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Automated Multi-Class Classification of Anterior Segment Eye Diseases Using Deep Learning

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ABSTRACT
Accurate and timely detection of anterior segment eye diseases is critical for preventing permanent loss of sight. In this paper, we present a framework for applying deep learning to identify five different types of external eye-related diseases at once, namely: cataracts; corneal ulcers; pterygia; conjunctivitis; and eyelid abnormalities. Labeled clinical images of the eyeball were collected from both publicly available and clinician-curated sources. We tested three different deep Learning-Based Convolutional Neural Network (CNN) models: (1) a custom designed 5-layer CNN, (2) VGG16 implemented with transfer learning, and (3) EfficientNet-B0. All three models were tested under the same preprocessing algorithms, stratified data splitting, and augmentation techniques. The multi-class performance of each model was measured using the four common performance metrics (i.e., accuracy, precision, recall, and F1-score). The experimental results show that the best performing model was the EfficientNet-B0, which achieved a maximum accuracy of 90.5% with also demonstrating superior computational performance compared to the other two CNNs. It is suggested that the proposed framework could be used for automated diagnostic screening and/or tele-ophthalmologic applications.

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Introduction
It is necessary to identify anterior segment eye diseases early to minimize the potential for permanent vision loss. Common disorders of the eye's front segment include cataracts, corneal ulcers, pterygia, conjunctivitis, and problems associated with the eyelid. Failure to diagnose or treat these anterior segment pathologies results in corneal scarring, neovascularization, chronic inflammation, and/or progression to irreversible loss of vision with an associated reduction in patients' quality of life. Slit-lamp examination performed by certified ophthalmologists has historically been the method used for clinical diagnosis of anterior segment pathology. Although this method is effective, it also requires the time and expertise of the examining ophthalmologist and therefore limits the ability to screen at large volumes. Automatic diagnostic support systems for clinical decision-making and tele-ophthalmology services have become newly relevant given the desire for earlier detection of diseases and large-volume screening capabilities. There has been a demonstrated increase in the ability for deep learning and computer vision technologies to analyze medical images over the last several years [1]. CNN's allowing for spatial and textural analysis of clinical eye images have excelled in their ability to learn discriminative features from previously unseen data sets [2]. In addition, transfer learning approaches have greatly enhanced the classification accuracy of existing medical data through training on limited labelled medical datasets [3,4].

As a result of these advancements, this study presents a unified deep learning framework to perform multi-class classification of anterior segment eye diseases using consistent image preprocessing techniques, stratifying distribution of labelled images, and utilizing augmentation techniques. In addition, this study will evaluate three different deep learning models including a custom five-layer CNN, VGG16 with transfer learning, and EfficientNet-B0 under the same experimental conditions. It is our goal to determine an optimal balance between classification accuracy and computational efficiency to support future applications involving tele-ophthalmology and other related clinical environments.

Related Work
Many research studies have examined how to use automation to diagnose eye diseases through different methods: traditional (older) machine learning concepts and new advanced deep Learning-Based algorithms; convolutional neural networks (CNNs). These two approaches have significantly improved the accuracy of diagnosis in clinical settings and have helped doctors make better decisions regarding their patients' care. Litjens et al. and Shen et al., published in-depth reviews of the literature that showed the advantages of using deep learning techniques, specifically CNNs, for analyzing images taken in a medical setting [5,6]. Their studies provide evidence that CNN-based systems are the most effective at automatically recognizing patterns within clinical images.

A large number of earlier studies on automated diagnosis of ocular disease (eye disease) have concentrated on the diagnosis of retinal diseases. For example, both Gulshan et al. and Gargeya and Leng achieved expert-level accuracy using deep learning techniques for diagnosing diabetic retinopathy, and fast-tracked the use of artificial intelligence (AI) in the field of ophthalmology. Lam et al. generated the ODIR-5K dataset that will allow researchers to classify and benchmark CNN-style models in a clinical environment for multiple types of eye disease [7-9]. Additionally, transfer learning has also resulted in better performance in situations that present researchers with limited data, as demonstrated by Abbas et al., while Choudhary et al. illustrate the increasing prevalence of deep Learning-Based diagnosis of multiple kinds of eye disease [10,11]. Ting et al. emphasize the need for AI systems capable of being greatly scaled with high efficiency across multiple sites and locations and provide a predictable cost structure for clinical application and use [12].

Recently, Researchers have expanded on the application of deep learning to classify diseases of the anterior segment. Li et al. demonstrated a CNN-based classification technique using a CNN to identify anterior segment diseases [13]. Islam et al. also reported success using a CNN-based technique to detect conjunctivitis [14]. Additionally, several researchers recently released a type of CNN known as Efficient Net which implements a compound scaling technique that allows a balanced adjustment to the depth, width, and resolution of the CNN to improve accuracy while reducing the computational requirements of the architecture [15].

Despite the progress made in implementing deep learning models in the classification of anterior segment diseases, the majority of studies focus on retinal diseases, or they are based on the use of a very large computationally intensive architecture that does not allow for the use of those architectures in a real-time or a teleophthalmology setting. Furthermore, the few studies that do provide an evaluation of lightweight custom CNN models, transfer learning architectures, and computationally efficient architectures to classify multi-class anterior segment diseases have not provided a unified comparison of those models under the same preprocessing and training conditions.

The purpose of the present study is to address this gap by creating a systematic comparison between a Custom CNN model, VGG16 with transfer learning, and EfficientNet-B0 using a common dataset, a common preprocessing pathway, and common evaluation metrics. The goal of this project is to determine a diagnostically acceptable yet computationally efficient architecture for integration into clinical practice.

Materials And Methodology

Dataset Collection

This investigation uses a data set of images of the anterior parts of eyes taken in a clinical setting to perform classification into five different categories of eye diseases: cataracts, corneal ulcers, pterygia, conjunctivitis and conditions associated with the eyelid. Normal images of healthy eyes were also included as a reference class for verification purposes. The anterior ocular clinic images used in this study were obtained from publicly available sources of ophthalmic images as well as from clinics where the images are stored until the clinic wants to remove them based on the same reasons for their inclusion. Each image included in this study was reviewed and assigned to a clinical diagnosis based on its contents. To ensure consistent processing across the models developed, the images were resized so they retained a similar resolution that was suitable for processing using Convolutional Neural Networks (CNNs). The complete dataset was divided into training and validation sets using an 80/20 stratified random sample to ensure that each class was represented in the sample in the same proportion as the complete set contained. The methodologies used for constructing the data set were done to facilitate the development of a model that is not affected by class imbalance or any factors that could potentially bias the classification of the images. sample images are shown in Figure 1.

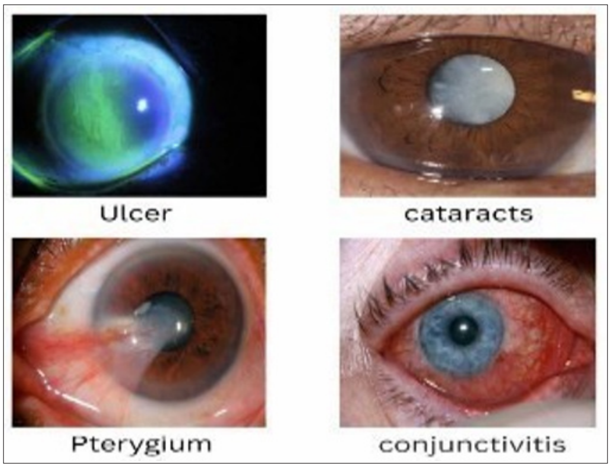

Figure 1: Sample Images form Dataset

Data Preprocessing

Every image in this study underwent identical standard preprocessing methods, and pixel normalization procedures helped to reduce the differences in illumination and improve numerical stability while training by reducing the light source variance. Basic noise reduction procedures were applied to the images to reduce the presence of common imaging artifacts that were present when taking photographs of eyes in the clinic.

To reduce overfitting and facilitate generalizing predictions made from the ocular fundus images, the data augmentation process described below was applied only to the training dataset. The training datasets had augmented data via the techniques of random rotation, horizontal flipping, zooming in or out of the image, adjusting the brightness, and slightly shifting the image either horizontally or vertically. These augmentation techniques replicate the variability that is typically seen in a clinical setting such as head tilt, lighting variance, and minor positional changes. Finally, strategies were implemented to balance the five classes equally during the training process. The same preprocessing and augmentation techniques were applied to the three models consistently to provide a fair comparison between the models during the evaluation process.

Performance Metrics

To assess the efficacy of the deep-learning models proposed to discriminate between diseases manifesting in the anterior. segment of the eye (such as conjunctivitis, pteryghium and corneal ulcer), we used some of the most common classification metric used in medical imaging to measure how accurately these models identify these specific diseases, while avoiding misdiagnosis of incorrectly identifying a disease when it does not exist. This is particularly important for use in screening programs.

When the output from the classification models is generated, there are four potential outcomes; True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Based on these four outcomes, we defined the subsequent performance metrics derived from them. Accuracy is the percentage of correctly classified instances (TP) to all instances (TP + TN + FP + FN), in the totality of classification, for each disease class.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision is defined as the ratio of true positive disease-diagnosis predictions divided by total predicted positives. Precision characterizes how well the model minimizes false-positive diagnostic predictions.

$$\text{Precision} = \frac{TP}{TP + FP}$$

True positive disease-diagnosis predictions are measured by recall (sensitivity). A sufficiently high level of recall is necessary for all medical screening tests because if a true disease case is missed, it may lead to serious harm to the patient.

$$\text{Recall} = \frac{TP}{TP + FN}$$

The F1-Score is derived from both precision and recall values. An F1-Score reflects the balance between these two metrics, making it a very informative metric for evaluating the performance of models creating medical imaging outputs where the effects of false-positive and false-negative predictions is seriously impactful on the health of patients.

In this research, the objective is to create a five-class model of classification (cataract, corneal ulcer, pterygium, conjunctivitis, and eyelid-related disorders). All metrics were generated using the one vs rest methodology of classification for all of the classes (the model generated binary values of true or false, which were utilized). The overall performance evaluation of the model across all classes was computationally generated through macro averaging of the precision, recall, and F1 score metric. Macro averaging calculates the metrics independently for each class and is evenly divided by the number of classes (five in this study). Therefore, macro averaging provides a more balanced performance evaluation, because it eliminates bias of all the other classes by including them equally in the macro averaging the overall accuracy of the model was calculated based on the number of true classifications divided by the total number of classifications found across all five classes of samples.

Proposed Methodology

The architecture proposed (Figure 2) involves three different Convolutional Neural Network (CNN) architectures to extract features and classify multiple classes of anterior segment disorders from clinical eye images. The focus of the framework is to classify the following pathological conditions: cataracts, corneal ulcers, pterygium, conjunctivitis and lid problems.

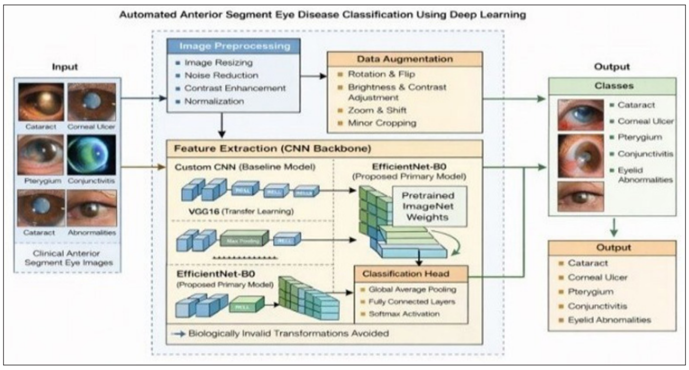

Figure 2: Architecture of the Proposed Deep Learning Framework for Automated Anterior Segment Eye Disease Classification

The architecture uses a baseline model consisting of a five- layer custom-built CNN (convolutional neural network) that learns basic features within an image based on spatial information. The VGG16 architecture is used to do deeper hierarchical feature extraction via transfer learning from the ImageNet data set (with pre-trained weights). The EfficientNet-B0 model uses "compound scaling" to find an optimal balance between network complexity (i.e., the number of parameters) and classification accuracy for a specific problem.

The identical set of hyperparameters - learning rate, optimizer (Adam), categorical cross-entropy loss, and batch size ensured that the three models could be compared fairly, without bias resulting from differences in training. To guarantee class balance throughout the five classes, the data was divided using stratified sampling; thus performance comparisons would reflect architectural differences only. Computational efficiency (including parameter count and inference feasibility) was also assessed to determine the models' potential use in tele-ophthalmology applications.

Custom CNN-Based Anterior Segment Eye Disease Classification The classification of Anterior Segment Eye Diseases via Multi-Class Using a Custom CNN. In the proposed architecture, the baseline architecture of the proposed framework is a Custom CNN. The architecture consists of five Convolutional Layers to create low to medium-level spatial features from Clinical Eye Images. Each Convolutional Layer has a non-linear ReLU activation function to increase feature extraction ability and add non-linearity to the Convolution Layers as well as to allow for better discrimination between extracted features. The network uses Max-Pooling Layers to reduce the convolved image spatial dimensions and computational complexity. The feature maps extracted from the Convolutional Layer are flattened and connected to Fully Connected Layers with a SoftMax activation function to provide the class probabilities of Cataract, Corneal Ulcer, Pterygium, Conjunctivitis, Eyelid-Related Abnormalities. To train the model, Adam optimizer is used with Categorical Cross-Entropy as the Loss Function. The training is conducted for a fixed number of epochs with a Large Batch Size.

By imitating the actual clinical variations that occur in the real world when patients receive imaging (e.g., differences in lighting, how the patient's eyes are positioned, and small spatial shifts), these augmentation methods increase the robustness of the model and allow it to generalize consistently across many different environments when imaging a patient.

While the Custom CNN model is Lightweight when compared to deeper architectures, it serves as a Robust Baseline for the Evaluation of the Advanced Transfer Learning and Efficient Net based Models for the Classification of Anterior Segment Eye Diseases.

VGG16-Based Anterior Segment Eye Disease Classification

VGG16 Architecture as the 2nd Model of the Framework. As the second model in this research framework, we use the VGG16 convolutional network architecture to capitalize on the benefits of transfer learning techniques for anterior segment eye disease classification. VGG16 is a deep convolutional neural network, which contains 16 weight layers and is well-known for its capacity to extract rich hierarchical feature representations from visual data.VGG16 was originally developed with ImageNet pre-trained weights in all of its convolutional layers; therefore, the ability of VGG16 to leverage and transfer to the ocular imaging domain knowledge learned from using a large-scale dataset of natural images helps to quickly adapt VGG16 to the study task. In order to adapt VGG16 for this study's task, we replaced the original fully connected classification layers with customized layers, which subsequently were followed by a SoftMax activation function to permit multi-class predictions of cataract, corneal ulcer, pterygium, conjunctivitis and eyelid-related abnormalities. During the training process, while we fine-tuned some of the convolutional layers of VGG16, we also left the remaining layers of VGG16 frozen to achieve a balance between reusing learned features versus specifically learning for the study task. Training of the model was accomplished using the same preprocessing and augmentation pipeline as that of the baseline CNN and the Adam optimizer with categorical cross-entropy loss; therefore, both trained models are comparable. Although the feature extraction capability of VGG16 is greater than the customized CNN used in this study, VGG16 contains greater computational complexity when compared to the other models used in this study.

Efficient Net-B0-Based Anterior Segment Eye Disease Classification

We have identified the use of EfficientNet-B0 as our base model. This model is an ideal selection because it has outstanding classification capabilities while requiring less computational effort to do so. EfficientNet-B0 utilizes a compound scaling method to optimize the depth, width and input resolution of the neural network, therefore it allows for an efficient method of learning fine-grained visual features. Once the neural network is built, it is initialized using weights modelled from the ImageNet database and the classification heads of the model are replaced with a task-based head which contains layers for global average pooling, fully connect layers, a SoftMax activation to allow for multi-class classification for cataract, corneal ulcer, pterygium, conjunctivitis, and eyelid disorders. All layers are then further trained using standard clinical eye images through a process called fine-tuning. The model has been trained on an Adam optimizer with a categorical cross-entropy loss and shows improved accuracy, faster inference speed and less memory utilization than the alternatives, making it a potential candidate for use in real-time ocular screenings and telehealth for ophthalmology.

Result and Discussion

In addition to overall precision, performance based on class breakdown was assessed to gauge how effectively each model could differentiate between anterior segment conditions that were visually similar to one another. Evaluation metrics were likewise selected for their clinical significance in that accurate diagnoses require that both false positives and negatives are kept to a minimum. Thus, precision and recall serve to round out accuracy and contribute towards the overall assessment of model performance comprehensively.

In addition to demonstrating performance comparative to one another for both Custom CNN (5 Layer), VGG16 using transfer learning methods, and the proposed EfficientNet-B0, it is important to show how VGG16 benefits from transfer learning in terms of improved feature representation, while the proposed EfficientNet-B0 model demonstrates a further improvement in performance due to the methodology of compound scaling allowing for better extraction of fine grain visual features with less computational load. Therefore, the progression of model performance can be determined from these results.

Table 1: Comparison of Model Performance

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Custom CNN (5-Layer)	86.4	85.7	84.9	85.3
VGG16 (Transfer Learning)	88.9	88.2	88.6	88.4
EfficientNet-B0 (Proposed)	90.5	91.0	90.2	90.6

A custom convolutional neural network (CNN) was created to see how well a CNN could perform classification for external eye disease using baseline classification accuracy, which came to 86.4%. The architecture and lack of a pre- trained feature set for the model were limiting in terms of how well it could generalize with changes to the degree of illumination and imaging conditions. Through transfer learning from ImageNet, the VGG16 model achieved a classification accuracy of 88.9%, but the complexity of the VGG16 model dramatically increased the cost and resources needed to run it due to a larger hierarchical representation of features as well as many more layers in the network than the custom CNN.EfficientNet-B0 had the best overall classification accuracy at 90.5% as well as better precision, F1 score, and recall compared to both models, and it can learn disease-specific detailed features, but can do so with less computational power than the other models.

The increased accuracy of diagnoses will result in fewer erroneous positive results and therefore also fewer inappropriate referrals. The higher recall will also reduce the number of missed diagnoses and this is particularly important for screening. EfficientNet-B0 was seen to improve both precision and recall equally, suggesting that it should be a good option for use in actual ophthalmic screening applications.

Training performance for all models is shown in Figure 3, which illustrates training performance by epoch.

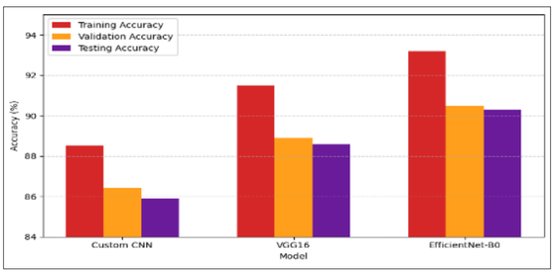

Figure 3: Training, Validation and Testing Accuracy Comparison of Models

As shown in Figure 3, EfficientNet-B0 is able to converge at an accelerated rate and consistently produce a higher level of accuracy than any other model. The rate of convergence and level of accuracy suggest that the feature representation learned through Efficient Net is much more stable and optimal than other models due to the use of the Efficient Net model's Compound Scaling method for defining network depth, width and input resolution, while not significantly adding any complexity to the model. In order to further study the prediction results achieved by the proposed framework, confusion matrix heatmaps were generated for the three models studied: Custom CNN, VGG16, and EfficientNet-B0 as shown in Figure 4 through Figure 6. The heat maps give a detailed breakdown of the classification of each architecture for five anterior segment disease categories (Cataract, Corneal Ulcer, Pterygium, Conjunctivitis, and Eyelid Related Disorders). According to the confusion matrices, there is further corroboration of the macro-averaged performance metrics that were discussed earlier. The matrices also support the classification accuracy of the classifier across all five categories instead of being dominated by one category.

The confusion matrices show that EfficientNet-B0 has much better class-wise consistency than either Custom CNN or VGG16 as indicated by strong diagonal dominance with less than average inter-class confusion. Overall, EfficientNet-B0's consistent multi-class performance demonstrates that it can be reliably used in clinical screening settings.

The heatmap in Figure 4 shows that the Custom CNN has a high level of misclassification across visually similar disease categories, which demonstrates its limited ability to represent the classes that have similarities to each other.

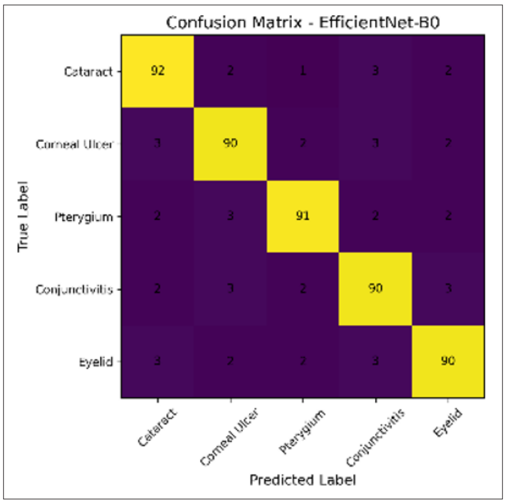

Figure 4: Confusion Matrix Heatmap for Efficient Net-B0

The exhibits in figure 5 demonstrate diagonal dominance for VGG16 through an effect of Transfer Learning which subsequently improves inter-class discrimination.

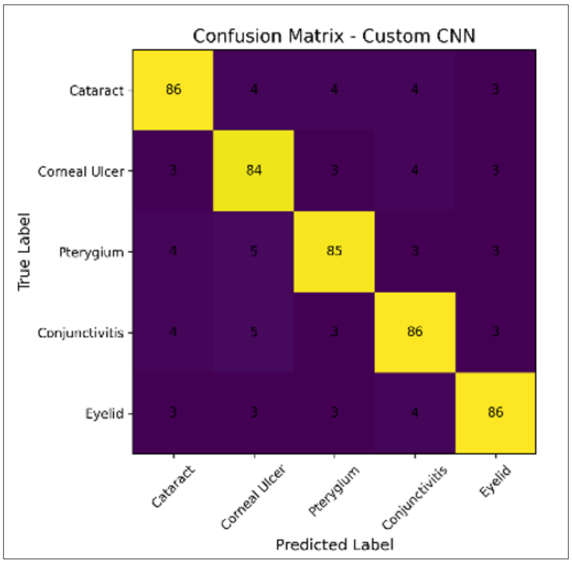

Figure 5: Confusion Matrix Heatmap for VGG16

The efficient net model (EfficientNet-B0) provides the best diagonal dominance with almost no off-diagonal classification errors (figure 6), confirming that it can correctly and consistently classify disease types.

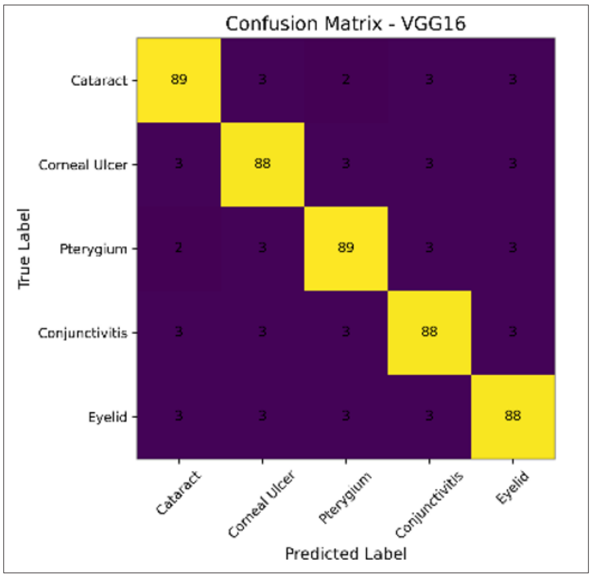

Figure 6: Confusion Matrix Heatmap for Efficient Net-B0

A large proportion of the misclassifications noted in the present study can be traced back to the similarities seen between specific anterior segment pathologies as described above. Based on the analysis of the confusion matrix, it can be concluded that EfficientNet-B0 has a high level of reliability and strength in terms of accurately classifying multiple anterior segment eye diseases.

The accuracy of diagnosis along with computational efficiency offers evidence of the model's possible use in automated screening systems, portable ophthalmic equipment, and teleophthalmology systems that require immediate performance and efficient use of resources.

Conclusion

This research provides an outline for deep-learning-enabled automatic classification of anterior segment ocular diseases [cataracts, corneal ulcers, pterygia, conjunctivitis, and eyelid disorders]. The researchers compared the performance of three convolutional neural networks (Custom CNN, VGG16, and EfficientNet-B0) in a systematic manner under identical experimental conditions. The models were evaluated using standard pre-processing, stratified splits, and macro-averaged multi-class performance metrics to provide fair and consistent comparison amongst disease types. It was found that EfficientNet-B0 had higher overall performance than the other models; it outperformed all other models in every category (precision/recall) including with a high level of accuracy (90.5%) with less computational complexity. The use of compound scaling in EfficientNet-B0 aids extraction of very fine [microscopic] pathological characteristics more rapidly and allows for utilization of more memory while doing so. Therefore, the proposed framework could be utilized effectively to support tele-ophthalmology or conduct real-time screening. The improvement in both the precision and recall estimates means that there is a lower probability of receiving a false-positive referral or missing a correct diagnosis, thus making it highly useful for clinical decision-support systems. Future work will include the creating of a larger data set, as well as the addition of new diseases for evaluation.

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