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## PAPER ID 494

**“Deep Learning-Based Cataract Detection Using CNN Architectures”**


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# Introduction

- Cataract is one of the leading causes of vision impairment and blindness worldwide.
- Traditional detection methods rely on manual examination, which can be time-consuming and subjective.
- Deep learning, especially Convolutional Neural Networks (CNNs), offers a powerful approach for automatic image-based diagnosis.
- This research proposes a deep learning-based model for accurate cataract detection from fundus images.
- Multiple CNN architectures are explored and compared to achieve optimal performance.
- The objective is to enhance detection accuracy and support ophthalmologists in early diagnosis.

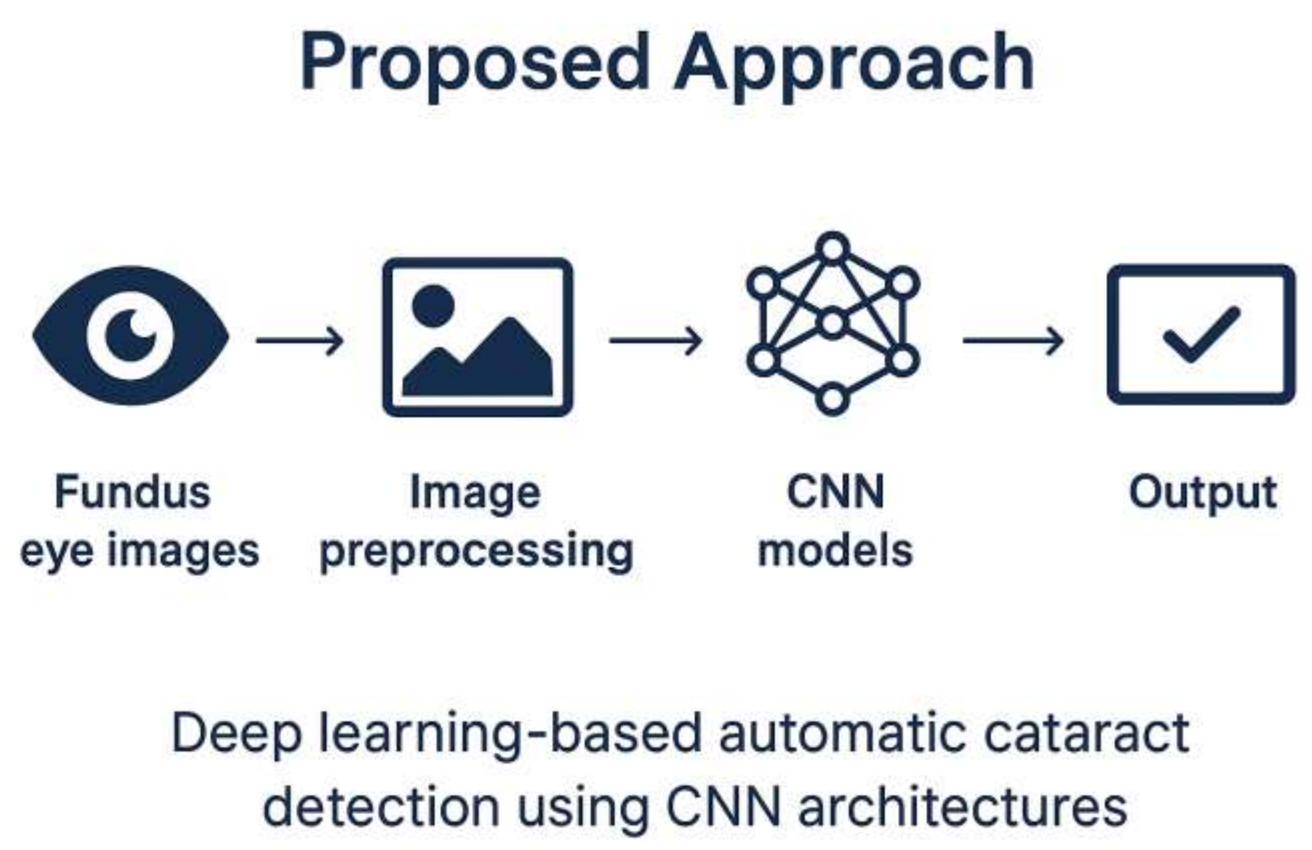
# Background

Several studies have shown the power of CNNs and transfer learning for cataract detection. Researchers like Varma, Yadav, and others demonstrated improved accuracy and faster diagnosis using deep learning. However, there’s still a need to enhance model reliability and generalization — which motivated our proposed approach.

- In recent years, deep learning has shown great potential for automatic cataract detection and classification.
- Several researchers have used CNN-based models to improve detection accuracy and reliability.
- Varma et al. designed a deep learning system proving CNNs can effectively detect cataracts from eye images.
- Yadav & Yadav demonstrated that deep learning provides more accurate results than traditional diagnosis methods.
- Studies using models like ResNet50 and hybrid CNN–Random Forest have improved early prediction and classification performance.
- Overall, CNN and transfer learning architectures enable faster, more accurate, and automated cataract diagnosis.

# Proposed Approach

- Goal: Automatic cataract detection using deep learning
- Input: Fundus images from public datasets
- Preprocessing: Resizing, normalization, augmentation
- Models: CNN, VGG16, DenseNet121, InceptionV3, MobileNetV2
- Workflow: Preprocessing → Training → Evaluation
- Evaluation: Accuracy, Precision, Recall, F1-Score
- Outcome: Early detection, high accuracy, reduced manual screening



# Development of the Proposed Approach

Dataset: Fundus eye images from publicly available datasets.

Image preprocessing: Resizing, normalization, and data augmentation (rotation, flipping, contrast adjustment).

Model implementation:

- Custom CNN with 3 conv layers + dense layers.
- Pre-trained models: VGG16, DenseNet121, InceptionV3, MobileNetV2 (fine-tuned).

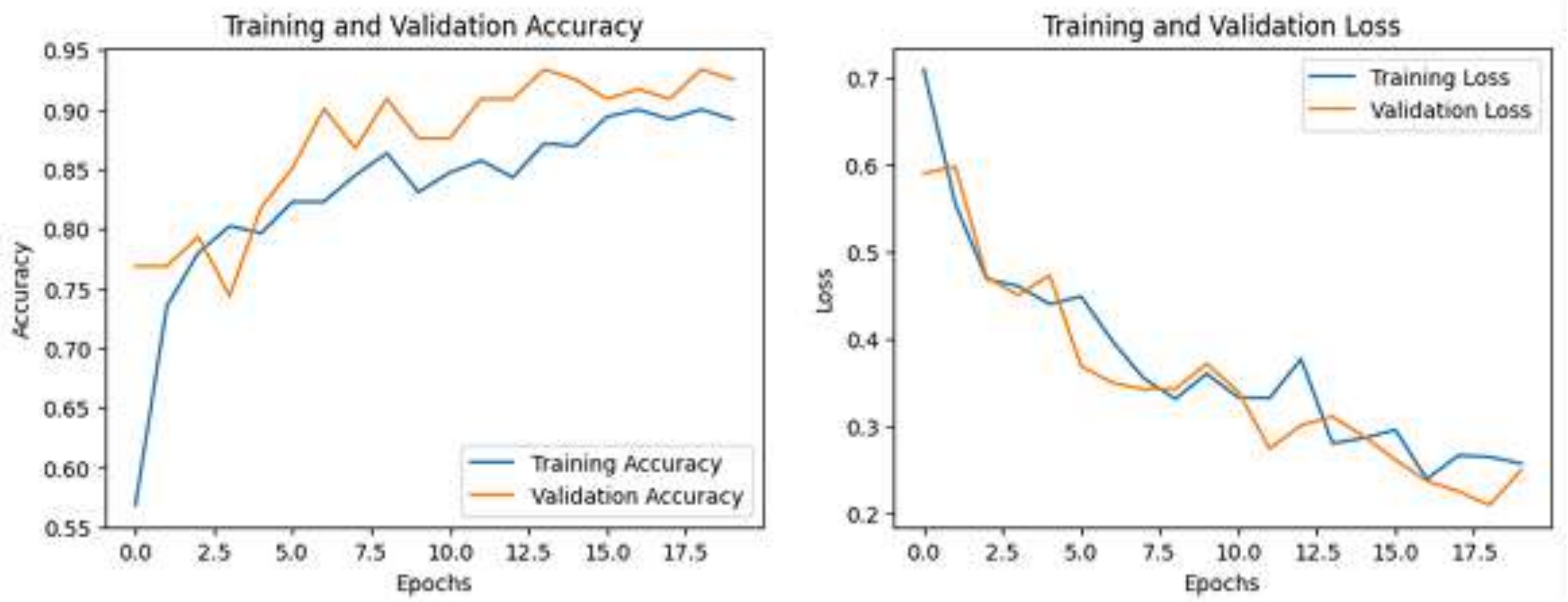
Training strategy:

- Split data into training, validation, and testing sets.
- Optimizer: Adam; Loss: Cross-Entropy.
- Early stopping and dropout to prevent overfitting.

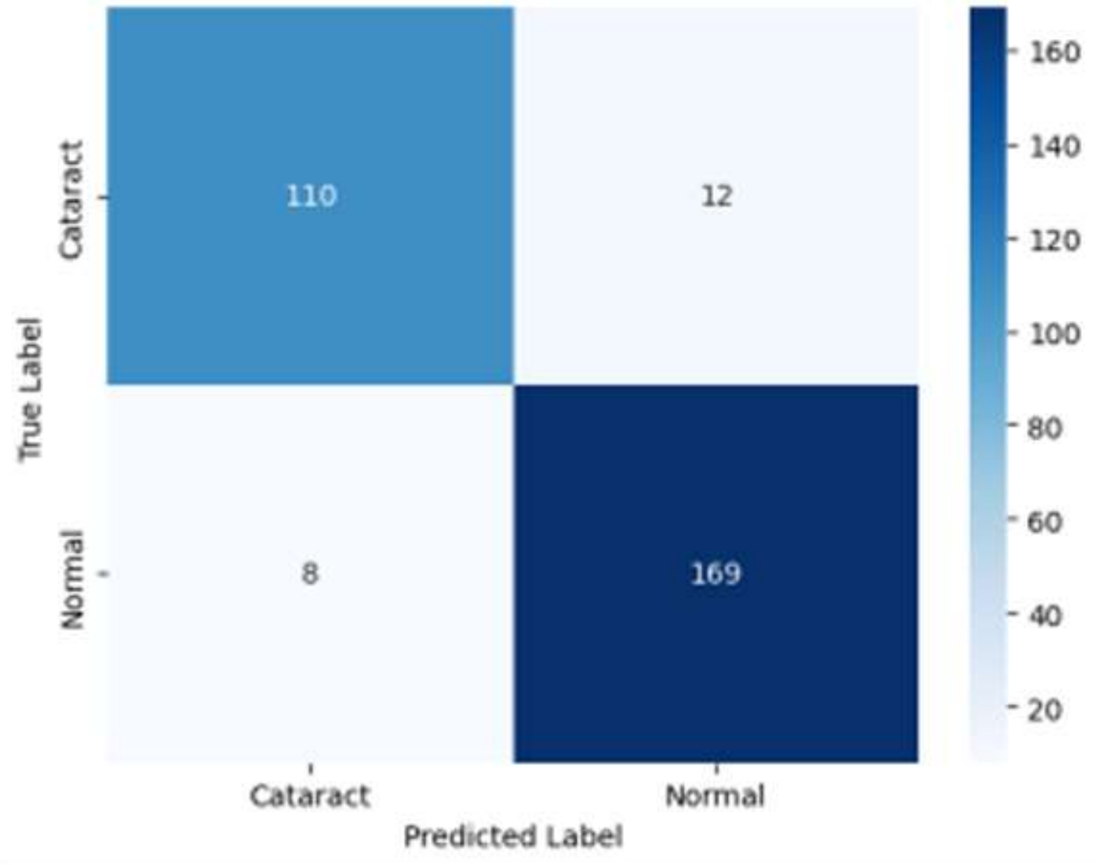
Framework: Implemented using **TensorFlow/Keras**.

# Validation of the Proposed Approach/Case Study

## Performance of Custom CNN Model




- Model trained for **20 epochs** showed smooth convergence.
- **Validation accuracy ≈ 93%**, indicating good generalization.
- Training and validation losses decreased steadily to **≈0.25**, showing minimal overfitting.
- **Confusion Matrix:**
    - Correctly classified → *Cataract: 110*, *Normal: 169*
    - Misclassified → *Cataract as Normal: 12*, *Normal as Cataract: 8*
- **Overall Accuracy: 91.7%**




*The proposed CNN demonstrates strong performance and reliable distinction between cataract and normal images.*

## Performance of VGG-16 Model

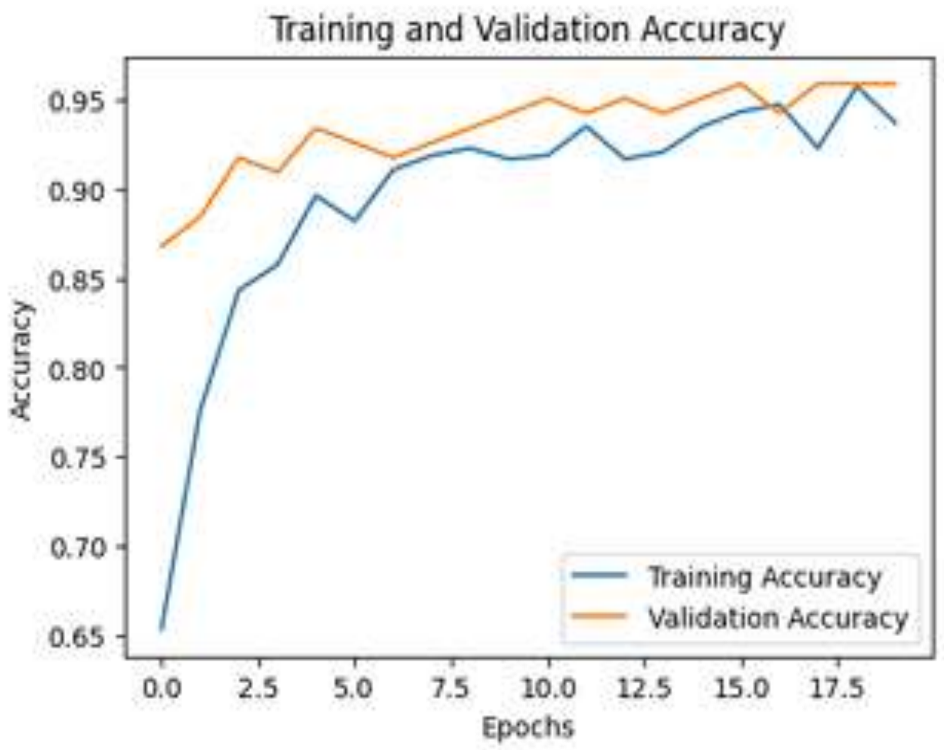
- Model trained for 20 epochs showed consistent accuracy improvement.
- Validation accuracy ≈ 96%, indicating strong generalization.
- Training and validation losses decreased steadily to ≈0.13, with minimal overfitting.

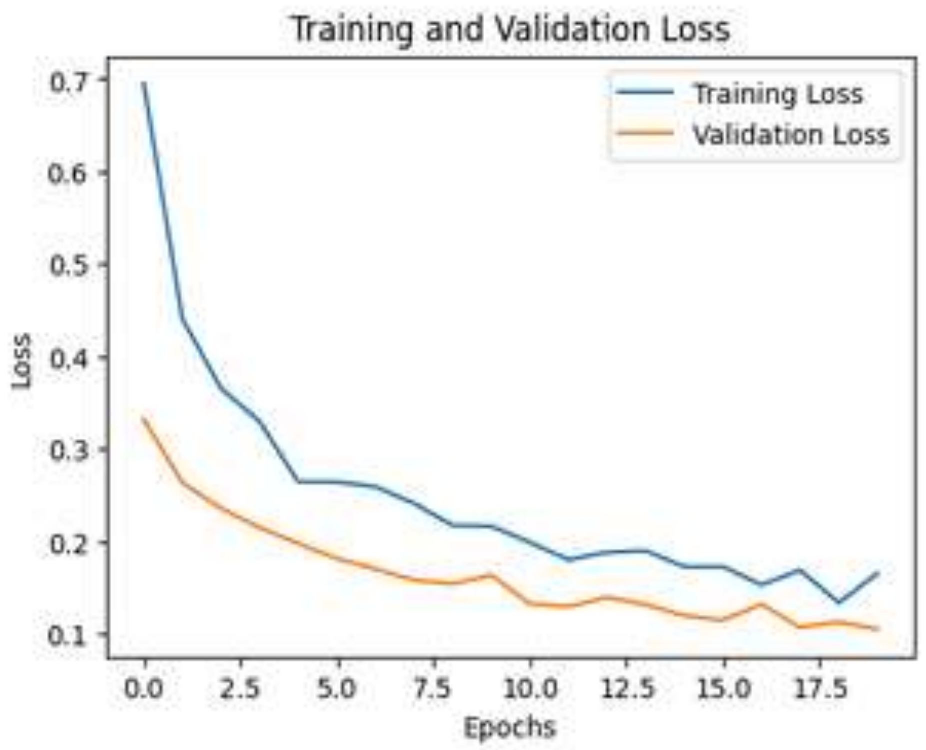
**Confusion Matrix:**

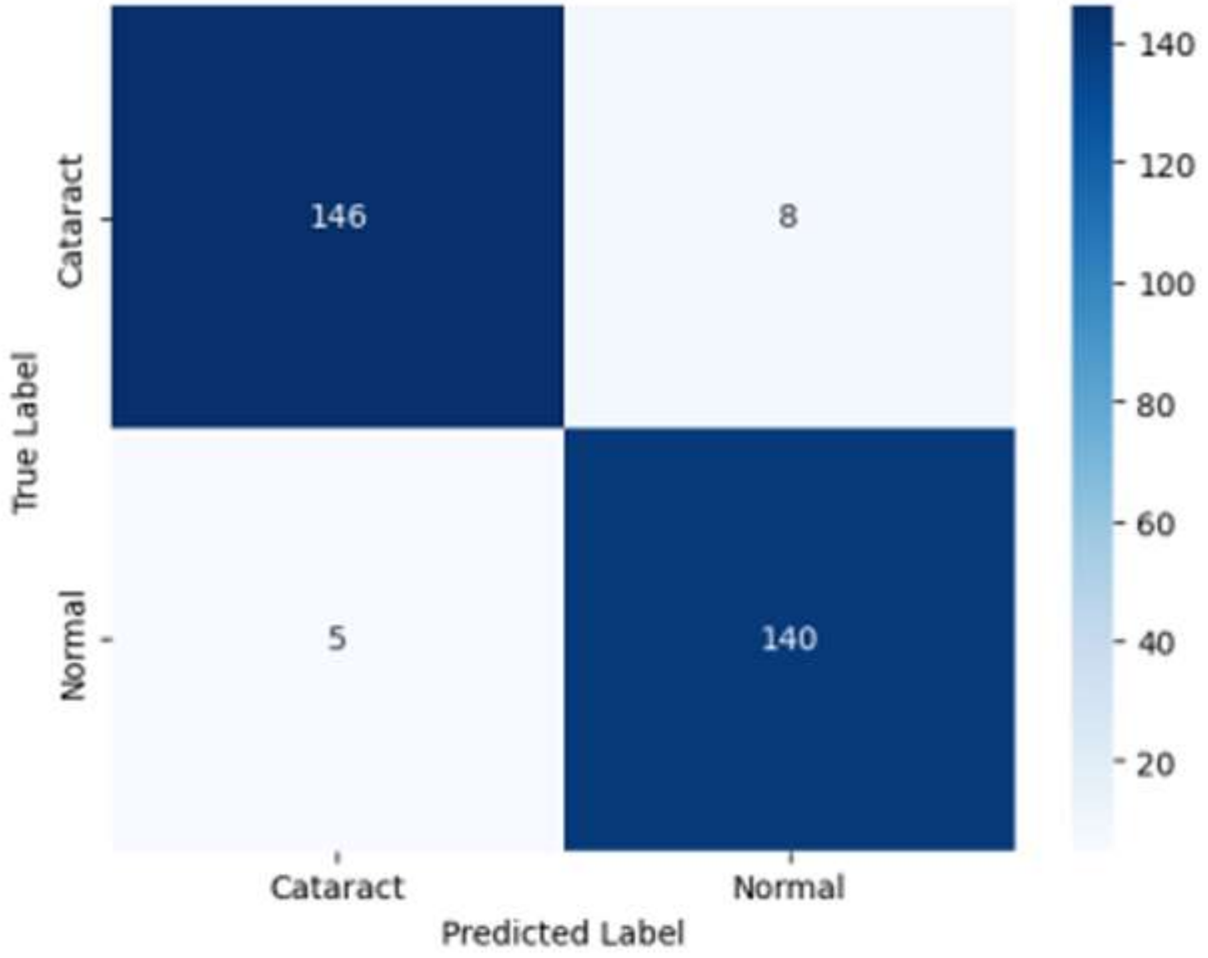
- Correctly classified → Cataract: 146, Normal: 140
  Misclassified → Cataract as Normal: 8, Normal as Cataract: 5

**Overall Accuracy:** 95.7%

- VGG-16 demonstrates high classification performance and reliable differentiation between cataract and normal eye images.



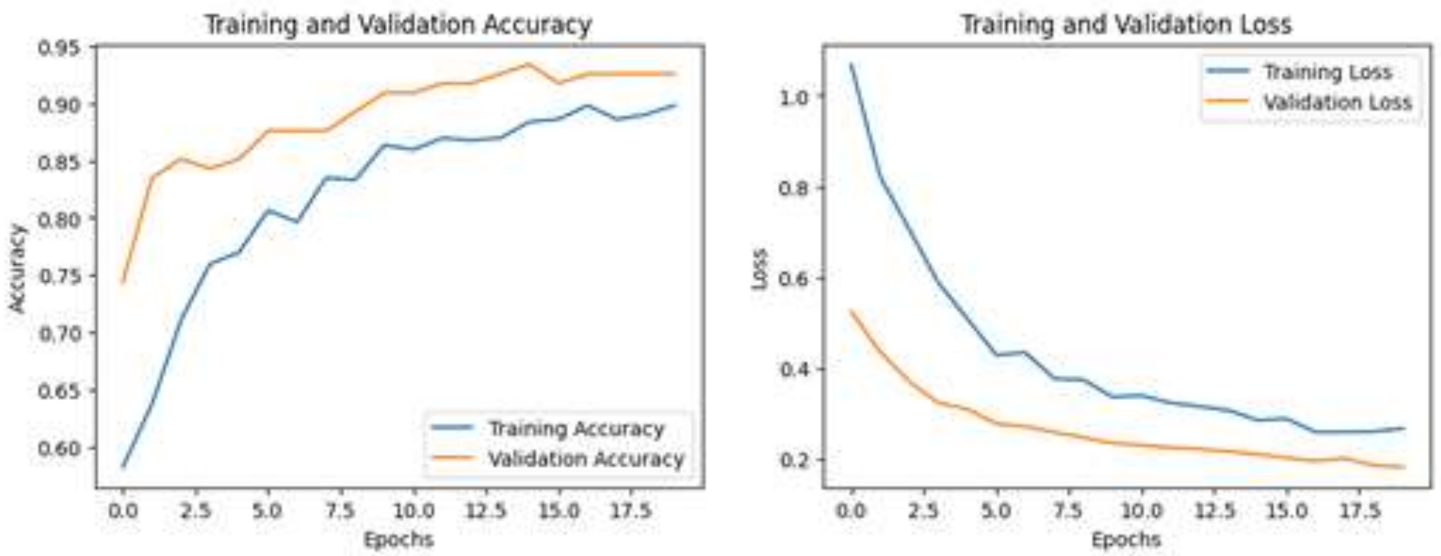



## Performance of DenseNet121 Model

**Objective:** Classify ocular images as Cataract or Normal

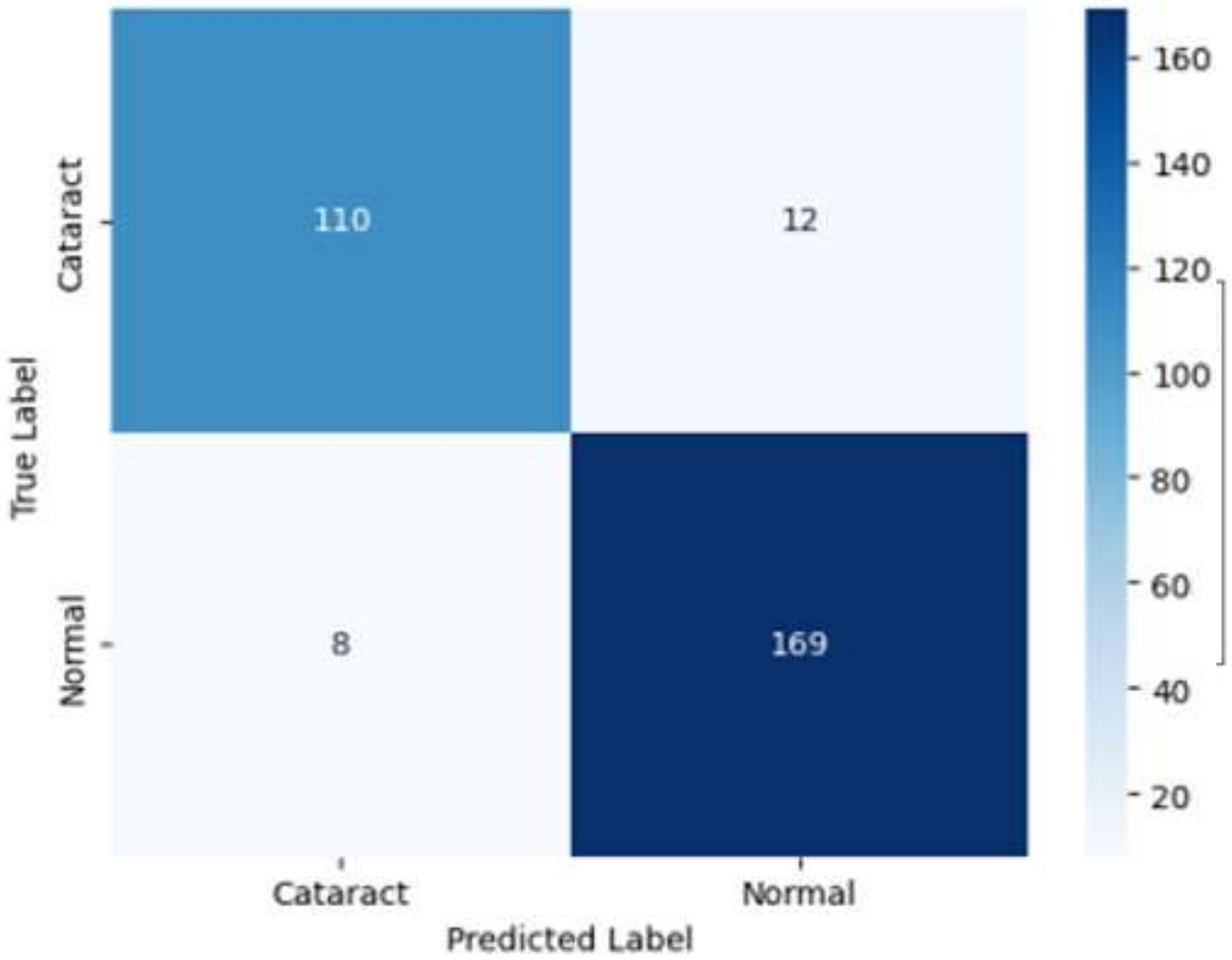
**Performance:**

- Validation Accuracy: ~92%
- Final Training Accuracy: ~90%
- Validation Loss: decreasing → good generalization
- No overfitting observed (20 epochs)



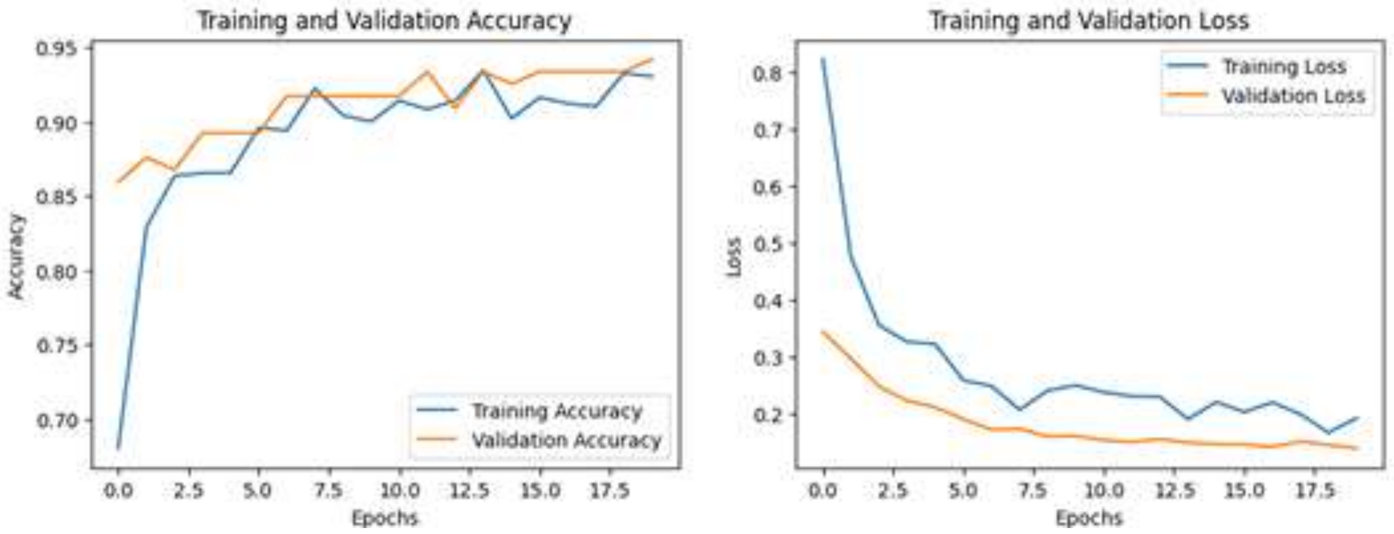

**Confusion Matrix Summary:**

- **Cataract:** TP = 110, FN = 12
- **Normal:** TN = 169, FP = 8
- **Overall Accuracy:** 93.3%

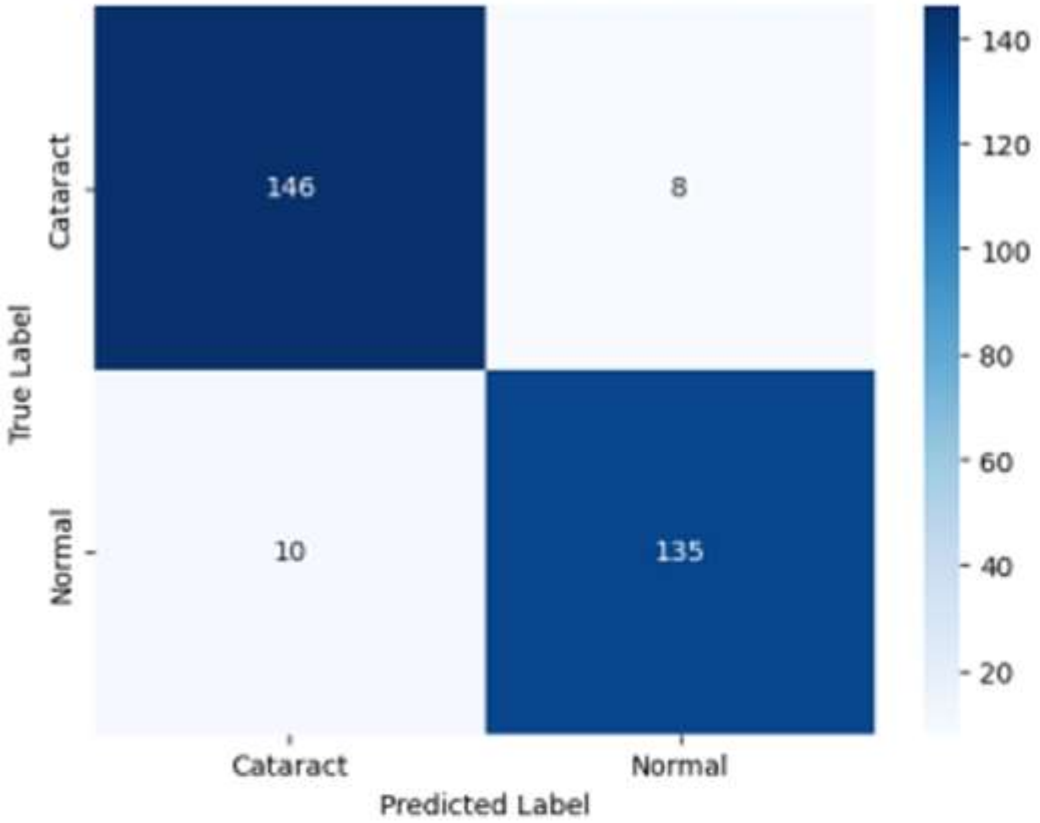


## Performance of InceptionV3 Model

- Trained InceptionV3 for **20 epochs** to classify **Cataract** and **Normal** eye images.
- Achieved **~93–94% accuracy** for both training and validation sets.
- **Loss curves** decreased and stabilized after around **10 epochs**, indicating good convergence.



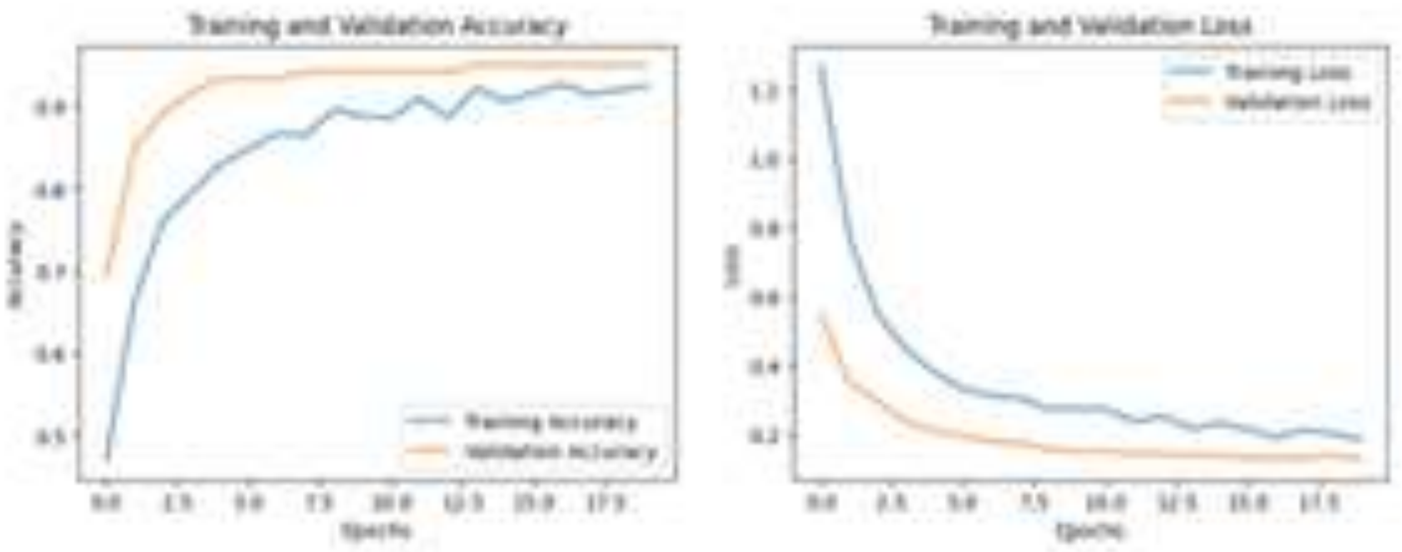

- **Confusion Matrix Results:**
  - Cataract: **146 correctly classified**, **8 misclassified**
  - Normal: **135 correctly classified**, **10 misclassified**



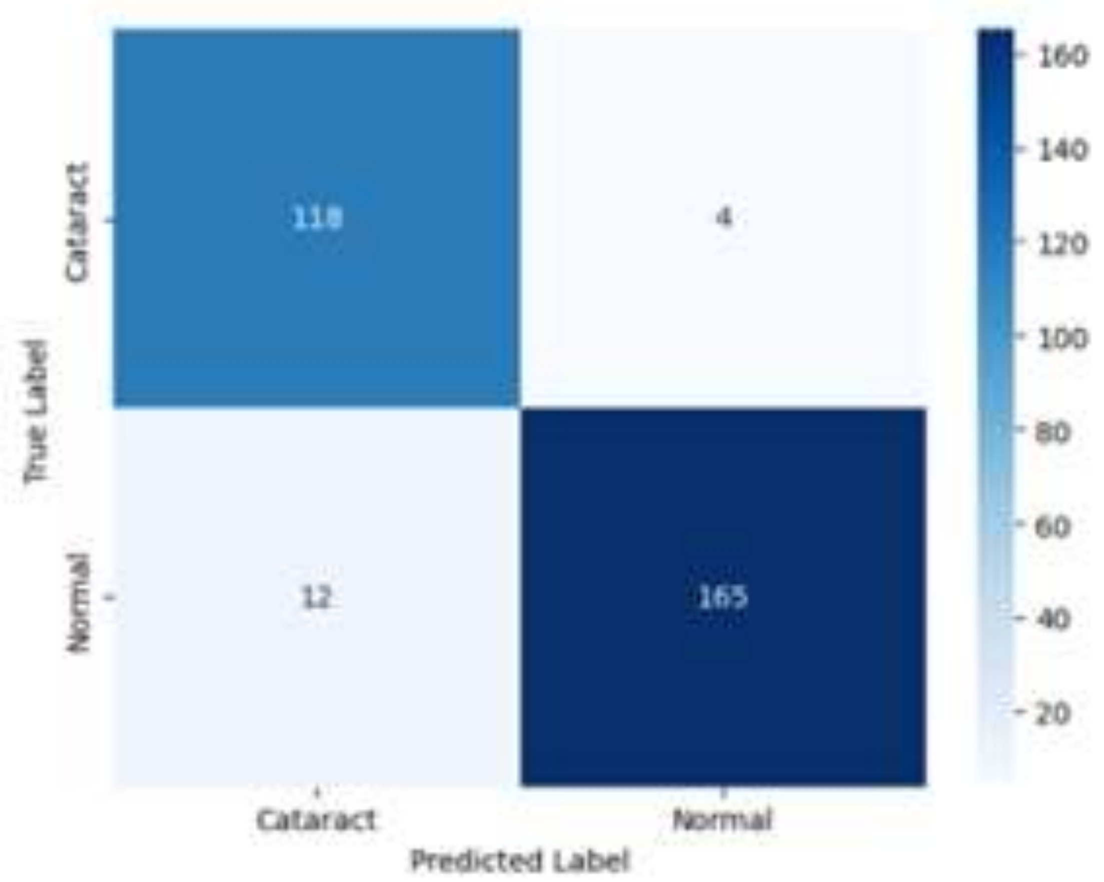

- Shows **minimal overfitting** and strong generalization.
- Overall model accuracy: **~93%**
- Demonstrates **high reliability and effectiveness** for cataract detection.

## Performance of MobileNetV2 Model

- Trained **MobileNetV2** for **20 epochs** to classify **Cataract** and **Normal** eye images.




- Achieved **~95–96% accuracy** on both training and validation datasets.
- **Loss curves** decreased smoothly and stabilized after around **8–10 epochs**, showing good model convergence.
- **Confusion Matrix Results:**
  - Cataract: **118 correctly classified**, **4 misclassified**
  - Normal: **165 correctly classified**, **12 misclassified**




- Indicates **strong generalization** and **minimal overfitting**.
- Overall model accuracy: **~95%**
- Demonstrates **excellent efficiency and accuracy** for cataract detection using a lightweight architecture.

## MODEL PERFORMANCE COMPARISON

| Model | Training Accuracy | Validation Accuracy | Test Accuracy | Training Loss | Validation Loss |
|---|---|---|---|---|---|
| Custom CNN | ∼90% | ∼94% | ∼93% | ∼0.25 | ∼0.22 |
| VGG16 | ∼95% | ∼96% | ∼95% | ∼0.20 | ∼0.10 |
| DenseNet121 | ∼90% | ∼93% | ∼92% | ∼0.26 | ∼0.17 |
| InceptionV3 | ∼93% | ∼94% | ∼94% | ∼0.20 | ∼0.13 |
| MobileNetV2 | ∼92% | ∼95% | ∼94% | ∼0.20 | ∼0.14 |

# Conclusion and Discussion

- **VGG16:** Best accuracy (96% val, 95% test), lowest loss (0.10)
- **MobileNetV2:** High accuracy (95%), low computation → mobile-friendly
- **Custom CNN:** Slightly lower performance → shows value of transfer learning
- **All models:** Converged well, minimal overfitting

**Conclusion:** CNNs are effective for accurate ocular image classification

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