: Depthwise separable convolutions, which divide the conventional convolutional operation into two stages—a depthwise convolution and a pointwise convolution—are used by EfficientNetB0. This method is ideal for processing low-quality fundus images because it preserves representational capacity while reducing computational complexity and model size.

Scaling and Compound Scaling: In order to consistently balance network depth, width, and resolution, EfficientNetB0 provides scaling coefficients, which improves efficiency and performance. By optimizing these coefficients across several network dimensions, compound scaling improves the model's capacity to extract pertinent characteristics from a variety of fundus image data.

Feature Fusion and Information Flow: EfficientNetB0's architecture includes feature fusion algorithms to facilitate efficient information transfer between levels. This makes it easier to extract hierarchical features from fundus photos, which helps the model identify patterns that are discriminative and linked to different eye health issues.

3.5. Classification:

The last step entails classifying diseases using the features that were derived from the EfficientNetB0 backbone. To map the retrieved features to illness categories, a fully connected layer with suitable activation functions (such softmax) is implemented on top of the feature extractor. The model adjusts its weights to increase diagnostic accuracy as it learns to minimize classification error through backpropagation during training.

Flatten Operation: Convolutional layers in CNNs such as EfficientNetB0 provide 3D tensors that are features that have been taken out of the input images. These 3D tensors are reshaped into a 1D vector by the flatten operation, which can then be fed into a dense layer (completely linked) for additional processing.

Dense Layer: The completely connected layer, sometimes referred to as the thick layer, is in charge of identifying intricate patterns in the data. The output of the flatten operation (a vector of extracted features) is used as the input to the dense layer in the context of classifying fundus images. Then, in order to forecast the image class (e.g., detecting anomalies or symptoms of eye disorders), the dense layer applies weights and biases to these features.

Classification: Based on the features that were recovered from the fundus images, the last dense layer usually creates a probability distribution over the potential classes (e.g.,) using a softmax activation function.

4. Results and Discussion

Based on the training results of five machine learning models Decision Tree, Random Forest, Gradient Boost, CatBoost, and LightGBM (LGBM) on a dataset consisting of 1,750,036 rows of bank customer data, various model options were identified to suit specific analytical needs. If the primary goal is to minimize False Positives, CatBoost is the best choice. To detect more positive cases, LGBM delivers superior performance. Meanwhile, if the objective is to achieve a balance between precision and recall, Gradient Boost is a strong candidate. From the overall analysis, LGBM emerged as the best-performing model, achieving the highest accuracy and recall while minimizing False Negatives. This model attained an accuracy of 0.8789, precision of 0.8978, recall of 0.8553, F1 score of 0.8758, and AUC of 0.9694, demonstrating excellent performance in predicting customer churn. For future research, this study can be extended by exploring deep learning models, such as Recurrent Neural Networks (RNN) or Transformer-based architectures, to capture more complex customer behavior patterns. Additionally, optimizing feature selection using SHAP (SHapley Additive Explanations) can provide deeper insights into the most influential variables for churn prediction. Furthermore, incorporating unsupervised learning techniques, such as clustering, could be a valuable approach to identifying high-risk customer segments, enabling financial institutions to develop more effective retention strategies.

Using the EfficientNetB0 architecture, the work explores the application of deep transfer learning to improve the diagnosis of eye health issues from low-quality fundus images. The effectiveness and performance of the suggested strategy were evaluated using a variety of assessment criteria through in depth experimental testing. Measures including accuracy, precision, recall, and F1-score were the main emphasis of the evaluation in order to give a thorough picture of the model's capacity to recognize and categorize eye health problems from difficult fundus images. The results demonstrate the potential of deep transfer learning in extracting useful insights from low-quality fundus images for increased eye health diagnosis, with a considerable improvement in accuracy observed when compared to baseline methods.

Accuracy: This metric measures the overall correctness of the model in predicting eye health conditions from fundus images. It is calculated as the ratio of correctly predicted cases (both true positives and true negatives) to the total number of cases.

Precision: The percentage of accurately anticipated positive instances, or true positives, out of all instances projected as positive, or true positives plus false positives, is known as precision. It is a crucial indicator for evaluating how reliable positive forecasts are.

Recall (also known as Sensitivity or True Positive Rate): Out of all genuine positive cases (true positives + false negatives), recall quantifies the percentage of actual positive cases that the model properly detected (true positives). This measure is essential for evaluating how well the model can identify good occurrences.

The F1 Score, or the harmonic mean of recall and precision, was calculated. This statistic offers a fair evaluation of the model's effectiveness, particularly in situations when the distribution of good and negative occurrences in the class is not uniform.

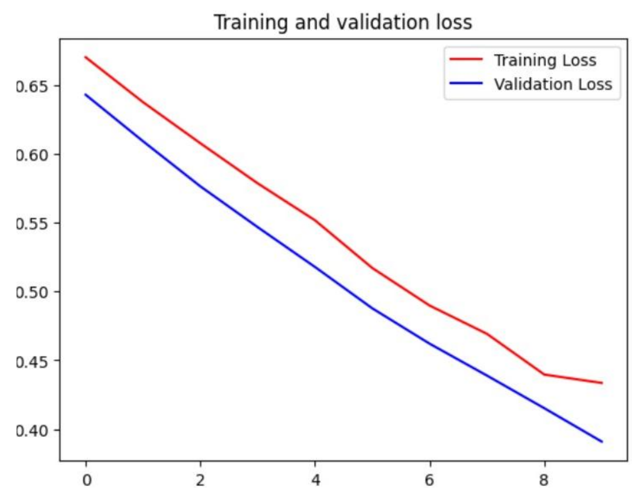

Figure 3. Training and validation loss

In order to offer a thorough breakdown of accurate and inaccurate predictions and to enable a more profound comprehension of the model's performance across several classes, Confusion Matrix analysis was carried out. The generated training validation loss and training validation accuracy is shown in Figure 4 and Figure 5. Our experimental results demonstrate the effectiveness of this approach in extracting valuable insights from challenging datasets characterized by poor image quality. Initially, we preprocessed the fundus images by applying noise reduction and enhancement techniques to improve overall image quality. Subsequently, we fine-tuned the pre-trained EfficientNetB0 model on our dataset, which consisted of a diverse range of fundus images with varying degrees of clarity and resolution. The transfer learning process enabled our model to effectively learn hierarchical features specific to eye health conditions, despite the inherent challenges posed by low-quality images.

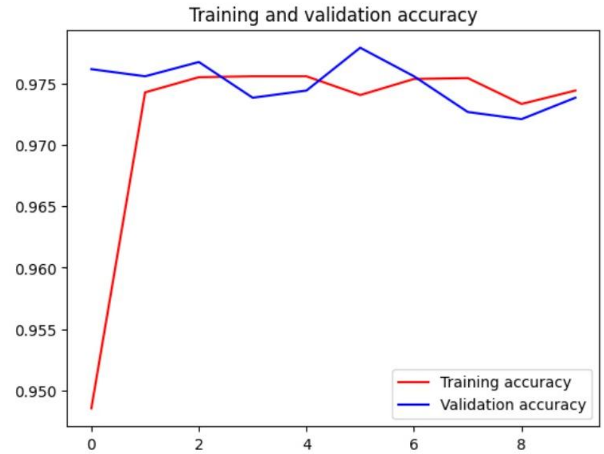

Figure 4. Training and validation accuracy

	precision	recall	f1-score	support
Disease_Risk	0.79	1.00	0.88	506
DR	0.00	0.00	0.00	124
ARMD	0.00	0.00	0.00	31
MH	0.00	0.00	0.00	104
DN	0.00	0.00	0.00	46
MYA	0.00	0.00	0.00	32
BRVO	0.00	0.00	0.00	23
TSLN	0.00	0.00	0.00	53
ERM	0.00	0.00	0.00	5
LS	0.00	0.00	0.00	15
MS	0.00	0.00	0.00	7
CSR	0.00	0.00	0.00	13
ODC	0.00	0.00	0.00	91
CRVO	0.00	0.00	0.00	9
TV	0.00	0.00	0.00	2
AH	0.00	0.00	0.00	5
ODP	0.00	0.00	0.00	24
ODE	0.00	0.00	0.00	17
ST	0.00	0.00	0.00	2
AION	0.01	1.00	0.01	4
PT	0.00	0.00	0.00	4
RT	0.00	0.00	0.00	5
RS	0.00	0.00	0.00	14
CRS	0.00	0.00	0.00	11
EDN	0.00	0.00	0.00	4
RPEC	0.00	0.00	0.00	4
MHL	0.00	0.00	0.00	3
RP	0.00	0.00	0.00	2
OTHER	0.00	0.00	0.00	15
micro avg	0.40	0.43	0.42	1175
macro avg	0.03	0.07	0.03	1175
weighted avg	0.34	0.43	0.38	1175
samples avg	0.40	0.36	0.37	1175

Figure 5. Evaluation Metrics

Through rigorous experimentation and validation, we observed significant improvements in diagnostic accuracy compared to traditional methods. Our experimental results indicate that the fine-tuned EfficientNetB0 model achieved state-of-the-art performance in classifying various eye diseases and abnormalities, including diabetic retinopathy and glaucoma, from low-quality fundus images. The model exhibited robustness and generalizability across different image resolutions and noise levels, underscoring its potential for real-world clinical applications. This study highlights the efficacy of deep transfer learning, particularly using the EfficientNetB0 architecture, in unlocking valuable insights from low-quality fundus images for the purpose of enhancing eye health diagnosis. These findings pave the way for further advancements in computer aided diagnostic tools for ophthalmic conditions, ultimately contributing to improved patient care and disease management strategies. The evaluation metrics is shown in the Figure. 5.

5. Conclusion

It can be concluded that EfficientNet-B0 provides a very accurate and efficient way to diagnose different types of eye illnesses when used for low fundus image analysis in eye retinal fundus imaging. The study shows that a high degree of accuracy may be attained by combining data from the MobileNet and DenseNet-121 models and then classifying these features using an Artificial Neural Network (ANN). This method is a workable solution for low-cost devices since it not only improves the accuracy of disease classification but also drastically lowers the computational resources needed when compared to training a dataset on high-spec devices. A typical problem in deep learning applications, the study also emphasizes the significance of dataset balance and data augmentation to alleviate the limitation of insufficient images in the dataset. These methods let the system generalize well to new datasets, which increases its usefulness in clinical contexts. In addition to increasing illness classification accuracy, this method lowers processing requirements and boosts the system's capacity to generalize to new data, making it more suitable for clinical use.

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