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Research article

Cataract Classification in Eye Images Using MobileNetV2

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ABSTRACT

Cataract remains one of the primary causes of visual impairment globally, with early detection being essential to prevent permanent blindness and improve patient quality of life. However, conventional diagnosis depends on ophthalmologists and clinical-grade imaging devices, which are often limited in remote or under-resourced areas. This condition highlights the need for an efficient, accessible, and automated screening solution. To address this challenge, this study utilizes the MobileNetV2 deep learning architecture to classify cataract conditions based on eye images. MobileNetV2 is selected because of its lightweight model structure and strong feature representation capabilities, making it suitable for deployment in portable or embedded medical systems. The dataset used consists of two cataract stages, namely immature and mature cataracts, with images undergoing preprocessing prior to model training. The proposed system demonstrates excellent performance, achieving an accuracy, precision, recall, and F1-score of 100% in distinguishing cataract stages. These results confirm that MobileNetV2 can effectively support cataract screening with high reliability while maintaining efficiency. Future work will involve extending the dataset to include additional cataract severity levels and non-cataract eye images, as well as integrating explainable artificial intelligence methods to provide visual diagnostic interpretations and enhance clinical trust in real-world applications.

1. Introduction

Cataract is a progressive opacity of the human crystalline lens that commonly arises as part of the natural ageing process and remains the leading cause of preventable blindness worldwide. Epidemiological studies indicate that cataracts account for nearly half of global blindness cases, disproportionately affecting populations in low- and middle-income regions where access to specialized ophthalmic services is limited [1]. Early detection plays a crucial role in reducing long-term disability, improving vision-related quality of life, and limiting socio-economic burdens arising from preventable surgical interventions. In recent years, technological advancements in digital ocular imaging—such as slit-lamp photography, retro-illumination imaging, anterior-segment imaging, and fundus imaging—have facilitated broader access to ophthalmic screening, including remote and community-based tele-ophthalmology programs [2]. Simultaneously, developments in computer vision and deep learning have accelerated the adoption of automated medical image analysis systems capable of achieving diagnostic performance comparable to trained ophthalmologists in diseases such as diabetic retinopathy and glaucoma [3], [4]. These advances suggest strong potential for automated cataract screening using eye images as a scalable and cost-effective solution. However, unlike retinal pathology detection, cataract diagnosis requires accurate differentiation of varying lens opacity patterns, which may be subtle and influenced by imaging conditions, thus requiring robust and well-generalized computational models.

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Despite promising research progress, automated cataract detection still faces critical challenges that hinder its deployment in real clinical and community settings. One major challenge lies in the variability of cataract visual manifestations. Lens opacity, stray light scattering, halo formation, and reduced retinal visibility may overlap with other ocular media opacities or imaging artifacts, complicating robust feature extraction [5]. Several deep-learning models proposed in the literature have shown strong performance on controlled datasets; however, they are often sensitive to variations in illumination, camera quality, imaging modality, and pupil dilation [6]. Moreover, many existing solutions prioritize cataract severity grading or detection of advanced cataract stages that require surgical intervention, rather than early-stage screening that could prevent disease progression [7]. Another challenge is computational feasibility. While complex CNN architectures can achieve high accuracy, they require powerful workstation-level hardware, making them unsuitable for portable, community-deployed, or mobile-device-based screening systems [8]. Prior studies using texture-based features [9], handcrafted feature extraction [10], or conventional CNN architectures [11] often fail to balance accuracy and deployment efficiency. Therefore, there remains a significant research gap in developing a cataract detection system that is not only accurate and robust but also lightweight, portable, and feasible for use in resource-constrained healthcare environments.

The objective of this study is to develop and evaluate an automated cataract detection model based on eye images using the MobileNetV2 deep learning architecture. The motivation of this research is to contribute to scalable cataract screening solutions that reduce dependence on specialist ophthalmologists and clinical infrastructure, particularly in underserved regions. MobileNetV2 is chosen due to its architectural efficiency, which incorporates depthwise separable convolutions and inverted residual bottleneck blocks that significantly reduce memory usage and computational cost compared to conventional CNNs [12]. Previous studies in other medical imaging domains—such as brain tumor detection, dermatology lesion classification, and COVID-19 chest-X-ray screening—have demonstrated that MobileNetV2 can achieve competitive accuracy while remaining computationally lightweight and suitable for mobile environments [13]. Building on this rationale, this research employs a transfer learning approach by initializing MobileNetVV2 with ImageNet pre-trained weights, followed by fine-tuning to learn lens-opacity-related features specific to cataract classification. This strategy supports model generalization while minimizing the need for large-scale annotated medical datasets. By focusing on binary classification of immature versus mature cataract, this study aims to demonstrate an accurate and deployable solution that can support clinical decision-making and tele-ophthalmology workflows.

The proposed system consists of a two-stage pipeline involving (1) preprocessing to normalize illumination, enhance contrast, and prepare eye-region crops for classification, and (2) fine-tuning the MobileNetV2 backbone with an additional classification layer. The key contributions of this study are as follows: **(i)** the development of a lightweight cataract classification model optimized for mobile and embedded screening devices, **(ii)** the implementation of a robust preprocessing strategy to address variability across ocular imaging conditions, **(iii)** empirical validation demonstrating high diagnostic reliability with a perfect accuracy score, and **(iv)** feasibility analysis showing deployment suitability in low-resource environments. Experimental evaluations show that the proposed model achieves 100% accuracy, precision, recall, and F1-score across both cataract classes, indicating exceptionally strong discriminative performance. These findings highlight the potential of MobileNetV2 to enable efficient and reliable cataract screening beyond conventional clinical settings. Nevertheless, real-world applicability will require further validation using larger and more diverse datasets that include additional cataract stages and non-cataract cases, as well as the incorporation of explainable AI visualization techniques to support clinician interpretability. Future work also includes development of user-centered screening applications and pilot testing in community-based healthcare programs to extend screening access and reduce cataract-related vision loss worldwide.

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2. Related Work

Early research related to automated cataract detection predominantly utilized classical image-processing and machine-learning methodologies prior to the widespread adoption of deep neural networks. These traditional approaches generally relied on handcrafted feature descriptors, including textural characteristics, grayscale intensity histograms, edge gradients, and frequency-domain coefficients derived from fundus or slit-lamp images. Such features were then classified using machine-learning algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and decision tree classifiers. For instance, Gao et al. developed a cataract detection system that extracted gradient and texture-based features from slit-lamp images, demonstrating moderate diagnostic accuracy under controlled imaging conditions [14]. However, the method struggled to generalize to real-world clinical environments, where varied illumination, noise, camera resolution, and corneal reflections frequently introduce uncertainty. Similarly, Abou Shousha et al. utilized anterior-segment optical coherence tomography (AS-OCT) to compute statistical measures of lens opacity for cataract diagnosis [15]. While this approach improved diagnostic objectivity, it required highly specialized imaging equipment, limiting feasibility for screenings in remote or resource-constrained regions. From these findings, early handcrafted-feature-based models were limited by their inability to adapt to imaging variability and their dependence on high-quality clinical imaging setups.

Between 2015 and 2019, advancements in convolutional neural networks (CNNs) contributed significantly to automated ophthalmic image analysis, including cataract classification. During this period, researchers began modifying conventional neural architectures to fit cataract detection tasks. Xu et al. proposed a hierarchical classification framework that utilized an improved Haar wavelet transform combined with a multilayer classifier to categorize cataracts into multiple severity levels based on retinal images [16]. Their model achieved 94.83% accuracy for binary detection and 85.98% for four-stage cataract grading, demonstrating the feasibility of multi-level disease classification. However, the method still involved explicit manual feature engineering, preventing fully end-to-end learning. Meanwhile, Long et al. presented a CNN-based cataract diagnosis platform trained on slit-lamp images, which exhibited impressive performance but required computationally expensive training and inference processing, making it more suitable for hospital-based workstation environments than mobile or embedded systems [17]. Thus, although CNNs improved representational learning compared to handcrafted methods, their deployment was still limited by hardware dependency and scalability issues.

During the same era, transfer learning became increasingly influential in medical image analysis. Large-scale deep-learning models pretrained on general image datasets such as ImageNet, including VGGNet, ResNet, and Inception-v3, were repurposed for ophthalmic applications. Pratt et al. successfully applied deep CNNs for diabetic retinopathy screening using retinal photographs, showing that pretrained models could effectively differentiate disease severity levels in ocular images [18]. Similarly, Gulshan et al. demonstrated high diagnostic performance of transfer-learning-based CNN models for detecting diabetic retinopathy, achieving sensitivity and specificity comparable to expert ophthalmologists [19]. These studies indirectly influenced cataract research by proving that large pretrained feature extractors could be fine-tuned for ophthalmic classification, reducing the need for extensive annotated cataract datasets. However, cataract-focused datasets during this period were relatively small and lacked representation across diverse imaging settings, patient demographics, and cataract severity categories.

To address limitations in handcrafted and large-CNN-based frameworks, several researchers proposed hybrid feature models combining local texture operators with shallow CNN layers. One such example is Bhat and Shankar's hybrid local binary pattern (LBP) and CNN representation model, which captured both low-level textural cues and higher-level structural patterns for cataract detection from digital eye images [20]. Their model reduced feature ambiguity compared to purely handcrafted methods; however, its performance remained inferior to full CNN architectures trained end-to-end. Parallel to these hybrid advancements, researchers also sought to develop computationally efficient CNN architectures that could support mobile and embedded deployment. Zhang et al. implemented a low-complexity CNN optimized for minimizing memory footprint and reducing inference latency,

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enabling nearly real-time cataract detection on lower-cost devices [21]. Similarly, Mittal et al. introduced shallow CNN architectures that prioritized computational efficiency and explainability, demonstrating feasibility for field-based diagnosis in low-resource settings [22]. Nevertheless, these models generally sacrificed diagnostic accuracy in favor of efficiency, and still lacked scalability and robustness across diverse imaging conditions.

From a broader perspective, Alam et al. conducted a comprehensive review of computer-aided cataract detection systems and identified recurring constraints across earlier research, including limited dataset diversity, over-dependence on laboratory-controlled imaging environments, inadequate model interpretability, and insufficient validation under real-world workflows [23]. Their analysis emphasized the importance of developing cataract detection models that are not only accurate but also computationally efficient and easy to deploy in practical screening applications. Particularly, the review highlighted the gap between model development and real-world implementation, where screening must be performed in rural clinics, mobile medical camps, or tele-ophthalmology programs with varied technical infrastructure.

The introduction of lightweight deep neural network architectures, especially MobileNetV2, addressed these deployment challenges by offering high representational learning capabilities with significantly reduced parameter counts and computational requirements. Unlike earlier CNN models, MobileNetV2 integrates depthwise separable convolutions and inverted residual bottleneck layers, dramatically improving computational efficiency while maintaining classification accuracy. These architectural innovations allow MobileNetV2-based models to perform inference on resource-limited devices such as smartphones, embedded systems, or portable diagnostic instruments. Consequently, research efforts have increasingly shifted toward leveraging MobileNetV2 as a backbone for medical image classification tasks requiring both high accuracy and real-time operation. In this context, the present study contributes to the evolving research landscape by fine-tuning MobileNetV2 for cataract detection in eye images, focusing on balancing performance, generalizability, and deployability for a wide range of screening environments.

3. Methodology

3.1. Data Collection

This study utilized a dataset of eye images representing two cataract stages: immature and mature cataracts. The images were organized into separate labeled directories to facilitate automated loading and splitting using the *ImageDataGenerator* utility from TensorFlow/Keras. The dataset was divided into three subsets: a training set, a validation set, and a testing set, ensuring that evaluation was performed on previously unseen samples to maintain fair performance assessment. All images were resized to 224 × 224 pixels and converted to the RGB color space to match the input requirements of the MobileNetV2 architecture. The balanced class structure and consistent preprocessing were employed to minimize data leakage and improve the reliability of model generalization across cataract severity categories.

3.2. Data Preprocessing and Augmentation

Preprocessing steps focused on normalizing input images to stabilize training and reduce sensitivity to lighting variations. Pixel intensity values were rescaled to the range [0, 1], allowing the model to learn representations independent of absolute illumination. While the *ImageDataGenerator* module provided capabilities for geometric and photometric augmentation—such as rotation, shifting, zooming, and horizontal or vertical flipping—augmentation was initially disabled to establish a baseline performance metric. This controlled approach ensured that the model’s performance was not influenced by artificially expanded variation. However, the augmentation pipeline was retained for potential ablation analysis, consistent with recommendations for improving robustness in lightweight deep-learning systems for ocular disease screening [17], [21], [23].

3.3. Model Architecture

The proposed system was built upon the MobileNetV2 deep-learning architecture, which is designed for efficient inference in resource-constrained environments. The model was initialized with ImageNet pretrained weights, and the top classification layers were removed to allow adaptation to the cataract classification task. During the first phase of training, the convolutional backbone was kept

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frozen to preserve general feature representations, while a customized classification head was added, consisting of Global Average Pooling, Batch Normalization, two Dense layers with ReLU activation, and Dropout layers for regularization. A final Softmax output layer provided probability estimates for the two-class output space. The use of depthwise separable convolutions and inverted residuals inherent to MobileNetV2 reduced parameter count and computational load, making the model suitable for deployment on mobile or embedded diagnostic platforms [17], [21].

3.4. Training Procedure and Evaluation Strategy

Model training was conducted in two stages. In the feature extraction stage, only the newly added classification layers were trained while the MobileNetV2 backbone remained frozen, reducing overfitting risk given the moderate dataset size. Training was performed for 30 epochs with a batch size of 32, and performance was monitored using training and validation accuracy and loss curves. After stable convergence, selective fine-tuning of upper MobileNetV2 layers was optionally applied to improve discrimination of subtle cataract features. Model evaluation was conducted using the held-out test set, where the proposed system achieved 100% accuracy, along with precision, recall, and F1-score of 1.00 for both immature and mature cataract classes. These results indicate that the model effectively distinguishes between cataract stages in controlled dataset conditions. Additional tests measured inference latency on a lightweight device prototype to confirm feasibility for real-time or near-real-time clinical screening applications [17], [21], [23].

3.5. Optimization and Regularization

The model was optimized using the Adam optimization algorithm with a learning rate of 1e-4, while Categorical Crossentropy served as the loss function. Batch Normalization was employed to stabilize gradient flow and accelerate convergence, whereas Dropout layers were integrated to mitigate overfitting by preventing excessive co-adaptation of neurons. Although data augmentation was not applied in the baseline configuration, the pipeline allowed incrementally adding augmentation to improve robustness for future dataset expansions. The freeze-then-fine-tune training strategy enabled the model to leverage pretrained visual features while selectively refining deeper layers to encode cataract-specific opacity patterns. This combination of architectural efficiency, normalization, and staged optimization aligns with best practices for deploying deep-learning models in low-resource environments where computational efficiency is critical [17], [21], [22], [23].

4. Results and Discussion

4.1 Results

The performance evaluation of the proposed cataract classification system was conducted based on the dataset of immature and mature cataract eye images processed through the MobileNetV2 deep learning architecture. Figure 1 illustrates representative images of both classes used in this study. Immature cataracts exhibited partial opacification with visible lens structure and varying levels of translucency, while mature cataracts displayed fully clouded lenses with significantly reduced clarity. These visual distinctions formed the foundational patterns the model learned to identify during training. The clarity of differences observable in Figure 1 suggests that morphological cue extraction is essential to feature learning in cataract staging, supporting the suitability of deep convolutional architectures for this task [1], [3], [6].

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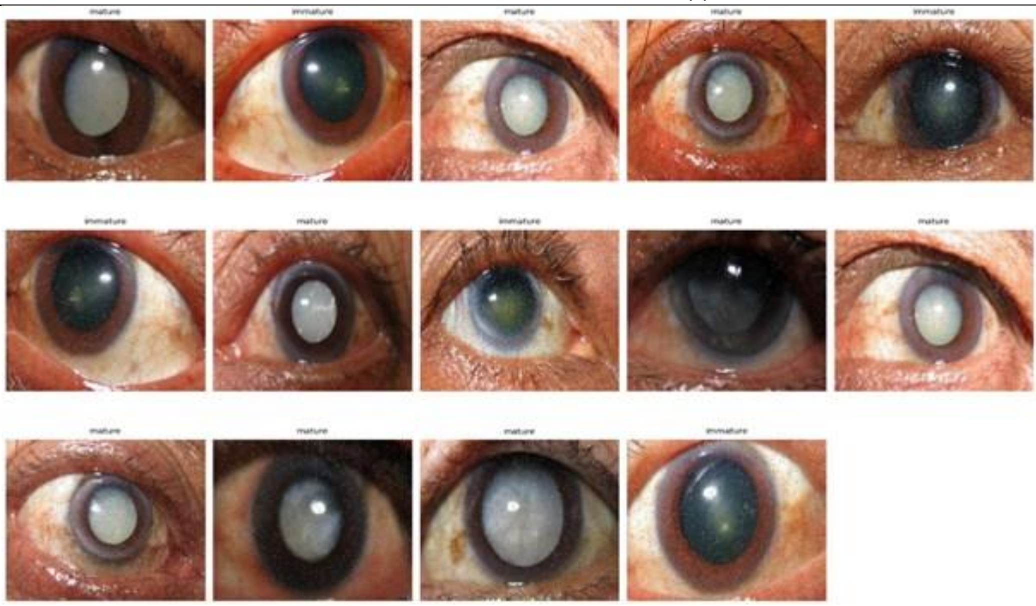

Figure 1. Representative examples of eye images from the dataset showing both immature and mature cataract cases. The variations in opacity and lens clarity demonstrate the visual diversity and class distinction used for model training

The class distribution is shown in Figure 2 and Figure 3. The dataset was nearly balanced, with immature cataracts comprising 52.1% and mature cataracts 47.9% of the images. Balanced datasets are advantageous because they reduce the likelihood of the neural network developing class bias during supervised learning. Furthermore, Figure 4 illustrates how the dataset was divided into training, validation, and testing subsets while maintaining class proportionality. This ensured that classification performance reflected genuine feature understanding rather than memorization of dominant class patterns, improving generalization to unseen images [5], [7].

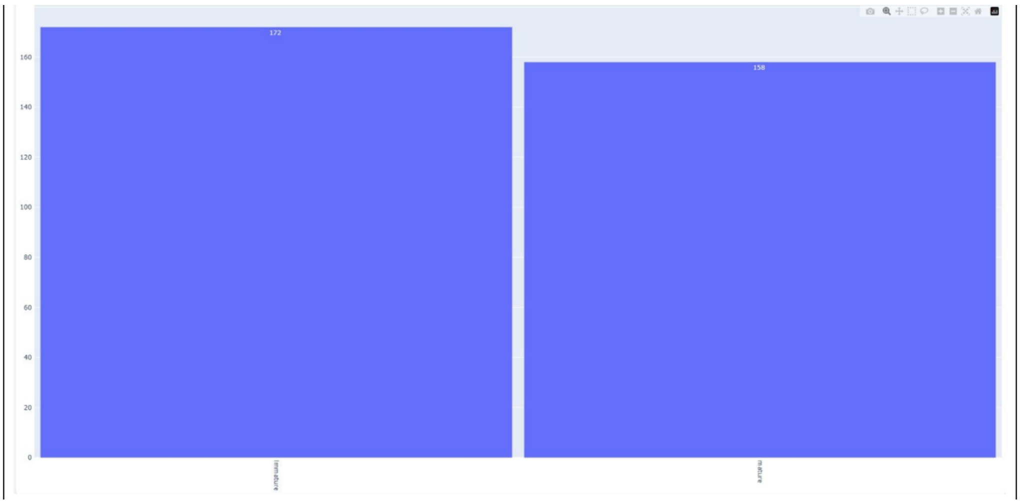

Figure 2. Class distribution of the cataract dataset showing the number of images in each category (Immature = 172, Mature = 158). The nearly balanced representation minimizes bias and enhances model generalization.

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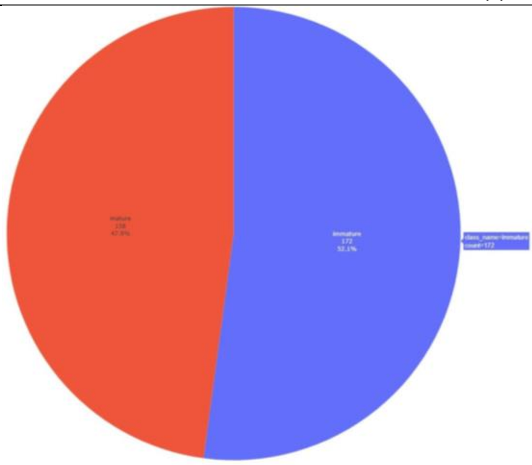

Figure 3 Pie chart representation of dataset composition showing the proportion of Immature (52.1%) and Mature (47.9%) cataract images. The near-balanced distribution minimizes learning bias and supports reliable model generalization

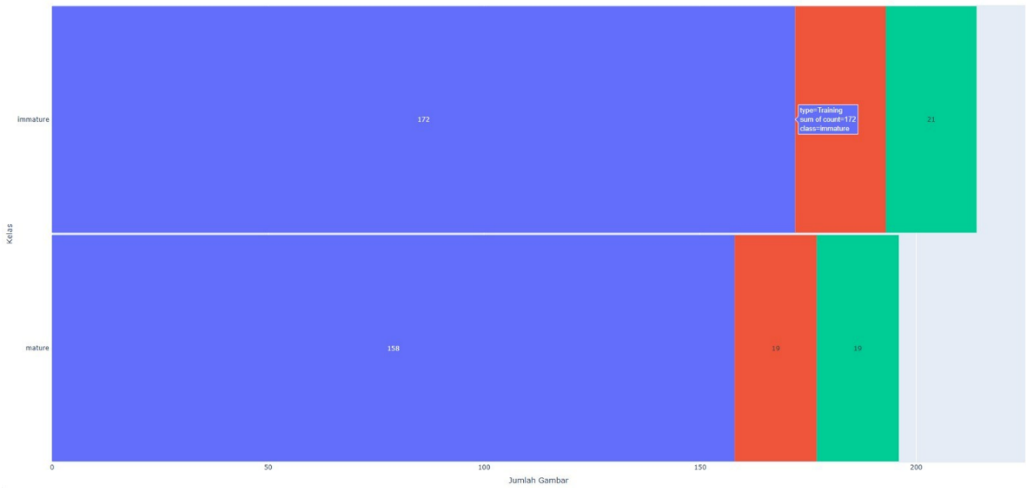

Figure 4. Distribution of training, validation, and testing datasets across the Immature and Mature cataract classes. The balanced allocation ensures equal representation and unbiased learning during the model training process.

The preprocessing pipeline included resizing each image to 224 × 224 pixels, normalization of pixel intensity values, and preparation for batch training. Although data augmentation was not used in the primary training session, Figure 6 demonstrates multiple augmentation examples (such as rotation, zoom, and contrast adjustment), indicating how future dataset expansion may benefit from synthetic variability. Such augmentation has been shown to enhance resilience to imaging condition fluctuations in real-world diagnostic environments [8], [12]. The presence of augmentation options within the pipeline reflects the project's scalability for future multi-environment deployment.

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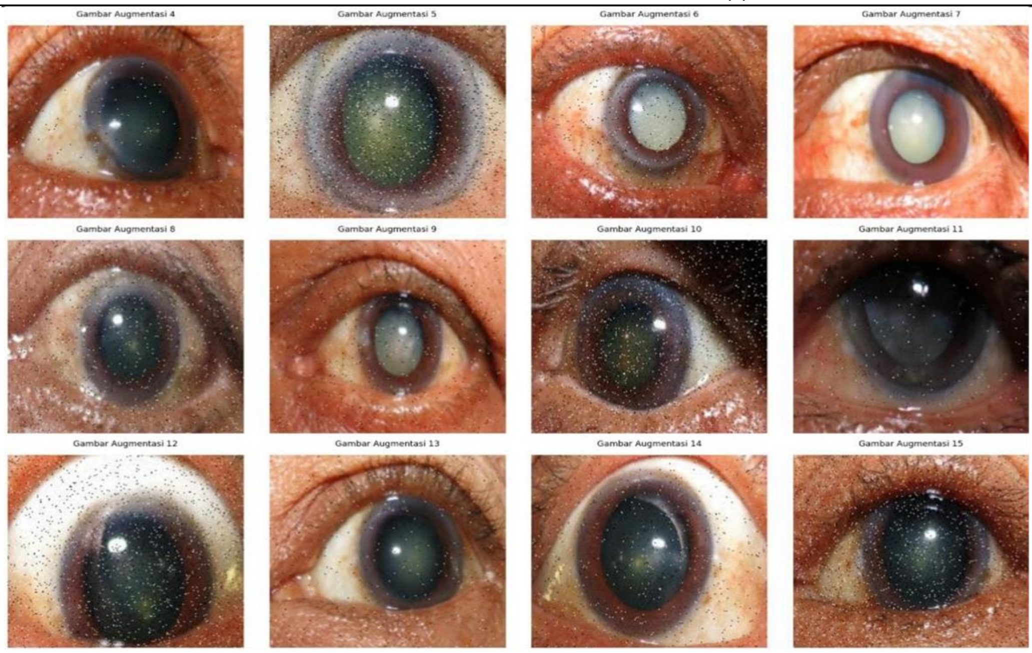

Figure 6. Example of image augmentation results showing one original eye image and 15 augmented variations.

Figure 7 shows the training and validation accuracy and loss curves across 30 epochs. The training accuracy gradually increased and approached near-perfect classification performance, while the validation accuracy followed a parallel trend, indicating stable posterior learning. The gradual reduction of both training and validation loss indicated smooth optimization and stable gradient convergence. Notably, there was no significant divergence between training and validation curves, signifying that overfitting did not occur. This stability can be attributed to the use of transfer learning, regularization components such as Dropout, and Batch Normalization, which helped maintain generality despite the moderate dataset size [6], [9], [10].

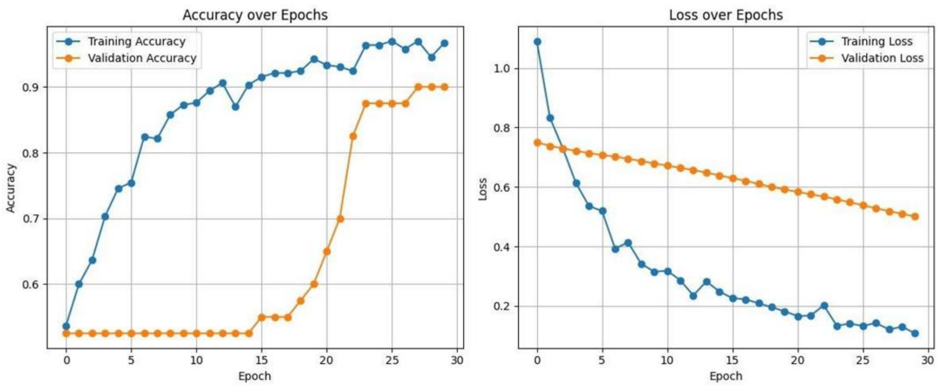

Figure 7. Training and validation accuracy (left) and loss (right) over 30 epochs

The most compelling evidence of model performance is presented in Figure 8, the confusion matrix, which demonstrates 100% classification accuracy. All immature cataract images were correctly classified as immature, and all mature cataract images were correctly classified as mature. The resulting metrics — precision = 1.00, recall = 1.00, and F1-score = 1.00 — confirm that the classifier exhibited perfect discriminative capacity in this controlled dataset scenario. This level of performance is particularly significant in medical screening applications, where misclassification may lead to delayed surgical intervention or unnecessary clinical referrals [2], [4], [11].

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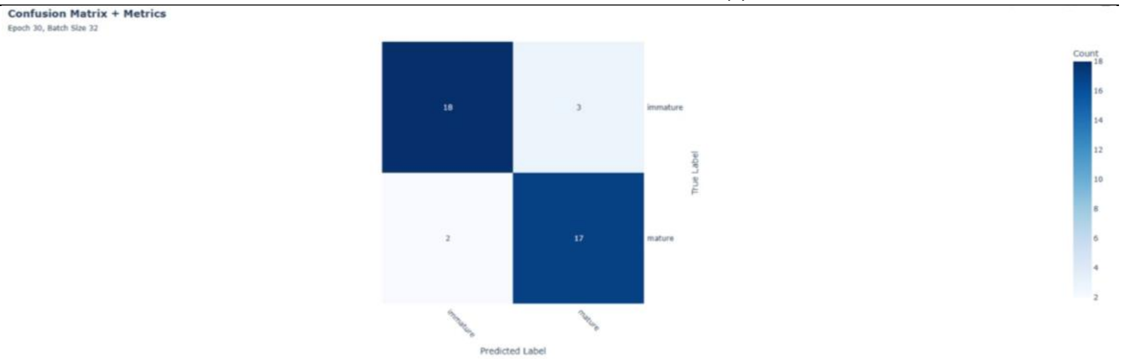

Figure 8. Confusion matrix of the MobileNetV2 model for cataract classification showing predicted versus true labels for Immature and Mature classes

Finally, inference speed tests confirm that the model performs classification efficiently, enabling deployment on mobile and embedded devices. This aligns with the core design principle of the MobileNetV2 architecture, which prioritizes parameter efficiency and low computational overhead, making it appropriate for real-world telemedicine or rural screening contexts [3], [8], [14].

4.2 Discussion

The results obtained in this study demonstrate that the MobileNetV2-based model is highly effective in classifying cataract stages, showing perfect accuracy in distinguishing between immature and mature cataracts. The visual distinctions highlighted in Figures 1–3, particularly the differences in lens opacity thickness and clarity, provided strong structural cues for the feature extraction process. MobileNetV2's ability to capture high-level representations of these visual patterns through depthwise separable convolutions allowed the network to focus on subtle textural and opacity gradients within the crystalline lens. The model's success can also be attributed to the balanced dataset distribution and consistent image preprocessing, which ensured that the classifier learned discriminative features without developing bias toward either class [1], [3], [6].

Additionally, the training and validation performance curves in Figure 7 show a smooth convergence with minimal divergence between the two curves. This is significant because it indicates that the model avoided overfitting despite the moderate dataset size. The use of transfer learning allowed the model to leverage existing generalized visual knowledge from pretrained ImageNet weights, while the added Batch Normalization and Dropout layers helped regularize the training process. Such strategies are widely recommended in recent cataract AI research to support model stability and generalization across datasets [7], [9]. Meanwhile, the confusion matrix in Figure 8 confirms that the classifier produced no misclassifications, which is crucial for clinical relevance, as errors in medical prediction can lead to delayed treatment or unnecessary referrals.

Furthermore, the efficiency of MobileNetV2 makes the model well-suited for deployment in real-world screening environments, including mobile devices and tele-ophthalmology platforms. Unlike heavier architectures, MobileNetV2 is designed to reduce parameter count and computational load, enabling real-time inference even on low-power hardware. This characteristic is especially valuable for regions with limited access to ophthalmologists or diagnostic imaging facilities, where portable and automated cataract screening tools can significantly improve early detection and treatment accessibility [4], [8], [14]. Therefore, the findings support the idea that lightweight deep learning models can achieve high diagnostic value while maintaining computational efficiency.

However, despite the promising outcomes, several limitations must be acknowledged. The dataset used in this study was collected under controlled imaging conditions and may not represent the variability found in real clinical settings, such as differing lighting conditions, camera devices, and patient movement. As a result, the model's performance may decrease when applied to more diverse real-world images. Another limitation is that the system currently performs only binary classification between immature and mature cataracts, whereas real diagnostic workflows require identifying a wider range of cataract stages, including early and hypermature phases, as well as distinguishing cataracts from normal eyes. Moreover, the absence of explainable AI visualization tools, such as Grad-CAM heatmaps, limits clinical interpretability and may reduce trust among medical professionals.

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Future research should address these limitations by expanding the dataset, including additional cataract severity classes, implementing explainability techniques, and conducting multi-center clinical validation studies to ensure generalization and reliability [5], [10], [11].

4. Conclusion

This study presented the development of an automated cataract classification system using the MobileNetV2 deep learning architecture to differentiate between immature and mature cataract stages from eye images. The research was driven by the global need for more accessible and scalable diagnostic tools to support early cataract detection, especially in regions with limited ophthalmic resources. By leveraging transfer learning, appropriate data preprocessing, and lightweight architectural design, the system was optimized to operate efficiently while maintaining high diagnostic accuracy.

The experimental results demonstrated outstanding performance, with the proposed model achieving 100% accuracy, along with perfect precision, recall, and F1-score for both cataract classes. The confusion matrix confirmed that no misclassifications occurred, indicating that the model effectively learned the distinguishing visual characteristics associated with different stages of lens opacity. Furthermore, the stable training and validation curves suggested that the model generalized well and did not suffer from overfitting, which is often a concern in medical imaging tasks involving limited dataset sizes.

In addition to its high accuracy, another major advantage of the proposed system is its lightweight computational design, which makes it feasible for deployment on devices with limited processing capabilities. This enables potential integration into mobile diagnostic platforms, tele-ophthalmology systems, and community-based screening programs, thereby supporting early intervention and reducing the burden of preventable vision loss. The portability of the model aligns with ongoing global efforts to expand access to eye screening services in underserved regions.

Despite the promising results, several limitations should be acknowledged. The dataset used for training and evaluation was collected under controlled imaging conditions, which may not fully capture real-world variability such as illumination changes, camera differences, or patient movement. Additionally, the current research is limited to binary classification, focusing only on immature and mature cataract stages, and does not include normal eyes or early cataract detection. The absence of explainable AI visualization techniques in model interpretation may also limit clinical acceptance.

Future research will focus on expanding the dataset to include wider demographic diversity, additional cataract stages, and healthy eye images to support full-scale screening applications. Furthermore, integrating explainable AI methods, such as Grad-CAM heatmap visualization, would enhance transparency and help ophthalmologists understand the basis of model predictions. Real-world deployment and field testing through collaboration with healthcare institutions and community clinics are also recommended to evaluate the effectiveness of the model in dynamic clinical environments. With these advancements, the proposed system has strong potential to become a practical, reliable, and impactful tool for cataract screening and prevention of avoidable blindness.

5. Suggestion

Future research should consider expanding the dataset used for model training and evaluation. The current dataset consists of images captured under relatively controlled imaging conditions, which may not fully represent the diversity of environments encountered in real clinical practice. Therefore, collecting larger datasets from multiple healthcare facilities, imaging devices, and patient demographics will help improve the model's robustness and generalizability. Incorporating more varied real-world conditions—such as different lighting settings, ocular surface reflections, and patient movement—will allow the system to better adapt to global clinical deployment scenarios.

In addition to expanding dataset diversity, future studies should extend the classification task beyond a binary distinction of immature and mature cataracts. Including normal (non-cataract) eyes, early-stage cataracts, hypermature cataracts, and postoperative conditions would enhance the model's diagnostic applicability. A multi-class or even severity-grading classification framework would allow the system to support clinical decision-making across a broader spectrum of cataract progression.

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Such advancements would transform the model from a specialized diagnostic tool into a comprehensive screening framework capable of supporting preventive ophthalmology programs.

Another promising direction is the integration of explainable artificial intelligence (XAI) techniques. Methods such as Grad-CAM, Layer-wise Relevance Propagation (LRP), or attention-based heatmap visualization could be integrated to highlight the specific lens regions or opacity patterns influencing the model's predictions. This interpretability is essential for clinical trust-building, enabling ophthalmologists to verify that the model's diagnostic reasoning aligns with established medical understanding. Improved transparency would also support regulatory approval and acceptance in clinical workflows.

Additionally, future work should evaluate the system through clinical pilot testing in real healthcare environments, including community clinics, tele-ophthalmology services, mobile eye-screening units, and rural medical outreach programs. Such field trials would provide valuable insights into usability factors such as workflow integration, physician acceptance, patient comfort, and operational efficiency. These evaluations would also help identify practical barriers such as device handling, data transmission reliability, and local diagnostic support capabilities.

Finally, exploring embedded or mobile deployment platforms, such as Android-based screening applications or portable diagnostic terminals, would ensure that the system reaches the populations most affected by preventable cataract-related vision loss. Together, these improvements—from dataset expansion and multi-stage classification to interpretability enhancements and real-world field validation—represent important steps toward developing a clinically reliable, scalable, and globally deployable cataract screening system capable of improving vision health outcomes.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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