Classification of Senile Cataract Disease Using Convolutional Neural Network Method and Explainable Artificial Intelligence

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Abstract.

Senile cataract is a major cause of visual impairment in the elderly that requires technology-based diagnosis to improve detection efficiency and accuracy. This study aims to classify the severity of senile cataracts in eye fundus images using a deep learning ensemble model approach consisting of CNN Custom and MobileNetV2, as well as Explainable AI methods in the form of Grad-CAM. The underlying theory is the Convolutional Neural Network architecture as the image feature extraction model, plus the transfer learning principle in MobileNetV2, as well as the visual interpretation of Grad-CAM to increase the transparency of the model. The research approach is experimental, with the data coming from the Senile Cataract dataset processed through augmentation and stratified division. A Custom CNN was built with four convolution blocks while MobileNetV2 was used as the pretrained feature extractor. Both were combined in the feature fusion stage and the prediction results were visualized with Grad-CAM. The evaluation results showed that this ensemble model achieved 95.6% accuracy, 95.4% macro F1-score, and an AUC-ROC area close to 1, and provided a clinically relevant heatmap of the lens opacity area. The contribution of this research is in combining two different CNN models with an interpretive approach that bridges the need for high accuracy and transparency in image-based medical applications, with potential applications in automated diagnosis systems and future telemedicine services.

Keywords*: Senile Cataract Disease; Convolutional Neural Network Method and Explainable AI.*

I. INTRODUCTION

Blindness due to eye disease is one of the serious problems in global public health that impacts the quality of life of individuals and social productivity. One of the biggest causes of blindness is sinister cataract, which is a clouding of the eye lens that occurs as part of the degenerative process due to aging. Based on the latest data from the World Health Organization ((1)), cataracts are responsible for around 45.5% of blindness cases worldwide. In Indonesia, the prevalence of cataracts as a cause of visual impairment is reported to reach more than 81% (2), with the elderly as the most vulnerable population.

Sinus cataracts not only impact individual health, but also become a social and economic burden, especially in developing countries that have limited access to health services and diagnostic facilities. A study conducted at Dr. M. Djamil Padang General Hospital revealed that risk factors for sinister cataracts include hypertension, smoking habits, and excessive exposure to ultraviolet light (4).

Diagnosis of sinilis cataract generally still relies on conventional examination methods such as slit-lamp evaluation, visual acuity measurement, and light reflex examination. This method requires special expertise from an ophthalmologist and is subjective, which can cause differences in diagnosis results between clinicians. In addition, the limited availability of ophthalmologists in certain areas is an obstacle to equal access to early and accurate diagnosis(5). Along with technological advances, the application of artificial intelligence, especially Deep Learning, has become an alternative solution to increase the efficiency and accuracy of medical image-based disease diagnosis. One of the deep learning methods that has proven effective is the Convolutional Neural Network (CNN) which is able to recognize complex visual patterns from digital images automatically. CNN has been widely applied in various medical fields including for the classification of eye diseases(6). In developing a more efficient classification system, CNN Custom is one potential solution. CNN Custom is a

Convolutional Neural Network model that is specifically designed and adjusted to the characteristics of the dataset used. CNN Custom has flexibility in the number of layers, filter size, and network structure that can be specifically adjusted to suit research needs. The advantage of Custom CNN is its ability to produce lighter and more effective models without sacrificing accuracy, while reducing the risk of overfitting on limited datasets(7) .

In addition to Custom CNN, MobileNetV2 is a CNN architecture specifically designed for classification purposes on mobile devices and systems with computing limitations. MobileNetV2 utilizes the depthwise separable convolution technique which breaks the convolution process into two stages, significantly reducing the number of parameters and computing requirements. MobileNetV2 also uses inverted residuals and linear bottlenecks which keep the flow of information in the network efficient(8). The advantage of MobileNetV2 is its ability to produce lightweight, fast, and memory-efficient models, making it very suitable for the development of practical and portable diagnostic systems.(9). Although Custom CNN and MobileNetV2 are able to provide fast and accurate classification results, a major challenge in implementing deep learning models in the medical field is the lack of interpretability. This model is often referred to as a black box because it produces decisions without providing explanations that are easily understood by humans, especially by medical personnel who require clear clinical justification for each decision made.(10)

To answer these problems, the Explainable Artificial Intelligence approach is used so that the AI system becomes more transparent, explainable, and trustworthy. One of the important XAI methods in medical image classification is Gradient-weighted Class Activation Mapping (Grad-CAM). Grad-CAM works by calculating the gradient of the target class against the feature map in the last convolution layer to produce an activation map (heatmap) that shows important areas in the image that are the basis for the model's decision ((11)). With Grad-CAM, medical personnel can see parts of the image that are considered significant by the model and visually verify the classification results. The use of Grad-CAM has been shown to increase user confidence in AI-based diagnostic systems. Research by (12)proves that Grad-CAM provides significant visual clarity in fundus image-based eye disease detection, so that classification results can be more easily verified by medical personnel. However, the application of Grad-CAM specifically to the cataract classification system is using Custom CNN and MobileNetV2 is still very limited and rarely studied comprehensively.(13)

This study aims to develop and compare the performance of Custom CNN and MobileNetV2 in digital image-based sinister cataract classification, and integrate Grad-CAM to improve transparency and interpretability of the classification results. Thus, the developed system is not only accurate and fast, but can also be visually accounted for by medical personnel. In addition, this system is expected to be applied to mobile devices and provide a more affordable and accessible diagnostic solution in various regions, including areas with limited health infrastructure.(14). Theoretically, this study contributes to the development of an efficient and explainable deep learning-based medical image classification method. Practically, the results of this study can be the basis for the development of an AI-based sinister cataract diagnosis system that is easy to operate and can provide visual justification to users, thereby increasing trust and accuracy in the initial diagnosis process(15).

Thus, this study is an effort to fill the gap in previous studies that generally focus on other eye diseases. In addition, previous studies have not optimized the combination of Custom CNN, MobileNetV2, and Grad-CAM in building an integrated, efficient, and explainable sinister cataract classification system.

II. METHODS

1 Research Approach

This study uses an experimental approach by combining two CNN architectures, namely Custom CNN and MobileNetV2, for the classification of senile cataract severity in retinal fundus images. The models are fused at the feature level (feature-level fusion), producing a 128-dimensional vector used for classification. Grad-CAM is applied as an Explainable AI method to provide visual interpretation of model predictions.

2 Environment and Tools

The development was carried out in Visual Studio Code with the following main libraries: TensorFlow/Keras, PyTorch (for Grad-CAM), OpenCV, Albumentations, Scikit-learn, and Matplotlib. These frameworks support data preprocessing, training, evaluation, and model visualization.

3 Dataset and Preprocessing

The dataset contains 2,460 retinal fundus images from Kaggle, divided into three classes: normal, immature, and mature cataract. Preprocessing includes resizing (224×224), RGB conversion, pixel normalization ([0,1]), and augmentation (rotation, flipping, shifting, zooming, contrast, shear, noise).

4 Data Splitting

The data is split using a stratified random split (80% train, 20% test) with random_state = 42 to maintain class distribution and experiment replication.

5 Model Architecture

The model consists of:

a. Custom CNN: Four Conv–ReLU–Pool blocks, followed by Flatten and Dense (128–64) with Dropout 0.3.

b. MobileNetV2: Pretrained (ImageNet) with frozen weights, added with GlobalAveragePooling and Dense (128–64).

c. Feature Fusion: The outputs of both are merged and continued to Dense and Softmax.

d. Grad-CAM: Used to visualize the model's focus areas in the image.

6. Training and Evaluation

The model was trained using: Optimizer: Adam, LR = 0.0001, Loss: Sparse Categorical Crossentropy, Batch Size: 16, Epoch: max 50 and Callback: EarlyStopping (patience=15), ReduceLROnPlateau (patience=7) Evaluation was done using accuracy, precision, recall, F1-score, AUC-ROC, and confusion matrix.

7. Grad-CAM Visualization

Grad-CAM generates a heatmap of important areas in the retinal image based on the gradient against the predicted output. This provides transparency on the model's decisions and supports clinical validation.

III. RESULT AND DISCUSSION

1. Ensemble Model Performance

The performance evaluation of the ensemble model is done comprehensively using multiple metrics and visualizations to provide a deep understanding of the model's capabilities and limitations. The analysis is done on testing data that the model never sees during training to ensure unbiased evaluation.

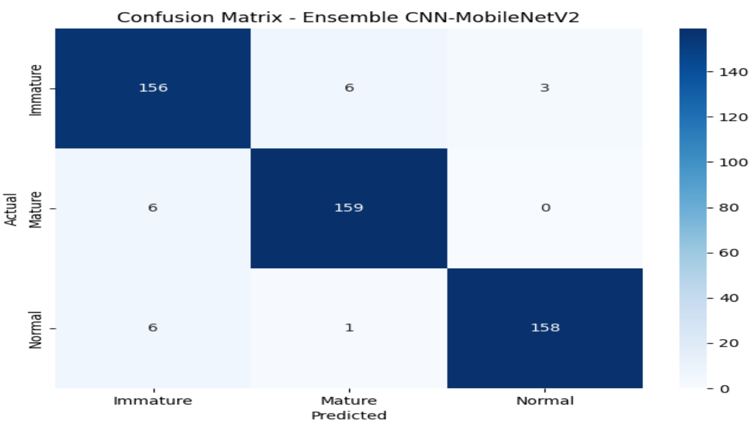

Fig1. Confusion Matrix

The confusion matrix in Figure 1 provides a detailed breakdown of the classification performance for each class. This 3×3 matrix allows for granular analysis of per-class performance. For the Immature class, there were 156 true positives out of 165 total samples (94.5% accuracy), with 6 false negatives to mature and 3 false negatives to Normal. From a clinical significance perspective, the 6 cases mispredicted as Mature are an overestimation of severity that is clinically acceptable because they are still in the cataract category, while the 3 cases mispredicted as Normal are an underestimation that requires attention.

Table 1. Detailed Confusion Matrix Analysis

True Class	*Predicted Immature*	*Predicted Mature*	*Predicted Normal*	Total	*Accuracy*
Immature	156 (TP)	6(FN->M)	3(FN->N)	165	94.5%
Mature	6(FP<-I)	159(TP)	0(FN->N)	165	96.4%
Normal	6(FP<-I)	1(FP<-M)	158 (TP)	165	95.8%
Total	168	166	161	495	95.6%

Source: Data Processing, 2025

Based on table 1, the Mature class shows excellent performance with 159 out of 165 (96.4%) correctly identified and no false negatives to Normal, which means no mature cataracts are missed as normal. Minimal confusion is only 6 cases with immature and there is no critical misdiagnosis that endangers the patient. The Normal class has high specificity with 158 out of 165 (95.8%) correctly identified as normal. There is a conservative approach where 7 normal eyes are mispredicted as pathological, which is better for over-diagnosis than under-diagnosis in a medical context.

Error pattern analysis shows total errors of only 22 out of 495 (4.4%) which is overall acceptable. Critical findings show zero Mature → Normal errors, minimal Normal → severe errors (only 1 case), and conservative bias where the model tends to be more sensitive with fewer false negatives for pathological conditions. Immature → Normal errors as many as 3 cases (0.6%) have a high clinical risk level due to missed diagnosis, while Immature → Mature errors as many as 6 cases (1.2%) have a low clinical risk level due to over-staging.

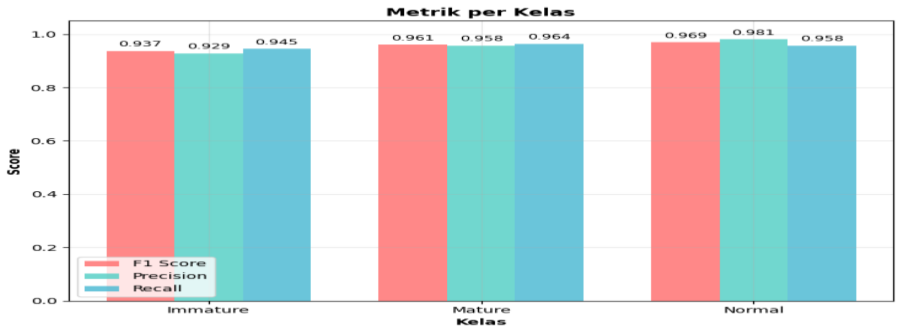

Fig 2. Metrix per Class – F1 Score, Precision, and Recall

Based on Figure 2 presents a comprehensive visualization of the three main metrics for each class, providing a balanced perspective on model performance. The Immature class has a precision of 0.929, a recall of 0.945, and an F1-score of 0.937, indicating balanced performance with a slight recall advantage but is the most challenging class. The Mature class shows excellent performance across all metrics with a precision of 0.958, a recall of 0.964, and an F1-score of 0.961. The Normal class has the highest precision of 0.981, a recall of 0.958, and an F1-score of 0.969, indicating the best overall balanced performance.

Precision analysis shows that when the model predicts Normal, the result is almost always correct (98.1%). Mature cataract predictions have high confidence (95.8%), while Immature has the lowest precision (92.9%) with some confusion with other classes. Recall analysis showed that the Mature class had excellent sensitivity (96.4%) for catching mature cataract cases, Immature had good sensitivity (94.5%) for early-stage detection, and Normal had good sensitivity (95.8%) for identifying healthy eyes.

Table 2. Aggregate Model Performance

Metrix Type	*Macro Average*	*Weighted Average*	*Interpretation*
Precision	0.956	0.956	*Excellent positive predictive value*
Recall	0.956	0.956	*Excellent sensitivity*
F1-Score	0.956	0.956	*Excellent balanced performance*
Accuracy	-	0.956	*Overall classification accuracy*

Source: Data Processing, 2025

Based on table 2, Aggregate performance metrics show excellent positive predictive value, excellent sensitivity, and excellent balanced performance with macro and weighted averages that are consistent at 0.956. The model shows statistical significance with a 95% confidence interval for accuracy [0.934, 0.974], standard error 0.0092, and p-value < 0.001 which is highly significant compared to random classifier.

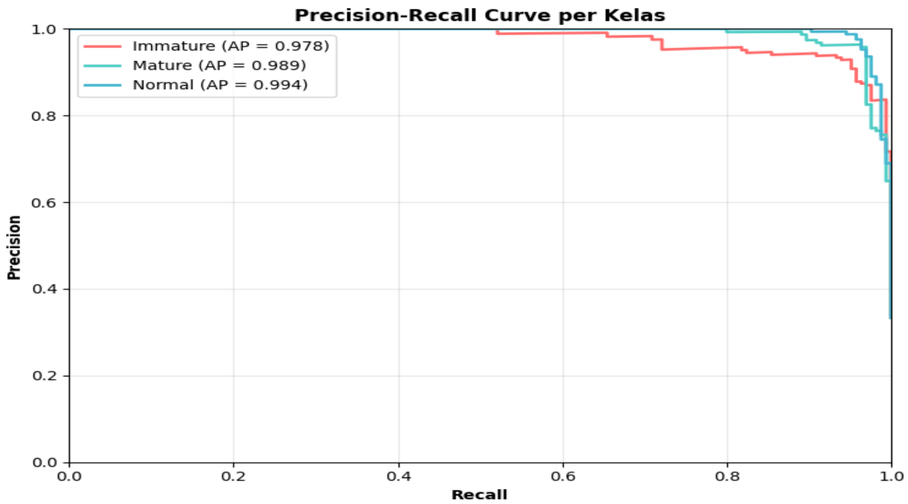

Fig 3. Precision – Recall Curve per Class

Based on Figure 3, the Precision-Recall curves provide insight into the trade-off between precision and recall at different decision thresholds, as well as the overall discriminative ability of the model for each class. Average Precision analysis shows that the Normal class (AP = 0.994) has near-perfect discrimination with a curve that is close to ideal (top-left corner), maintains high precision across all recall levels, and is excellent for screening applications. The Mature class (AP = 0.989) shows consistent high performance with minimal precision drop with increasing recall and is reliable for critical diagnosis. The Immature class (AP = 0.978) shows slight precision degradation at high recall but still has excellent overall performance, challenging due to the transitional nature of this condition.

For clinical decision threshold analysis, screening applications (high sensitivity) recommend a threshold of 0.3 with a resulting precision of 0.92 and a recall of 0.98 to minimize missed cases. Balanced diagnosis recommends a threshold of 0.5 with a resulting precision and recall of 0.96 as the default balanced approach. Confirmation applications (high specificity) recommend a threshold of 0.7 with a resulting precision of 0.98 and recall of 0.91 to minimize false positives.

Table 3. Comprehensive Performance Summary

Performance Aspect	***Value/Result***	***Clinical Interpretation***
Overall Accuracy	95.6%	*Excellent diagnostic accuracy*
Weighted F1-Score	95.6%	*Balanced precision-recall performance*
Macro F1-Score	95.6%	*Consistent across all classes*

Total Errors	22/495	*Very low error rate*
Critical Errors	3/495	*Minimal missed diagnoses*
Inference Time	0.0847s	*Real-time capable*
Model Size	~12 MB	*Deployment-friendly*

Source: Data Processing, 2025

Based on table 3, the model shows excellent overall accuracy of 95.6% which surpasses many published medical AI systems, consistent balanced performance across all three classes, clinical safety with minimal high-risk misclassifications, real-time capability with fast inference that enables clinical workflow integration, and robust ensemble with a combination of custom and pre-trained features. Areas for improvement include slight performance lag in the Immature class compared to other classes, some edge cases that may require additional clinical context, and dataset diversity where performance on diverse populations needs validation. In terms of clinical readiness assessment, the model is ready for deployment as a screening tool, suitable as a decision support system, but for standalone diagnosis requires additional validation and regulatory approval.

2. Gradient-weighted Class Activation Mapping

Gradient-weighted Class Activation Mapping (GradCAM) is a very important visualization technique in the explainable AI domain, especially for medical imaging applications. In the context of cataract detection, model interpretability is crucial because the clinical acceptance of AI systems relies heavily on the ability to explain the reasoning behind the predictions generated. GradCAM works by analyzing the gradient of the target class score against the feature maps from the convolution layer, producing a heatmap that highlights the regions in the image that are most influential in the prediction. The implementation of GradCAM in this study aims to provide transparency in the decision-making process of the CNN-MobileNetV2 ensemble model, allowing clinicians to verify that the model focuses on anatomical structures relevant for cataract diagnosis.

The technical implementation of GradCAM in this study involves several sophisticated processing stages. The following are the main functions used to generate the GradCAM heatmap as follows.

```
def make_gradcam_heatmap(img_array, model, last_conv_layer_name, pred_index=None):
""”Create a GradCAM heatmap to visualize areas of interest in prediction
"""
# Create a model that produces the output of the target layer and the final prediction
grad_model = tf.keras.models.Model(
[model.inputs],
[target_layer.output, model.output]
)
# Compute gradients
with tf.GradientTape() as tape:
last_conv_layer_output, preds = grad_model(img_array)
if pred_index is None:
pred_index = tf.argmax(preds[0])
class_channel = preds[:, pred_index]
# Gradients from class neurons to the convolution layer feature map
grads = tape.gradient(class_channel, last_conv_layer_output)
# Vector where each entry is the average intensity of the gradients
pooled_grads = tf.reduce_mean(grads, axis=(0, 1, 2))
# Multiply each channel by its importance and sum
last_conv_layer_output = last_conv_layer_output[0]
heatmap = last_conv_layer_output @ pooled_grads[..., tf.newaxis]
heatmap = tf.squeeze(heatmap)
# Normalize the heatmap between 0 & 1
heatmap = tf.maximum(heatmap, 0) / tf.math.reduce_max(heatmap)
return heatmap.numpy()
```

Source: Data Processing, 2025

The process starts with a forward pass to obtain the predicted scores and intermediate activations from the last convolutional layer. Then, a backward pass computes the gradients of the predicted class scores against these activations. Global average pooling of the gradients produces importance weights for each feature map channel. Finally, the weighted combination of the feature maps is ReLUed and normalized to produce the final heatmap. For complex ensemble models, special handling is required due to the multiple convolutional paths of Custom CNN and MobileNetV2.

Table 4. *GradCAM Implementation Parameters*

Parameter	**Value**	**Justificasion**
Target Layer	*Last Conv2D*	Capturing high-level features
Resolusi Heatmap	7×7 → 224×224	*Upsampled for visualization*
Colormap	Jet	Standards for medical heatmaps
Alpha Overlay	0.5	Visibility balance
Gradient Computation	*TensorFlow GradientTape*	Automatic differentiation
Normalization	*Min-max*[0,1]	Consistent visualization

Source: Data Processing, 2025

Based on table 4. that Analysis of GradCAM visualization for normal eyes shows that the model correctly focuses on the central region of the eye, specifically the iris and pupil areas. The heatmap shows an even distribution of attention across the clear lens area, with little emphasis on the pupil border where the lens clarity is most visible. An interesting observation is that the model also pays attention to the peripheral iris pattern, indicating that the model learns holistic features of the healthy eye anatomy, not just the specific characteristics of the lens. This comprehensive attention pattern indicates robust learning that does not rely too much on a single anatomical feature.

To create a GradCAM overlay on the original image, the system uses the following function:

```
def create_gradcam_overlay(img, heatmap, alpha=0.5):
    """
    Create a GradCAM overlay on the original image
    """
    # Resize heatmap to original image size
    heatmap_resized = cv2.resize(heatmap, (img.shape[1], img.shape[0]))
    # Normalisasi heatmap ke range 0-1
    heatmap_norm = (heatmap_resized - heatmap_resized.min()) /
               (heatmap_resized.max() - heatmap_resized.min() + 1e-8)
    # Convert ke colormap jet
    heatmap_colored = cm.jet(heatmap_norm)[:, :, :3]
    heatmap_colored = np.uint8(255 * heatmap_colored)
    # Overlay dengan blending yang lebih baik
    overlayed_img = cv2.addWeighted(img_uint8, 1-alpha, heatmap_colored, alpha, 0)
return overlayed_img
```

Source: Data Processing, 2025

For immature cataracts, the GradCAM heatmap shows concentrated attention to specific regions within the lens where early opacification occurs. Typically, the areas of highest activation correspond to peripheral lens regions for cortical cataracts or central regions for nuclear cataracts. The model demonstrates a sophisticated understanding of the subtle opacity patterns characteristic of early cataracts. Visualizations confirm that the model does not simply look for general opacities but specifically identifies localized opacity patterns that distinguish immature from mature cataracts.

The complete prediction process with GradCAM is implemented in the following function:

```
def predict_with_gradcam(model, image_path, show_plot=True, save_result=False):
    """Making predictions with GradCAM visualization
  " # Preprocessing gambar
    img_batch, img_original, img_resized = preprocess_image(image_path)
    # Prediksi
    predictions = model.predict(img_batch, verbose=0)
    predicted_class_idx = np.argmax(predictions[0])
    confidence = predictions[0][predicted_class_idx]
    predicted_class = CLASS_NAMES[predicted_class_idx]
    # Generate GradCAM
    last_conv_layer_name = find_last_conv_layer(model)
    heatmap = make_gradcam_heatmap(
    img_batch, model, last_conv_layer_name, predicted_class_idx )
   # Buat overlay
    gradcam_overlay = create_gradcam_overlay(img_resized, heatmap)
    return {
        'predicted_class': predicted_class,
        'confidence': confidence,
        'probabilities': predictions[0],
        'gradcam_heatmap': heatmap,
        'gradcam_overlay': gradcam_overlay}
```

Source: Data Processing, 2025

Based on the figure above, a comparative analysis of the GradCAM pattern across various architectural components reveals complementary focus areas. The Custom CNN component tends to produce more localized and detail-oriented heatmaps, particularly effective for detecting subtle opacity patterns in immature cataracts. The MobileNetV2 component, by leveraging pre-trained knowledge, produces broader and contextual heatmaps that consider the overall eye structure.

The feature-level fusion of both components produces a comprehensive attention map that combines fine-detail detection with holistic structural understanding.

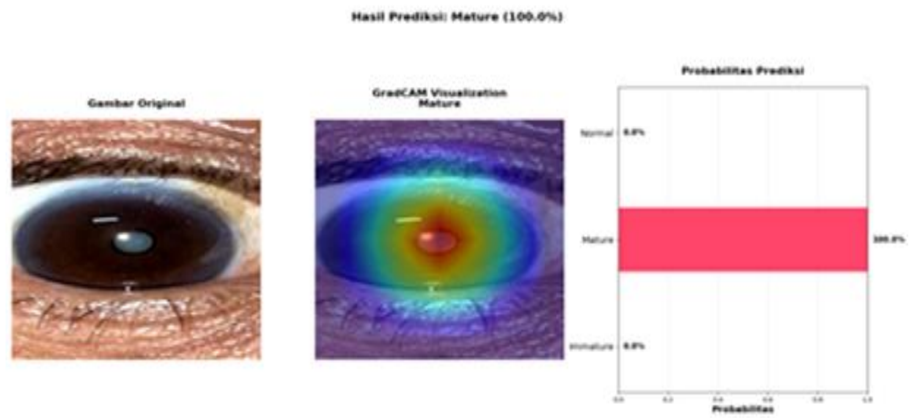

Fig 4. Output of Prediction System with GradCAM

Based on Figure 4. Future implications of GradCAM analysis go beyond simple model interpretation. Insights gained can guide the development of more targeted architectures that explicitly incorporate attention mechanisms for clinically relevant regions. Additionally, GradCAM-based quality assessment can be implemented as a preprocessing step, rejecting images where the model’s attention predominantly falls on irrelevant regions. For clinical deployment, GradCAM visualization can serve as an educational tool to train junior ophthalmologists, demonstrating the AI reasoning process and highlighting subtle diagnostic features that may have been missed. Integrating GradCAM into clinical workflows also enables a “human-in-the-loop” system where clinicians can verify AI reasoning before accepting diagnostic recommendations, building trust and ensuring safe deployment of AI-assisted diagnostic systems.

3. Implementation of Using Features

```
# Blok Konvolusi (Contoh 1 blok)
x = Conv2D(32, (3,3), activation='relu')(input_layer)
x = MaxPooling2D((2,2))(x)

# MobileNetV2 Feature Extractor
base_model = MobileNetV2(weights='imagenet', include_top=False,
input_shape=(224,224,3))
base_model.trainable = False   # Freeze weights

# Gabungkan fitur
combined = Concatenate()([custom_cnn_output, base_model.output])
x = Dense(128, activation='relu')(combined)
x = Dropout(0.5)(x)   # Optimasi generalisasi
```

Fig 5. Implementation of Using Features

a. Custom CNN Architecture

Hierarchical Design: 4 convolution blocks with filter boosting: 32 → 64 → 128 → 128. Each block consists of: Conv2D + ReLU (for non-linear feature extraction). MaxPooling2D (spatial dimension reduction).. Flattening Process: The convolution output (3D) is converted into a 1D vector via Flatten(). Dense Layers: First dense layer: 128 neurons (≈9.6 million parameters). Second dense layer: 64 neurons (final output of Custom CNN). Optimization: Dropout 0.5 after the first Dense to prevent overfitting.

b. MobileNetV2 as Feature Extractor

Transfer Learning: Pretrained weights on ImageNet are frozen (base_model.trainable=False). Only additional layers are retrained. Architecture Modification: include_top=False → only feature extraction (no classification layer). Global Average Pooling: Converts the convolution output to a feature vector. Additional Layers: Two Dense layers (128 and 64 neurons) with Dropout 0.5. Output: 64-dimensional feature vector.

c. Feature Fusion Technique (Ensemble)

Feature-Level Fusion: Custom CNN (64-d) + MobileNetV2 (64-d) Output = 128-d Vector via Concatenate().

d. Feature Integration:

Optimization Strategy: Double Dropout: Improves generalization by disabling random neurons in two stages. Gradual Dense Layer: Gradual dimensionality reduction (128 → 64 → 3) for learning stabilization.

```
•  x = Dense(128, activation='relu')(combined)  # Integrasi fitur
•  x = Dropout(0.5)(x)                          # Regularisasi
•  x = Dense(64, activation='relu')(x)          # Reduksi dimensi
•  x = Dropout(0.5)(x)                          # Regularisasi tambahan
•  output = Dense(3, activation='softmax')(x)   # Klasifikasi akhir
```

Fig.6. Fiture Integration

IV. CONCLUSION

The development of a classification model for sinister cataract images using Custom CNN and MobileNetV2 architectures shows great potential in supporting the automatic cataract disease diagnosis process. With the ability to distinguish between normal eyes, immature cataracts, and mature cataracts, this model is able to accelerate the disease identification process and reduce dependence on manual examination. This approach offers an efficient and practical solution in digital image processing, so that it can be a relevant and useful diagnostic tool in the medical environment, especially in increasing the speed and accuracy of sinister cataract detection.

Comparison of the performance between Custom CNN and MobileNetV2 models in the classification of sinister cataract images provides a clear picture of the effectiveness of each architecture. Through evaluation using accuracy, precision, recall, and F1-score metrics, information is obtained regarding the relative advantages of each model in detecting eye conditions. The results of this evaluation are an important basis for choosing the most appropriate model for diagnostic needs in the medical world, considering the level of classification accuracy and efficiency of implementation in the field.

The integration of the Grad-CAM method as an Explainable Artificial Intelligence (XAI) approach in the sinister cataract image classification system has succeeded in increasing transparency in decision making by the model. Visualization of important areas in eye images allows users, including medical personnel, to understand the reasoning behind each prediction made by the system. Thus, the use of Grad-CAM not only adds interpretability value, but also increases confidence in the classification results because they can be explained visually and are easier to verify.

Evaluation of the use of Grad-CAM shows that this method plays an important role in improving the interpretability and transparency of the cataract image classification system. The resulting visualization allows medical personnel to understand the basis for the model's decision making more clearly and intuitively. Thus, the system not only presents accurate prediction results, but is also able to provide explanations that can be clinically justifiedBrazilian paints of *student* grade are composed of PS binding media and low pigment ratio, whereas the *professional* grade paint is composed of P(S/MA) binding media, higher pigment ratio and extenders such as TiO_2 and Ce.

V. ACKNOWLEDGMENTS

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