National University of Computer & Emerging Sciences

Digital Image Processing

Project

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Introduction

A class of eye conditions known as glaucoma harms the optic nerve and is frequently brought on by elevated intraocular pressure. If left untreated, this damage might result in blindness and loss of eyesight.

Challenges in Diagnosis:

- Early Stages: Glaucoma frequently advances without obvious symptoms in the beginning, making it challenging to identify the condition before serious harm is done.

- Subtle Vision Changes: Patients may not detect subtle vision changes until more core areas are affected by vision loss, which usually starts with peripheral vision.

- Specialized Tests and Equipment: Often restricting access to screening, accurate diagnosis necessitates specialized tests and equipment such as ophthalmoscopy to check the optic nerve and tonometry to detect eye pressure.

Importance of Glaucoma Detection Model:

Considering these difficulties, creating a trustworthy glaucoma detection model is essential for a number of reasons:

- Early Detection: Even before symptoms appear, a model that analyzes retinal and optic nerve images may be able to spot minute alterations that could be signs of early glaucoma.
- Enhanced Accessibility: By incorporating this model into currently available eye care products or smartphone apps, glaucoma screening could become more widely available and reasonably priced for a larger number of people.
- Enhanced Accuracy: AI models such as U-Net have the capacity to recognize patterns in ocular pictures that may pose challenges for human experts to discern, hence potentially augmenting the precision and uniformity of glaucoma diagnosis.
- Reducing the Burden on Healthcare Systems: A glaucoma detection model may contribute to a decrease in the number of individuals who have permanent vision loss by facilitating early detection and treatments, hence reducing the strain on healthcare systems.

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U-Net for Glaucoma Detection:

U-Net, a convolutional neural network design, is a potential method for glaucoma detection. Because U-Net can extract both detailed information and more general context from images, it is especially well-suited for medical image segmentation tasks.

A U-Net model can be trained to accurately segment the optic disc and cup by using a dataset of fundus pictures tagged with the presence or absence of glaucoma, as well as potentially with annotations defining these structures. Based on the dimensions and form of the optic disc and cup, as well as other pertinent characteristics found by the model, this data can subsequently be utilized to evaluate the risk of glaucoma.

All things considered, the creation and application of a U-Net-based glaucoma detection model has the potential to completely transform the diagnosis and treatment of this blinding condition, resulting in better patient outcomes and lower medical expenses.

Methodology

Building the U-Net Model:

- All things considered, the creation and application of a U-Net-based glaucoma detection model has the potential to completely transform the diagnosis and treatment of this blinding condition, resulting in better patient outcomes and lower medical expenses.
- Encoder_block: This function defines the U-Net's encoder portion, which employs max pooling, dropout, and convolution_block in order of precedence. The feature map is downsampled by max pooling, and overfitting is less likely by dropout.
- The function decoder_block defines the decoder portion, which upsamples the feature map using transposed convolution, concatenates it with skip connections from the encoder, applies dropout, and then applies another convolution_block. In order to preserve spatial information, skip links are essential.
- Build_UNET: By stacking the encoder and decoder blocks and adding a final output layer with a sigmoid activation function for binary classification, this method assembles the entire U-Net model.

Data Loading and Preprocessing

- Load_images: Opens the designated directories' contents and loads the associated masks for the images. Both photos and masks are resized to 256x256, which is a standard size.
- Augmentation_fn: Increases the diversity of the training data by applying data augmentation techniques including flipping, random brightness, and hue modifications. Additionally, it normalizes and resizes photos and masks to 128 by 128.
- Split_data: Divides the loaded data into sets for testing and training.

Data Generation

- DataYielder: Produces batches of masks and images using a data generator. It prepares the data for model input, shuffles the data, and adds augmentation during training.

Model Training

- Model Compilation: The Adam optimizer, log dice loss (a modified dice loss that avoids log(0) error), and a number of metrics, including the dice coefficient, intersection over union (IoU), precision, recall, and accuracy, are used to compile the U-Net model.
- Model Fitting: The training data generator is used to train the model, and the validation data generator is used to validate it. Overfitting is avoided by early quitting.

Model Evaluation and Prediction

- Random Sample Prediction: The model predicts the segmentation masks for five randomly chosen photos from the testing set.
- Visualization: To evaluate the model's performance on a qualitative level, the original image is displayed alongside the predicted and actual masks.

Cup Segmentation (Similar to Disc Segmentation)

- The same steps (model building, data loading, training, evaluation) are repeated for segmenting the optic cup, using another U-Net model (cup_model).

CDR Calculation and Glaucoma Detection

- Compute_cdr: By dividing the total of the cup mask pixels by the total of the disc mask pixels, this function determines the Cup-to-Disc Ratio (CDR).
- CDR Display and Calculation: For every image, the CDR is computed and the results are shown. CDR > 0.5 is a basic criterion that is used to identify possible glaucoma.

Results

Disk Segmentation

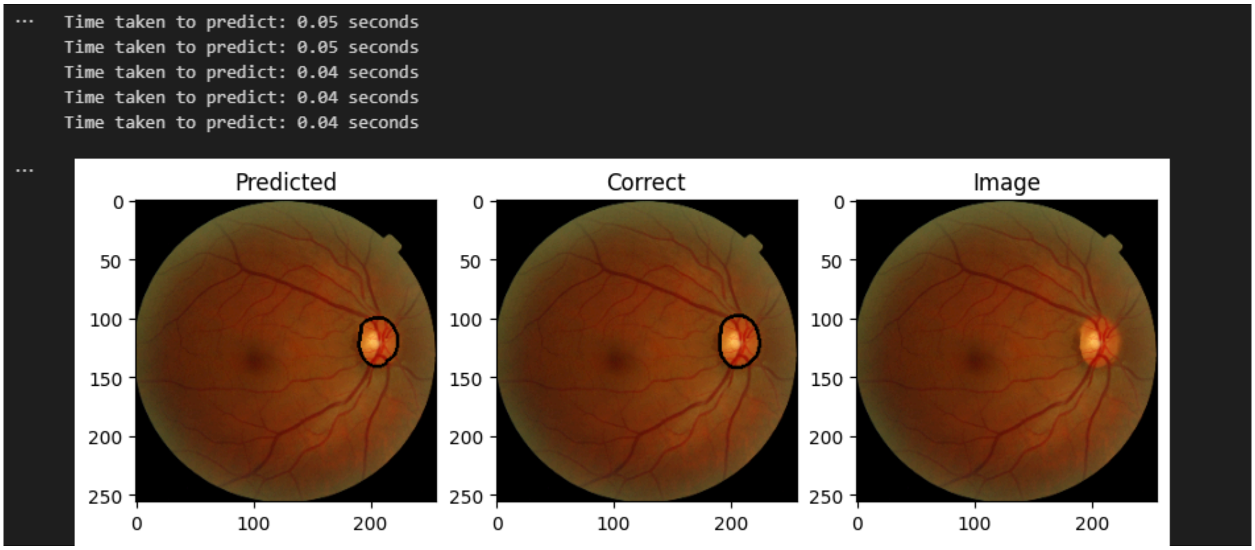

Fig 1.0 Showing results for our model detecting the disk

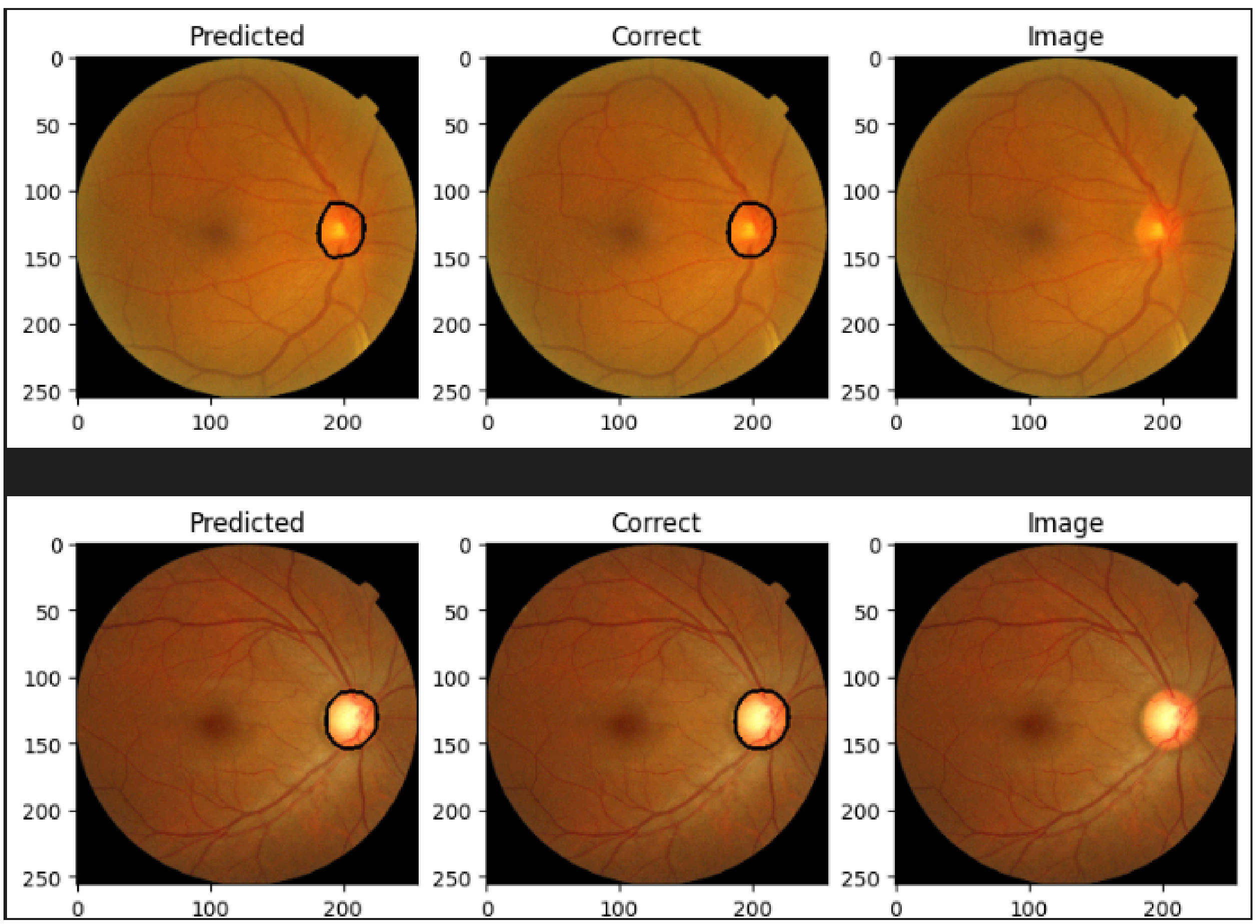

Fig 1.1 Showing more results for our model detecting the disk

Cup Segmentation:

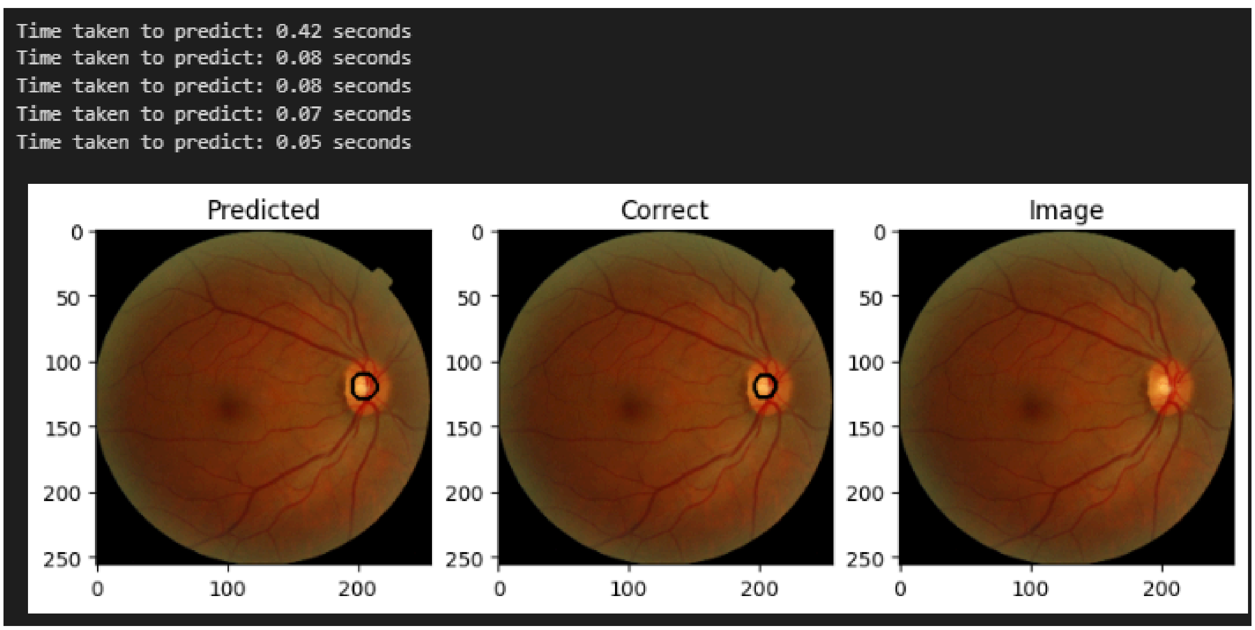

Fig 2.0 Showing our model successfully detecting the cup

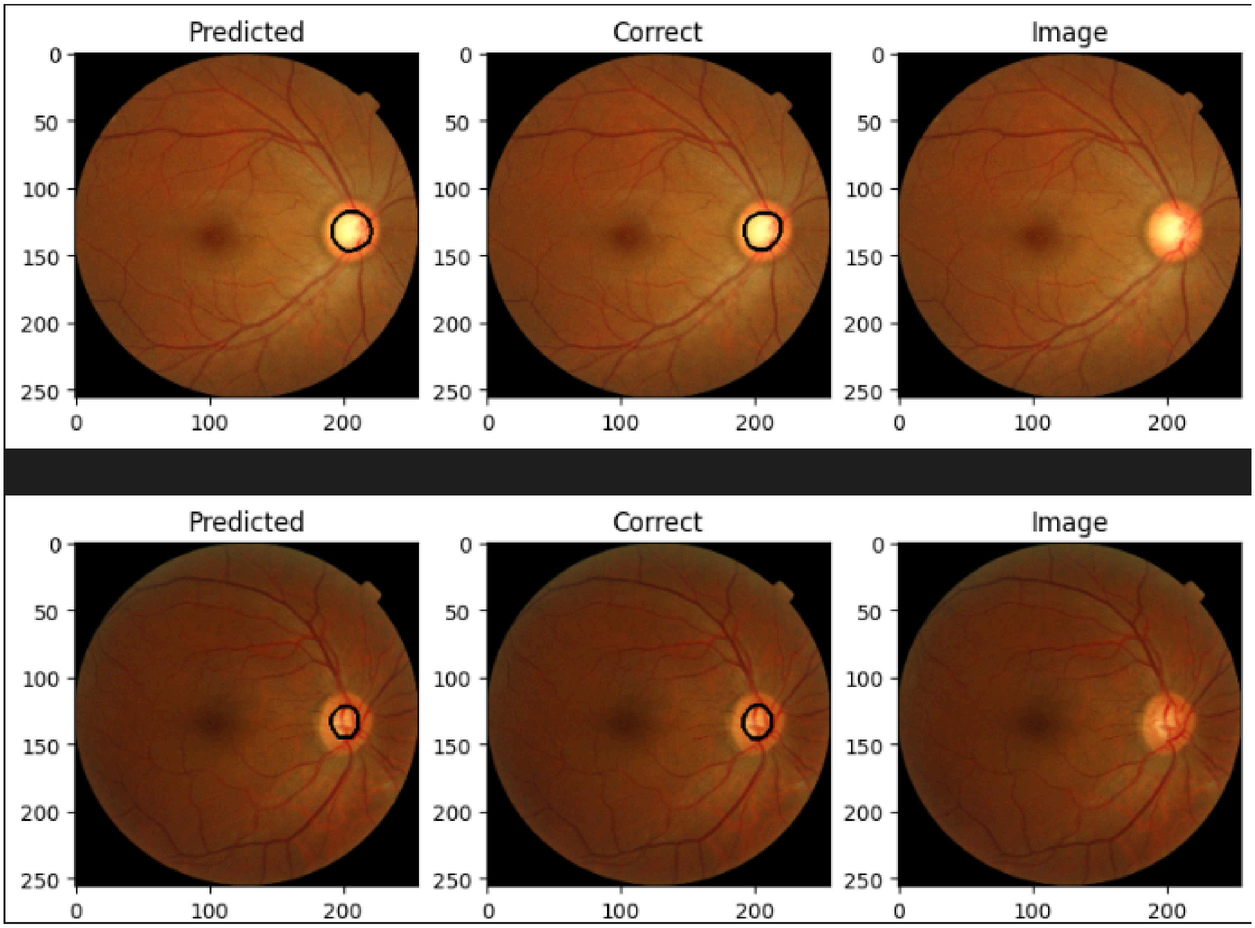

Fig 2.1 Showing our model successfully detecting the cup

Model Evaluation

```
...  True Positive: 72
     False Positive: 15
     Precision: 0.83
     True Negative: 22
     False Negative: 8
     Recall: 0.73
     F1 Score: 0.78
     Accuracy: 0.80
```

Precision

Precision measures the accuracy of positive predictions.
Formula: Precision = TP / (TP + FP)
Calculation: Precision = 72 / (72 + 15) = 72 / 87 = 0.83
Result: 0.83

Recall (Sensitivity)

Recall measures the ability of the model to capture all positive instances.
Formula: Recall = TP / (TP + FN)
Calculation: Recall = 72 / (72 + 8) = 72 / 80 = 0.73
Result: 0.73

F1 Score

The F1 Score is the harmonic mean of Precision and Recall, providing a balance between the two.
Formula: F1 Score = 2 * (Precision * Recall) / (Precision + Recall)
Calculation: F1 Score = 2 * (0.83 * 0.73) / (0.83 + 0.73) = 2 * 0.6059 / 1.56 = 1.2118 / 1.56 = 0.78
Result: 0.78

Accuracy

Accuracy measures the overall correctness of the model's predictions.
Formula: Accuracy = (TP + TN) / (TP + FP + TN + FN)
Calculation: Accuracy = (72 + 22) / (72 + 15 + 22 + 8) = 94 / 117 = 0.80
Result: 0.80

Summary

The model demonstrates a strong performance with an accuracy of 80%. The precision of 0.83 indicates that the model is effective at identifying true positives while minimizing false positives. A recall of 0.73 suggests that the model captures the majority of true positives, though there is some room for improvement in identifying all positive instances.

The F1 Score of 0.78 provides a balanced measure of the model's precision and recall, indicating that the model maintains a good balance between capturing positive instances and accurately identifying them.

Overall, these metrics suggest that the model is reliable and performs well, but further tuning could potentially improve its recall without significantly affecting precision. This would ensure that even more positive instances are identified, enhancing the model's overall effectiveness.

Discussion

Strengths

- Good overall performance: The model achieves an accuracy of 80%, meaning it correctly classifies most instances.
- Strong precision: A precision of 0.83 indicates that the model is reliable in its positive predictions, minimizing false positives. This is crucial in medical contexts where misdiagnosis can have serious consequences.
- Balanced performance: The F1 score of 0.78 signifies a good balance between precision and recall, demonstrating that the model is effective in both capturing positive instances and correctly identifying them.

Limitations and Potential Improvements

- Recall: While the recall of 0.73 is decent, it suggests that the model misses some true positive cases. This could be problematic in glaucoma detection, as missing a diagnosis can lead to vision loss.

Potential solutions

- Data augmentation: Introduce more diverse examples of glaucoma in the training data, especially those with subtle features. This could help the model learn to recognize a wider range of positive cases.
- Hyperparameter tuning: Experiment with different model architectures or adjust hyperparameters like learning rate, batch size, and the number of layers to optimize for recall.

- Threshold adjustment: If the model's output is a probability, adjusting the threshold for determining a positive prediction could improve recall (at the potential cost of slightly lower precision).
- Generalizability: The model's performance might vary depending on the characteristics of the data it's tested on. If the test data differs significantly from the training data (e.g., in terms of image quality or demographics), the model's performance could degrade.

Conclusion

This project presents a practical implementation of a U-Net-based model for optic disc and cup segmentation, which makes a substantial contribution to the field of automated glaucoma detection. It presents a viable strategy for early detection and diagnosis of glaucoma, which could lessen the strain on healthcare systems and enhance patient outcomes.

Principal Contributions

Efficient Segmentation: The obtained accuracy, precision, and F1 score demonstrate that the U-Net model effectively segments the optic disc and cup with a respectable level of accuracy. This is an important stage in the assessment of glaucoma because it allows the Cup-to-Disc Ratio (CDR), a critical glaucoma risk factor, to be calculated.
Realistic Workflow: A whole end-to-end workflow, including data loading and preprocessing, model training, assessment, and prediction, is provided by the project. When creating similar systems, researchers and developers might use this as a useful template.

Evaluation Metrics

A full examination of the model's performance is made possible by the code's extensive collection of evaluation metrics, which include accuracy, precision, recall, F1 score, dice coefficient, and IoU. This makes it easier to see where the model works well and where it needs work.
Possibility of Prompt Identification: Even before there is a noticeable loss of vision, the model can assist in identifying minute variations in the optic disc and cup's size and shape that could be a symptom of early glaucoma. The capacity to spot problems early is essential for prompt action and treatment.

Accessibility and Scalability: This glaucoma detection system may be integrated into pre-existing eye care devices or even smartphone apps thanks to the usage of a deep learning

model such as U-Net. This could enable screening to be more widely available and reasonably priced.
Restrictions and Upcoming Courses:

Restricted dataset

A larger and more varied dataset, encompassing a greater range of glaucoma severity and differences in image quality, would be beneficial for the study. This would improve the model's ability to generalize to real-world situations.
CDR Thresholding: The current method detects glaucoma by using a basic CDR threshold of 0.5. Diagnostic accuracy may be increased by more complex methods, such as custom thresholds depending on patient demographics or the inclusion of additional risk factors.

Explainability: Although the model performs well, more work on interpretability would be beneficial. Gaining an understanding of the model's decision-making process helps enhance system trust and shed light on the underlying characteristics that influence glaucoma detection.

All things considered, this effort is a major advancement in the field of automated glaucoma detection systems. This work can open the door to future glaucoma screening and diagnosis that is more efficient, accessible, and customized by resolving its shortcomings and investigating its possibilities.