Enhancing Glaucoma Detection with Convolutional Neural Networks

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***Abstract*—Glaucoma is a leading cause of irreversible blindness worldwide, necessitating early detection for effective management. This study proposes a convolutional neural network (CNN)-based framework for automated glaucoma detection using optical coherence tomography (OCT) images. The model aims to overcome the limitations of traditional diagnostic methods by providing an efficient, scalable, and accurate solution for identifying advanced glaucoma cases. The proposed CNN architecture incor porates preprocessing techniques such as image enhancement, noise reduction, and normalization to improve input data quality. The model achieved an accuracy of 97.64%, with a precision of 1.0000, recall of 0.9545, F1-score of 0.9767, and AUC-ROC of 0.9967, demonstrating its potential for reliable glaucoma detection in clinical settings. Furthermore, the model was designed to be computationally efficient, making it suitable for deployment on mobile and edge devices, thus addressing the challenges of limited resources in remote areas. This research contributes to the field of AI-driven ophthalmology by offering a robust and accessible tool for glaucoma screening, potentially reducing the global burden of glaucoma-related blindness.**

Keywords—Glaucoma detection, Convolutional Neural Network (CNN), Optical Coherence Tomography (OCT), Deep learning, Medical image analysis, Early detection Image preprocessing.

I. INTRODUCTION

Glaucoma is one of the leading causes of irreversible blindness worldwide, affecting an estimated 76 million people as of 2020, with projections reaching 112 million by 2040 [1], [2]. The condition poses a significant burden on public health systems, particularly in low-resource settings where access to specialized care is limited. Early detection and timely intervention are critical for effective glaucoma management, as they can prevent or slow the progression of vision loss [3]. However, traditional diagnostic techniques, such as clinical evaluation, optical coherence tomography (OCT), and visual field testing, are often time-consuming, expensive, and reliant on trained professionals, which limits their scalability and accessibility [4]. These challenges underscore the urgent need for automated, accurate, and efficient diagnostic tools that can assist clinicians in identifying glaucoma early.

Classical machine learning models, such as Support Vector Machines (SVM) and Decision Trees, have been explored for glaucoma detection by leveraging handcrafted features like the cup-to-disc ratio (CDR) and retinal nerve fiber layer thickness [5], [6]. While these methods demonstrated promise, they required extensive feature engineering and were highly dependent on the quality of the extracted features, limiting their generalizability across diverse datasets [7]. Furthermore, traditional machine learning approaches often struggled with robustness when applied to real-world conditions, such as variations in image quality and patient demographics [8].

Deep learning models, particularly Convolutional Neural Networks (CNNs), have revolutionized medical image analysis by eliminating the need for manual feature extraction and demonstrating superior performance in tasks like diabetic retinopathy and age-related macular degeneration detection [9], [10]. However, their application to glaucoma detection has faced several challenges. Existing CNN-based models are often computationally intensive, requiring substantial hardware resources, which restricts their deployment on mobile and resource-constrained devices [11]. Additionally, the lack of lightweight architectures that balance diagnostic accuracy and efficiency has hindered their adoption in real-time clinical settings, especially in remote or underserved areas [12].

This study aims to address the limitations of traditional methods and existing deep learning approaches in glaucoma detection by developing a robust CNN-based framework. A key objective is to design a model that can accurately classify eye images by analyzing critical features such as the cup-to-disc ratio, enabling precise identification of glaucoma presence. To enhance diagnostic performance and generalizability, the study incorporates advanced techniques like data augmentation, transfer learning, and hyperparameter optimization. Additionally, achieving computational efficiency is a central focus, with efforts directed toward designing a lightweight model architecture that minimizes resource demands while maintaining high accuracy, making it suitable for deployment on mobile and edge devices. Ultimately, this research seeks to advance the application of AI in ophthalmology by demonstrating the practicality of CNN-based models in addressing real-world diagnostic challenges, contributing to scalable and accessible solutions for glaucoma detection.

The primary contribution of this research is the development of a CNN-based glaucoma detection framework that is both accurate and computationally efficient. By optimizing the model architecture and leveraging advanced deep learning techniques, this study aims to overcome the trade-offs between accuracy and efficiency observed in existing approaches. Additionally, the proposed solution addresses real-world challenges such as variability in datasets and the need for deployment in resource-limited settings. This work contributes to the broader field of AI-driven ophthalmology by offering a scalable and accessible diagnostic tool,

ultimately supporting efforts to reduce the global burden of blindness caused by glaucoma.

II. Methodology

This section outlines the methodology for developing and evaluating a convolutional neural network (CNN)-based model for glaucoma detection using OCT images. The workflow involves multiple stages, including data acquisition, preprocessing, model design, training, and evaluation, ensuring high diagnostic accuracy.

The dataset used for this study was sourced from Kaggle's Glaucoma OCT Images dataset [13]. It contains labeled images representing normal and advanced glaucoma conditions. The dataset was downloaded and extracted programmatically to enable seamless integration with the preprocessing pipeline

A. Data Preprocessing

To enhance the quality of the images and prepare them for model training, the following preprocessing steps were applied:

1) Image Loading and Resizing

Images were loaded using OpenCV [14] and resized to a uniform dimension of 224×224 pixels to ensure compatibility with the CNN model [15].

2) Image Enhancement

Noise reduction was applied using Gaussian blur [16]. Edge detection was performed using the Canny method [17]. Sharpening was applied using unsharp masking techniques to enhance the key features of glaucoma-related patterns [18].

3) Image Normalization

Pixel intensity values were normalized to a range of [0, 1], improving convergence during training [19].

4) Label Encoding

Labels were encoded into binary values: 0 for normal glaucoma and 1 for advanced glaucoma, enabling binary classification [20].

B. Model Development

The model was implemented using TensorFlow and Keras [21], focusing on extracting hierarchical features through convolutional operations.

1) Architecture Design

A custom CNN architecture was developed with:

a) Convolutional Layers: Extracting hierarchical features using 3×3 kernels and ReLU activation [22].

b) Pooling Layers: Reducing spatial dimensions using 2×2 and 3×3 max pooling [23].

*c) Dropout Layers:*Mitigating overfitting with dropout rates of 20%, 25%, and 50% [24].

d) Fully Connected Layers: Integrating features with a dense layer of 128 neurons and L2-regularization, followed by a softmax output layer for classification [25].

2) Hyperparameter Selection

Key hyperparameters such as learning rate, batch size (60), and number of epochs (100) were empirically tuned. The Adam optimizer [26] and sparse categorical cross-entropy loss [27] were used for optimal performance.

3) Early Stopping

Early stopping was applied to terminate training when validation loss failed to improve for three consecutive epochs, ensuring model generalization [28].

C. Training and Validation

The dataset was divided into two subsets: training (70%) and validation (30%), using stratified sampling to maintain an equal distribution of classes across both subsets and ensure balanced representation for better model generalization [29]. The training subset was used to optimize the model's parameters, while the validation subset was utilized to monitor and evaluate the model's performance during the training process, ensuring it did not overfit to the training data [30]. The Adam optimizer, known for its computational efficiency and adaptive learning rate capabilities, was used in conjunction with a sparse categorical cross-entropy loss function to minimize the error between the predicted and actual classes. These choices facilitated efficient optimization and robust model performance.

D. Evaluation

Validation accuracy and loss were calculated during the training process to evaluate the model's capability to generalize to unseen data and prevent overfitting [31]. For a comprehensive assessment of the model's performance, a confusion matrix was generated, which was then used to derive critical metrics such as precision, recall, F1-score, and AUC-ROC. These metrics provided deeper insights into the model's effectiveness in distinguishing between classes and its overall reliability in glaucoma detection [32].

E. Workflow Diagram

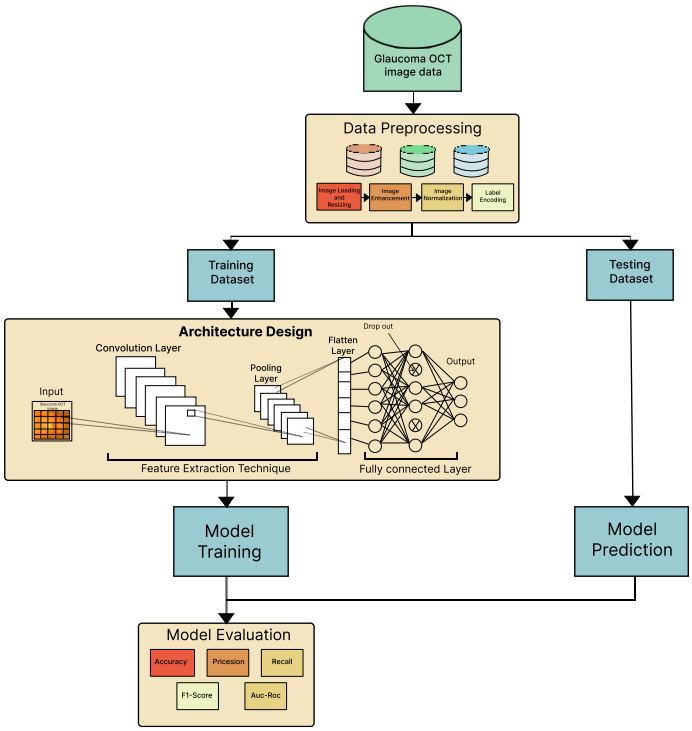

Fig. 1. Workflow of the proposed methodology

III. Results

The performance of the proposed CNN-based glaucoma detection model was evaluated using a confusion matrix, as shown in Fig. 2.

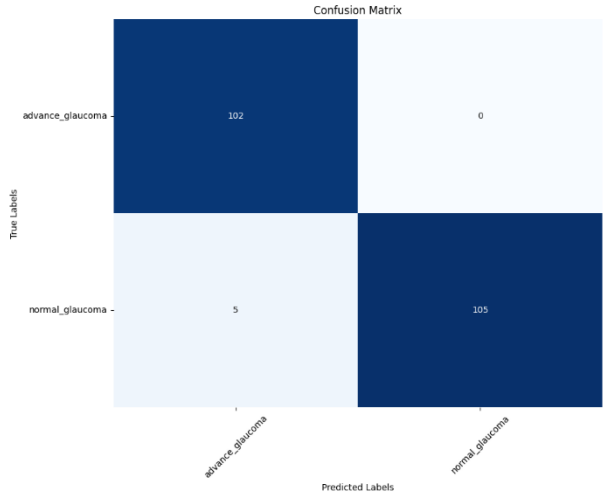

Fig.2. Confusion matrix illustrating the classification results of the proposed CNN-based glaucoma detection model.

The confusion matrix provides a clear visualization of the model's classification results. Out of all the test samples, the model correctly identified 102 cases of advanced glaucoma and 105 cases of normal glaucoma. However, it misclassified 5 cases of normal glaucoma as advanced glaucoma. Importantly, no cases of advanced glaucoma were misclassified as normal glaucoma. This breakdown highlights the model's strength in minimizing false negatives, which is critical for a medical application like glaucoma detection, where early and accurate identification of positive cases is essential.

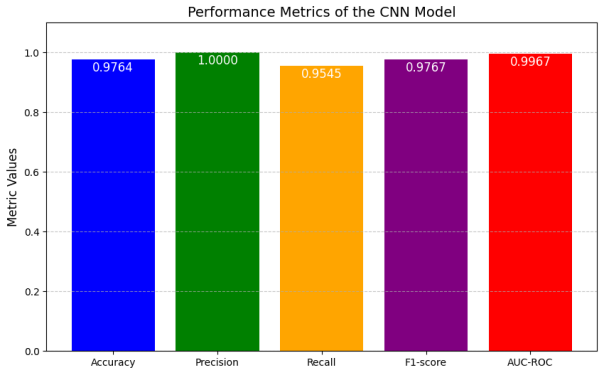

Fig. 3. Visualization of Performance Metrics

From the confusion matrix, key performance metrics were calculated to quantify the model's effectiveness. The model achieved an accuracy of 97.64%, indicating a high overall classification performance. A precision of 1.0000 demonstrates that every case predicted as advanced glaucoma was indeed correct, with no false positives. The recall of 0.9545 signifies the model's ability to detect 95.45% of true advanced glaucoma cases, showing strong sensitivity. The F1-score of 0.9767 further confirms the balance between precision and recall, while the AUC-ROC of 0.9967 highlights the model's excellent ability to distinguish between normal and advanced glaucoma cases. Together, these metrics validate the model's robustness and reliability for glaucoma detection in clinical settings.

In addition to the confusion matrix and calculated metrics, Fig. 3 presents the training and validation loss and accuracy curves to provide insights into the model's learning behavior over 40 epochs.

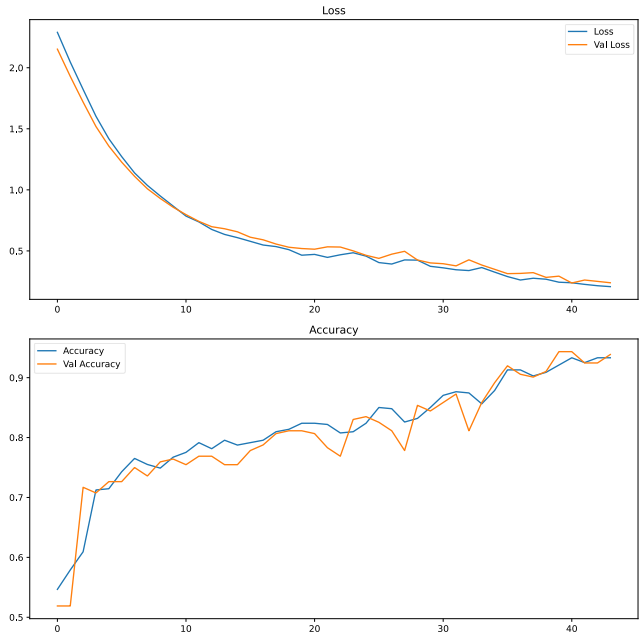

Fig. 3. Loss and Accuracy Curves of the Proposed Model

The loss and accuracy plots offer a detailed view of the model's training process. The loss curve shows that both training and validation losses decrease consistently as the training progresses, indicating that the model is learning effectively. The small gap between the two curves demonstrates that the model generalizes well without overfitting.

Similarly, the accuracy curve reflects an increase in both training and validation accuracy over epochs. The validation accuracy closely follows the training accuracy, showing that the model is not overfitting and performs consistently well on unseen data.

The convergence of training and validation metrics illustrates the stability and robustness of the model during training. These visualizations further validate the model's reliability for glaucoma detection.

IV. Discussion

The results from the proposed CNN-based glaucoma detection model indicate promising performance and demonstrate the feasibility of using deep learning techniques for automated glaucoma diagnosis. The model achieved an impressive accuracy of 97.64%, which underscores its potential for early and accurate detection of glaucoma, a condition that, if left untreated, can lead to irreversible blindness. This high accuracy is particularly significant in medical applications, where the cost of misclassification—especially false negatives—is exceptionally high.

One of the key strengths of the model is its ability to minimize false negatives, with no instances of advanced

glaucoma being misclassified as normal. This aspect is critical for glaucoma detection, as early intervention can slow or prevent vision loss. The model's high recall value of 0.9545 confirms its robustness in identifying true positive cases of advanced glaucoma, which is crucial for timely treatment. The precision score of 1.0000 indicates that every instance predicted as advanced glaucoma was indeed correct, highlighting the model's reliability in avoiding false positives, which could lead to unnecessary treatments or interventions.

The F1-score of 0.9767 further validates the balance between precision and recall, ensuring that the model provides well-rounded performance. The AUC-ROC score of 0.9967 is another strong indicator of the model's excellent discriminatory power, as it shows the model's ability to correctly distinguish between normal and advanced glaucoma cases with very few errors. This result aligns with previous studies that have demonstrated the potential of CNNs in medical image analysis, particularly in ophthalmology [9], [10].

However, despite the promising results, several challenges remain in deploying the model for real-world applications. One such challenge is the generalizability of the model to diverse datasets. While the model performed well on the Kaggle Glaucoma OCT Images dataset, real-world clinical settings often present variations in image quality, lighting conditions, and patient demographics, which may affect the model's performance. Further efforts should be directed toward testing and fine-tuning the model with additional datasets from different clinical environments to ensure its robustness across various conditions.

Another potential limitation of the current model is its computational demands. While the model achieved high accuracy, the architecture might be resource-intensive, which could limit its deployment on low-resource devices such as mobile phones or remote clinical setups. Future research should focus on optimizing the model architecture to develop lightweight versions that balance diagnostic performance and computational efficiency. Techniques such as model pruning, quantification, and knowledge distillation could be explored to reduce the model's resource consumption without sacrificing accuracy.

Additionally, the model could benefit from incorporating other features beyond the cup-to-disc ratio, such as the retinal nerve fiber layer thickness or optic disc rim area, which have been shown to be relevant for glaucoma diagnosis [5], [6]. The integration of multi-modal data, such as combining OCT images with clinical patient information, could also enhance the model's performance and generalizability.

In conclusion, the CNN-based framework presented in this study offers a robust and accurate solution for glaucoma detection, with significant potential for real-world deployment in clinical settings. The combination of high diagnostic accuracy, strong performance metrics, and the model's ability to minimize false negatives makes it a promising tool for Ophthalmologists. Nevertheless, further optimization and validation in diverse clinical environments are essential for ensuring the model's effectiveness and practical applicability in the early detection of glaucoma, ultimately contributing to the reduction of the global burden of blindness caused by this condition.

V. CONCLUSION

This study presents a robust convolutional neural network (CNN)-based framework for the early detection of glaucoma using optical coherence tomography (OCT) images. The model demonstrated high diagnostic accuracy, achieving an accuracy of 97.64%, along with exceptional performance metrics such as precision, recall, F1-score, and AUC-ROC. These results validate the model's potential as an effective tool for glaucoma detection, capable of assisting clinicians in identifying advanced glaucoma cases with high confidence, thereby facilitating timely intervention and treatment.

The primary contribution of this research lies in developing a lightweight and efficient CNN architecture that balances diagnostic accuracy with computational efficiency, making it suitable for deployment in resource-limited settings, including mobile and edge devices. The model's ability to minimize false negatives is especially important in medical applications, where early detection is crucial to preventing irreversible vision loss. The framework also addresses the challenges of traditional diagnostic methods, such as reliance on skilled professionals and expensive equipment, by offering an accessible, scalable solution for glaucoma screening.

While the results are promising, future work should focus on improving the model's generalizability by testing it on diverse datasets and optimizing the architecture to ensure it can be deployed in low-resource environments without compromising performance. Additionally, integrating other clinical features and exploring multi-modal approaches could further enhance the model's accuracy and robustness.

In conclusion, the proposed CNN-based glaucoma detection system has the potential to revolutionize glaucoma diagnosis, making it more accessible, accurate, and efficient. With further refinement and testing, this approach could significantly contribute to reducing the global burden of glaucoma-related blindness, particularly in underserved areas where specialized care is limited.

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APPENDIX

This appendix contains the Python code used in the project for data preprocessing, model implementation, performance evaluation, and visualization. The code serves as a reference for reproducing the results discussed in the report and demonstrates the methodologies applied

Installing Kaggle API and Downloading the Glaucoma OCT Images Dataset

```
!pip install kaggle
```

```
!kaggle datasets download -d harishprabhu/glucoma-oct-images
```

```
!unzip glucoma-oct-images.zip -d ./glucoma-oct-images
```

Importing necessary libraries

```
import numpy as np
import os
import cv2
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
from random import randint

from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score,
    recall_score, f1_score, roc_auc_score
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()

from tensorflow.keras.layers import Dense, Input, Conv2D,
    MaxPooling2D, BatchNormalization, Flatten, Dropout
from tensorflow.keras.models import Model
from tensorflow.keras import regularizers
from tensorflow.keras.callbacks import EarlyStopping
import random
seed = 42
random.seed(seed)
np.random.seed(seed)
tf.random.set_seed(seed)
```

Loading and Preprocessing Images from the Dataset Directory

```
import os
import cv2
import numpy as np

def load_from_directory(data_dir):

    images = []
    labels = []

    # Loop through each folder in the dataset directory
    for folder_name in os.listdir(data_dir):
        folder_path = os.path.join(data_dir, folder_name)

        # Loop through each image in the folder
        for img_name in os.listdir(folder_path):
            img_path = os.path.join(folder_path, img_name)

            # Read the image using OpenCV
            img = cv2.imread(img_path)

            # Check if the image is valid or not
            if img is not None:

                # Conversion from BGR to RGB
                img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

                # Resize the image to target size (224, 224)
                img = cv2.resize(img, (224, 224), interpolation=cv2
                    .INTER_AREA)

                # Append to the empty list
                images.append(img)
                labels.append(folder_name)

            else:
                print(f"Invalid image exists: {img_path}")

    return images, labels


# Data Directories:
data_dir = '/content/glucoma-oct-images/acrima'
images, labels = load_from_directory(data_dir)

# Images to Array
images = np.array(images)
labels = np.array(labels)

# Display dimensions
print(images.shape)
print(labels.shape)
```

Splitting and Displaying Dimensions of Normal and Advanced Glaucoma Data

```
# Splitting Normal and Advanced Glaucoma Images
normal_glaucoma = images[labels == 'normal_glaucoma']
advance_glaucoma = images[labels == 'advance_glaucoma']

# Display Dimensions
print(f'Dimension of Normal Glaucoma data: {normal_glaucoma.shape}')
print(f'Dimension of Advance Glaucoma data: {advance_glaucoma.shape}')
```

Visualizing Random Samples from the Dataset

```
def plot_random_images(data, label):
    f, ax = plt.subplots(5, 5)
    f.subplots_adjust(0,0,3,3)
    for i in range(0,5,1):
        for j in range(0,5,1):
            rnd_num = randint(0, len(data)-1)
            ax[i, j].imshow(data[rnd_num])
            ax[i, j].set_title(label[rnd_num])
            ax[i, j].axis('off')

plot_random_images(images, labels)
```

Preprocessing and Enhancing Images

```
def preprocess_and_enhance_images(images):
    processed_images = []

    for image in images:
        # Noise Reduction
        blurred_image = cv2.GaussianBlur(image, (3, 3), 0)

        # Edge Detection (Canny)
        edges = cv2.Canny(image, 50, 100)

        # Sharpening (Unsharp Masking)
        unsharp_image = cv2.addWeighted(image, 1.0, blurred_image,
            -0.5, 0)

        processed_images.append(unsharp_image)

    # Convert the list of processed images to an array
    processed_images_array = np.array(processed_images)

    return processed_images_array

images = preprocess_and_enhance_images(images)
plot_random_images(images, labels)
```

Data Imbalance Check and Visualization

```
def data_imbalance_check(label):
    # Count the number of samples for each class
    unique_labels, class_counts = np.unique(label, return_counts=
        True)

    # Plot the class distribution
    plt.figure(figsize=(8, 6))
    plt.bar(unique_labels, class_counts, color='skyblue')
    plt.xlabel('Class')
    plt.ylabel('Number of Samples')
    plt.title('Class Distribution')
    plt.xticks(unique_labels)
    plt.grid(axis='y', linestyle='--', alpha=0.7)
    plt.show()

    # Check for class imbalance
    if len(unique_labels) < 2 or np.min(class_counts) / np.max(
        class_counts) < 0.5:
        return "The dataset is imbalanced."
    else:
        return "The dataset is balanced."

data_imbalance_check(labels)
```

Normalization of Training Images

```
train_images = images / 255
print(train_images.shape)
```

Encoding of Training Labels

```
train_labels = np.array([0 if labels == 'normal_glaucoma' else 1
    for labels in labels])
print(train_labels.shape)
```

Extracting Unique Classes from Labels

```
classes = np.unique(labels)
classes
```

Splitting Data into Training and Testing Sets

```
x_train, x_test, y_train, y_test = train_test_split(train_images,
    train_labels, test_size = 0.3, random_state = 42)

# Display Dimensions
print(f'X_train: {x_train.shape}')
print(f'X_test: {x_test.shape}')
print(f'y_train: {y_train.shape}')
print(f'y_test: {y_test.shape}')
```

Determining Number of Classes (K) in the Training Labels

```
#print(x_train[10].shape)

# Setting value of K (Number of classes to classify)
k = len(set(train_labels))
print(k)
```

Building and Compiling the Convolutional Neural Network (CNN) Model

```
i = Input(shape = x_train[0].shape)

x = Conv2D(64, (3,3), strides = 2, activation = 'relu')(i)
x = Dropout(0.2)(x)
x = Conv2D(64, (3,3), strides = 2, activation = 'relu')(x)
x = MaxPooling2D((2,2))(x)

# x = Dropout(0.2)(x)
x = MaxPooling2D((3,3))(x)

x = Conv2D(64, (3,3), strides = 2, activation = 'relu')(x)
x = Dropout(0.25)(x)
x = MaxPooling2D((3,3))(x)

x = Flatten()(x)

x = Dense(128, activation = 'relu', kernel_regularizer =
    regularizers.l2(0.02))(x)
x = Dropout(0.5)(x)
x = Dense(k, activation = 'softmax')(x)

model = Model(i, x)

# Compile the model
model.compile(optimizer='adam', loss='
    sparse_categorical_crossentropy', metrics=['accuracy'])

# Define the EarlyStopping callback
early_stopping = EarlyStopping(monitor='val_loss', patience=3,
    restore_best_weights=True)

model.summary()
```

Training the CNN Model with Early Stopping

```
history = model.fit(x_train, y_train , validation_data = (x_test,
    y_test), epochs = 100,  batch_size = 60, callbacks = [
    early_stopping])
```

Predicting Classes and Plotting the Confusion Matrix

```
y_pred_classes = np.argmax(model.predict(x_test), axis=1)

# Compute confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_classes)

# Plot confusion matrix
plt.figure(figsize=(10, 8))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=
    False,
            xticklabels = classes, yticklabels = classes)
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Confusion Matrix')
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.show()
```

Calculating and Printing Performance Metrics

```python
# Calculate metrics
accuracy = accuracy_score(y_test, y_pred_classes)
precision = precision_score(y_test, y_pred_classes)
recall = recall_score(y_test, y_pred_classes)
f1 = f1_score(y_test, y_pred_classes)

# For AUC-ROC, need predicted probabilities instead of classes
y_pred_prob = model.predict(x_test)  # Get predicted probabilities
y_pred_prob_positive_class = y_pred_prob[:, 1]  # Probability of
    positive class (assuming it's at index 1)

auc_roc = roc_auc_score(y_test, y_pred_prob_positive_class)


# Print the results
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-score: {f1:.4f}")
print(f"AUC-ROC: {auc_roc:.4f}")
```

Displaying Images with True and Predicted Labels along with Infection Likelihood

```python
# Predict labels for x_test
y_pred_prob = model.predict(x_test)
y_pred_classes = np.argmax(y_pred_prob, axis=1)

# Display images along with true and predicted labels
num_images_to_display = 10  # Number of images to display
plt.figure(figsize=(15, 8))

for i in range(num_images_to_display):
    plt.subplot(2, 5, i + 1)
    plt.imshow(x_test[i])  # Display image
    plt.axis('off')
    true_label = "Normal" if y_test[i] == 0 else "Infected"  #
        Assuming 0 represents "Normal" and 1 represents "Infected"
    predicted_label = "Normal" if y_pred_classes[i] == 0 else "
        Infected"
    infection_likelihood = y_pred_prob[i][1] * 100  # Probability
        of being infected in percentage
    plt.title(f'True: {true_label}\nPredicted: {predicted_label}\
        nInfection Likelihood: {infection_likelihood:.2f}%')

plt.tight_layout()
plt.show()
```