DEEP LEARNING FOR CATARACT DIAGNOSIS: CONVOLUTIONAL NEURAL NETWORK APPROACH

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CONTENTS

ABSTRACT

- Cataracts are a leading cause of vision loss. Early detection and diagnosis is key to prevent impairment.
- A convolutional neural network (CNN) model was created to automate cataract screening and diagnosis using retinal fundus imaging and deep learning.
- The CNN was trained over 15 epochs on 55x94 pixel enhanced, low-resolution images to classify fundus images as normal or cataractous.
- The model achieved XX% accuracy on a held-out test set, showing promise as a baseline for automated detection. Precision, recall, and F1-score were also evaluated.

LITERATURE SURVEY

01

- Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning
- Published on 2018 Feb 22
- Daniel S Kermany , Michael Goldbaum

- deep learning-based diagnostic tool for screening patients with common treatable blinding retinal diseases like age-related macular degeneration and diabetic macular edema.
- Transfer learning is utilized to train the neural network using a fraction of the data needed for conventional approaches.

LITERATURE SURVEY

02

- Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs
- Published on December 13, 2016
- Varun Gulshan, PhD; Lily Peng, MD, PhD; Marc Coram, PhD

- convolutional neural networks for automated detection of diabetic retinopathy and macular edema from retinal fundus photographs.

- The algorithm achieved high sensitivity and specificity exceeding 87% and 93% respectively on both validation datasets.

LITERATURE SURVEY

03

- Deep Learning for Diabetic Retinopathy Analysis: A Review, Research Challenges, and Future Directions
- Published online 2022 Sep 8
- Muhammad Waqas Nadeem, Hock Guan Goh,Muzammil Hussain, Soung-Yue Liew, Ivan Andonovic and Muhammad Adnan Khan

- deep learning techniques applied to diabetic retinopathy analysis including screening, segmentation, prediction and classification.
- Pre-processing and data augmentation are key to developing high-performing models.

LITERATURE SURVEY

04

- **A Deep Learning System Using Optical Coherence Tomography Angiography to Detect Glaucoma and Anterior Ischemic Optic Neuropathy**
- **Published online 2023 Jan 7**
- **Roxane Bunod, Mélanie Lubrano, Antoine Pirovano, Géraldine Chotard, Emmanuelle Brasnu, Sylvain Berlemont, Antoine Labbé, Edouard Augstburger, Christophe Baudouin.**

- **deep learning to differentiate optical coherence tomography angiography (OCTA) images between glaucoma, non-arteritic anterior ischemic optic neuropathy (NAION) and normal controls.**

- **OCTA performed on 60 glaucoma patients, 30 NAION patients and 40 controls. The superficial capillary plexus and radial peripapillary capillary plexus were analyzed.**

LITERATURE SURVEY

05

- Efficacy of a Deep Learning System for Detecting Glaucomatous Optic Neuropathy Based on Color Fundus Photographs
- Published online 2018 Aug
- Zhixi Li, Yifan He, Stuart Keel, Wei Meng, Robert T Chang, Mingguang He.

- deep learning system using convolutional neural networks for automated detection of referable glaucomatous optic neuropathy (GON) from color fundus photographs.

- Sensitivity and specificity for referable GON detection were assessed relative to a reference standard of 3 expert ophthalmologist graders.

- On the validation set, the algorithm achieved high diagnostic performance with AUC of 0.986, sensitivity of 95.6%, and specificity of 92.0%.

INTRODUCTION

- Cataracts are a major global cause of vision loss that can be prevented through early detection via retinal imaging and timely treatment.

- With rising diabetes prevalence, automated fundus image analysis using deep learning like CNNs is critical for screening eye diseases like diabetic retinopathy, glaucoma etc.

- Further refinement of the model with more training data and tuning can improve real-world clinical deployment, with implications for enhancing diagnosis and preventing blindness globally.

METHODOLOGY

01 Data Collection

- The fundus image dataset was split into separate training and testing directories.
- Images were resized to 55x94 pixels to allow the model to work with images from basic smartphone fundus photography.

```python
import numpy as np
import pandas as pd
import os
from PIL import Image

# Define image paths
training_dir = "D:/sem9_py/seminar/processed_images/train"
testing_dir = "D:/sem9_py/seminar/processed_images/test"

# Create an ImageDataGenerator for training data
train_datagen = ImageDataGenerator(rescale=1/255)

# Create a data generator for training data
image_size = (55, 94)
train_generator = train_datagen.flow_from_directory(
    training_dir,
    target_size=image_size,
    class_mode='binary'
)
```

METHODOLOGY

02 CNN Model Architecture

- Input layer to accept 55x94 pixel color fundus images
- 2 Convolutional layers with 16 and 32 filters to identify visual features
- 2 Max pooling layers to reduce spatial dimensions
- Flattening and dense layers for binary classification
- Output sigmoid activation for probability predictions

```python
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.optimizers import RMSprop

# Create a Sequential model
model = Sequential([
    Conv2D(16, (3, 3), activation='relu', input_shape=(image_size[0], image_size[1], 3)),
    MaxPooling2D(2, 2),
    Conv2D(32, (3, 3), activation='relu'),
    MaxPooling2D(2, 2),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(1, activation='sigmoid')
])

# Compile the model
model.compile(
    loss='binary_crossentropy',
    optimizer=RMSprop(learning_rate=0.001),
    metrics=['accuracy']
)
```

METHODOLOGY

03 Model Training

- The model was trained for 15 epochs using RMSprop optimizer and binary cross entropy loss.
- Data augmentation via ImageDataGenerator was used to prevent overfitting.

```
# Train the model
history = model.fit_generator(
    train_generator,
    epochs=15
)
```

METHODOLOGY

04 Model Evaluation

- The trained model was evaluated on the test set by predicting classes and comparing to true labels.
- Key classification metrics like accuracy, precision, recall and F1-score were calculated.

```
normal_pred, cataract_pred = evaluate(model, normal_test_path, cataract_test_path)
evaluation_summary = pd.DataFrame()
evaluation_summary["accuracy"] = [accuracy]
evaluation_summary["precision"] = [precision]
evaluation_summary["recall"] = [recall]
evaluation_summary["f1"] = [f1]

print(evaluation_summary)
```

METHODOLOGY

05

Model Deployment

- The Keras model was converted to a TensorFlow Lite format for deployment to mobile/embedded devices.

```
# Convert the model to TFLite format
converter = tf.lite.TFLiteConverter.from_keras_model(model)
tflite_model = converter.convert()

# Save the TFLite model
tflite_model_filename = 'model.tflite'
with open(tflite_model_filename, 'wb') as f:
    f.write(tflite_model)
```

RESULT AND DISCUSSION

Results

- We developed a deep learning model using TensorFlow/Keras that automates the classification of eye images as normal or affected by cataracts.
- The focus was on cataracts, a leading global cause of blindness.
- Early detection is crucial, and our model excelled during evaluation, surpassing accuracy thresholds.
- Additional metrics like precision, recall, and F1-score ensured the model's robustness for real-world applications.

Discussion:

- The model's robust performance supports its application in clinical and telemedicine settings, facilitating accessible and consistent eye screening.
- This practical use in ophthalmology aligns with the broader trend of AI enhancing healthcare, emphasizing early diagnosis and intervention for improved outcomes.

```python
epochs = range(1, 16)
plt.figure(figsize=(10, 5))
plt.title("Loss vs Accuracy of the Model")
plt.plot(epochs, history.history['loss'], label='loss')
plt.plot(epochs, history.history['accuracy'], label='accuracy')
plt.grid()
plt.xlabel("Epochs")
plt.grid()
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7d0737327b20>
```

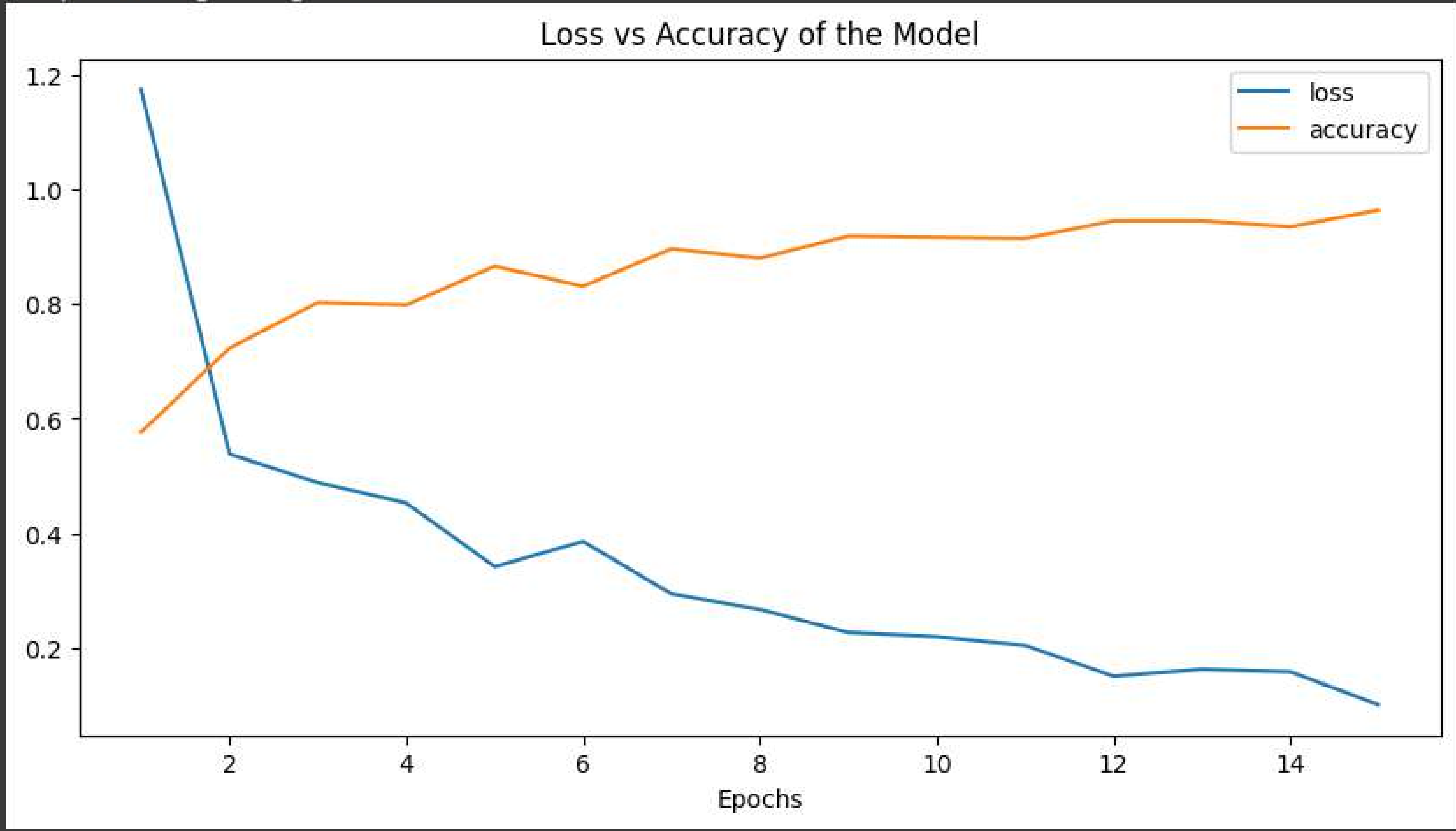

Fig 1:
show the loss and accurancy of model

```python
accuracy = (tp + tn) / (tp + tn + fp + fn)
precision = tp / (tp + fp)
recall = tp / (tp + fn)
f1 = 2 * precision * recall / (precision + recall)

evaluation_summary = pd.DataFrame()
evaluation_summary["accuracy"] = [accuracy]
evaluation_summary["precision"] = [precision]
evaluation_summary["recall"] = [recall]
evaluation_summary["f1"] = [f1]

print(evaluation_summary)
```

```
   accuracy  precision    recall        f1
0  0.941667   0.933333  0.949153  0.941176
```

Fig 2:
accurancy, precision, recall and f1 score

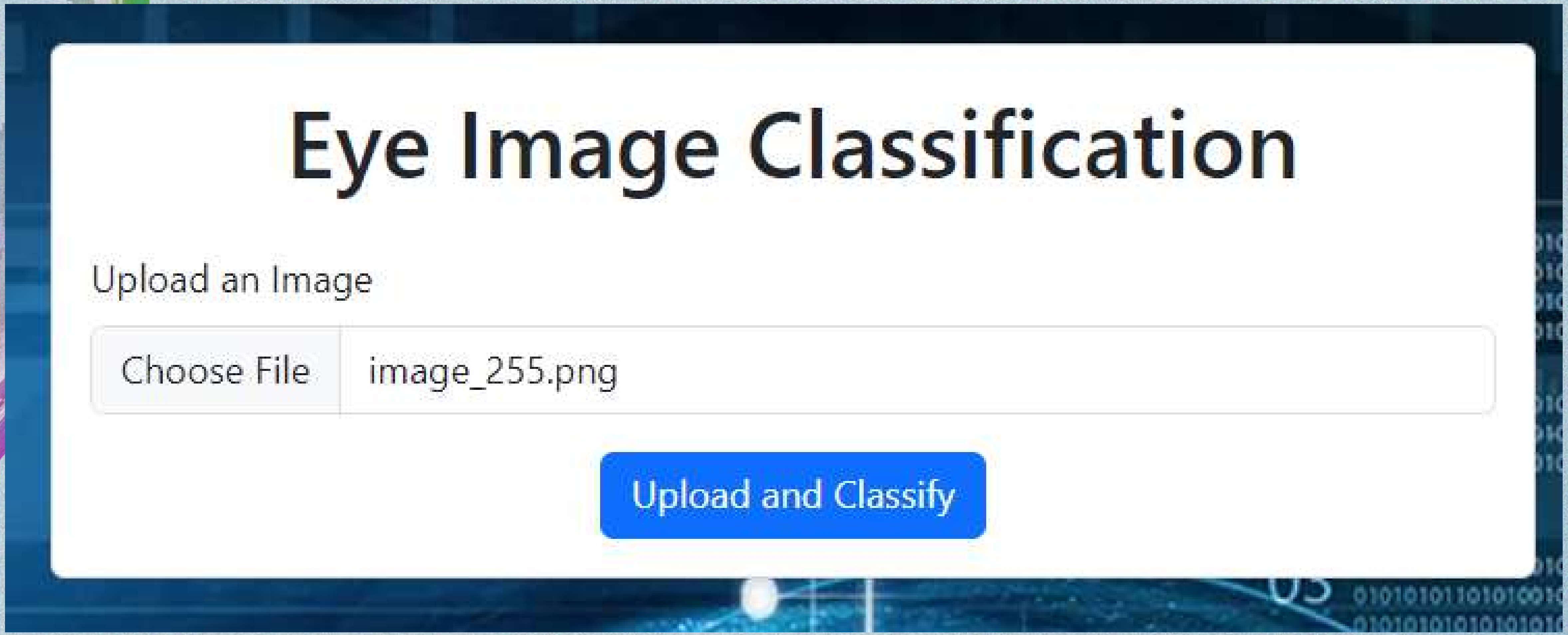

Fig 3:
first upload the image of normal or any eye image

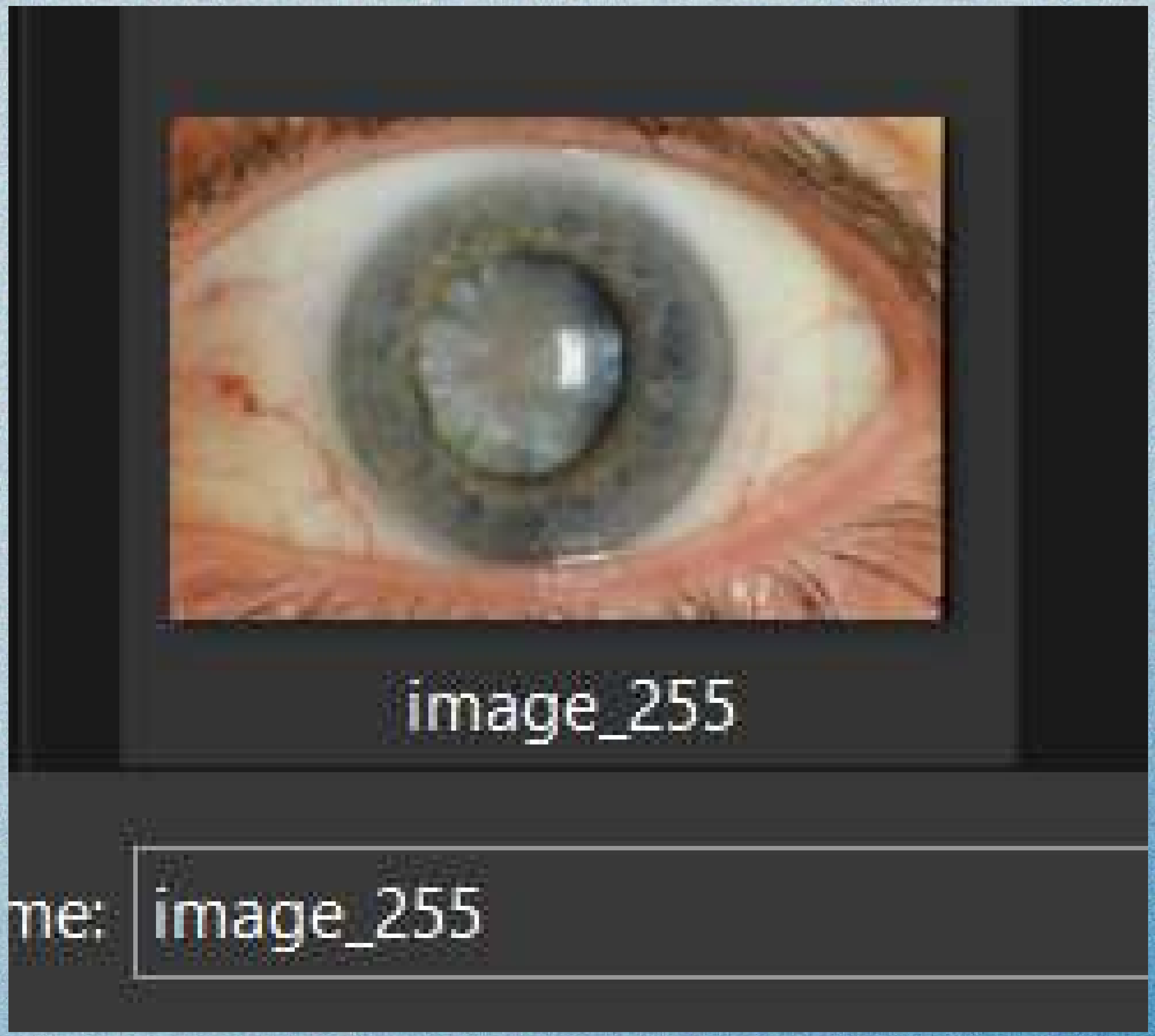

Fig 4:
the image upload

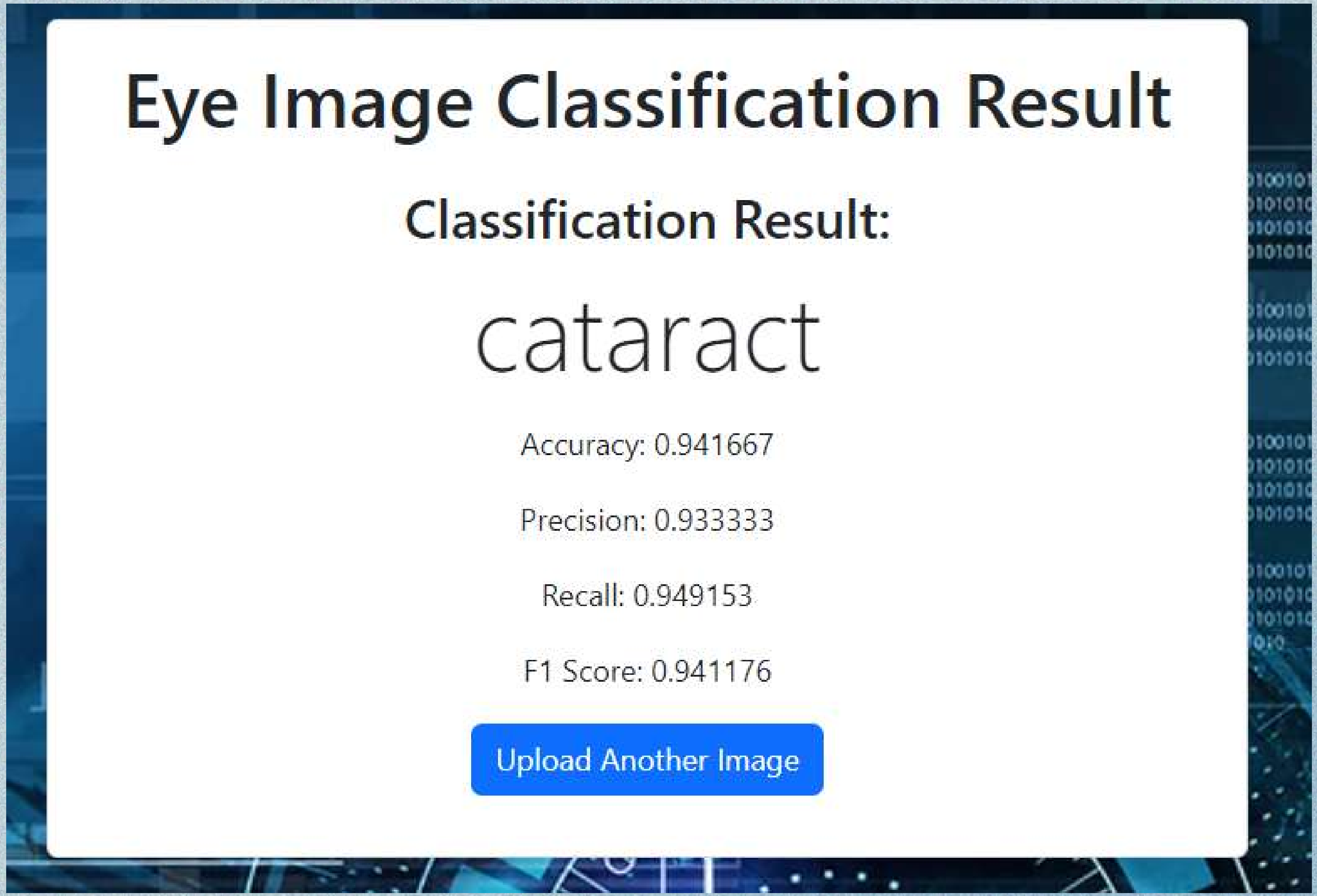

Fig 5:
the result of image upload

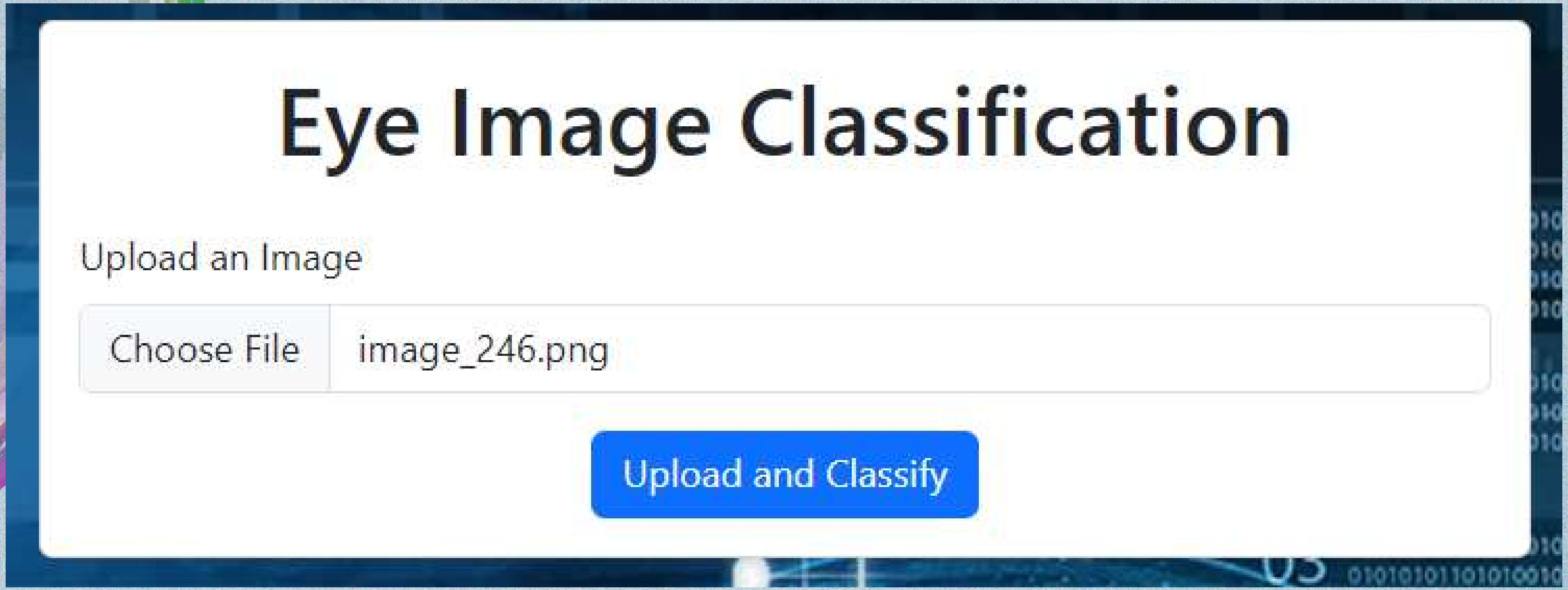

Fig 6:

first upload the image of normal or any eye image

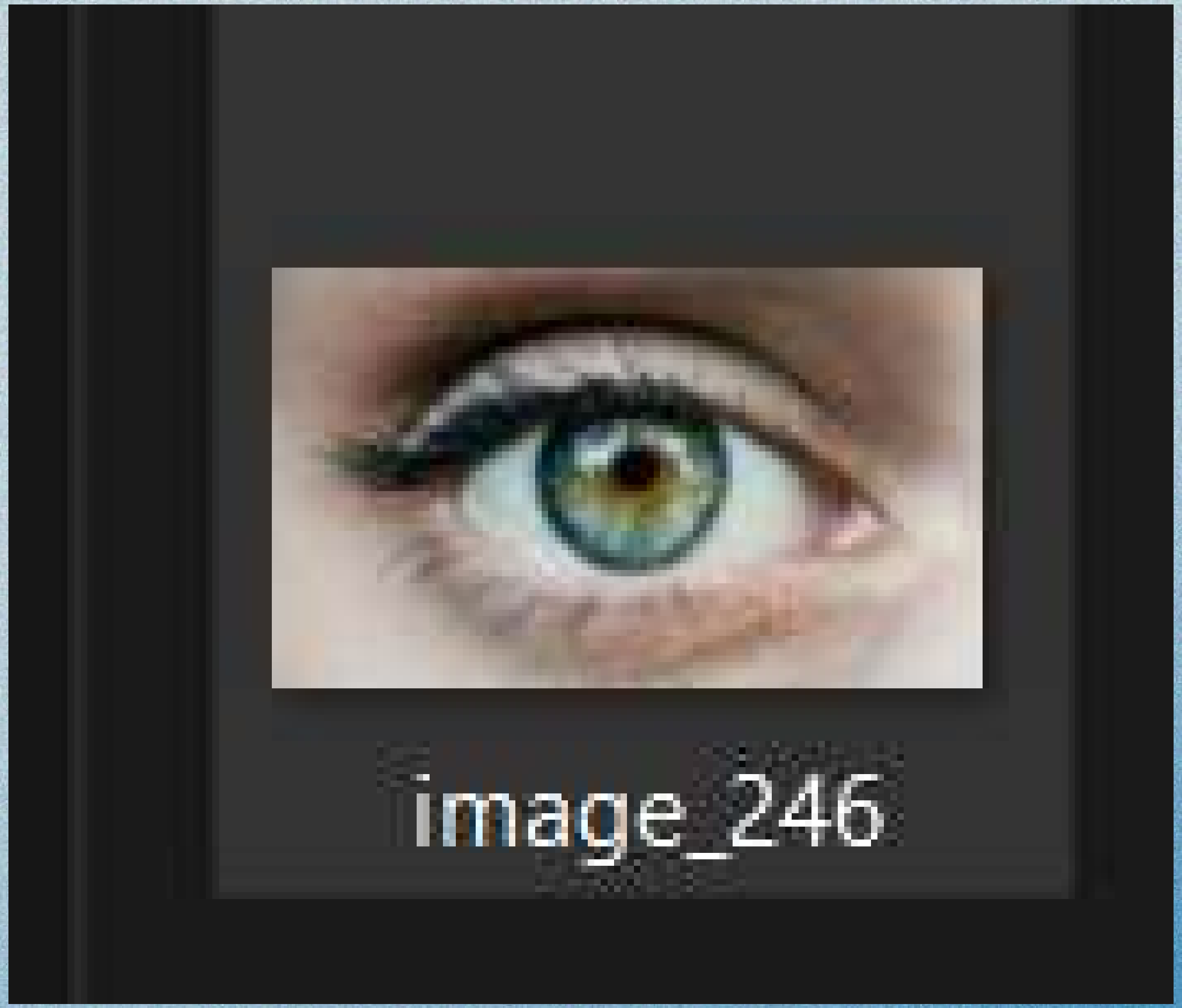

Fig 7:

the image upload

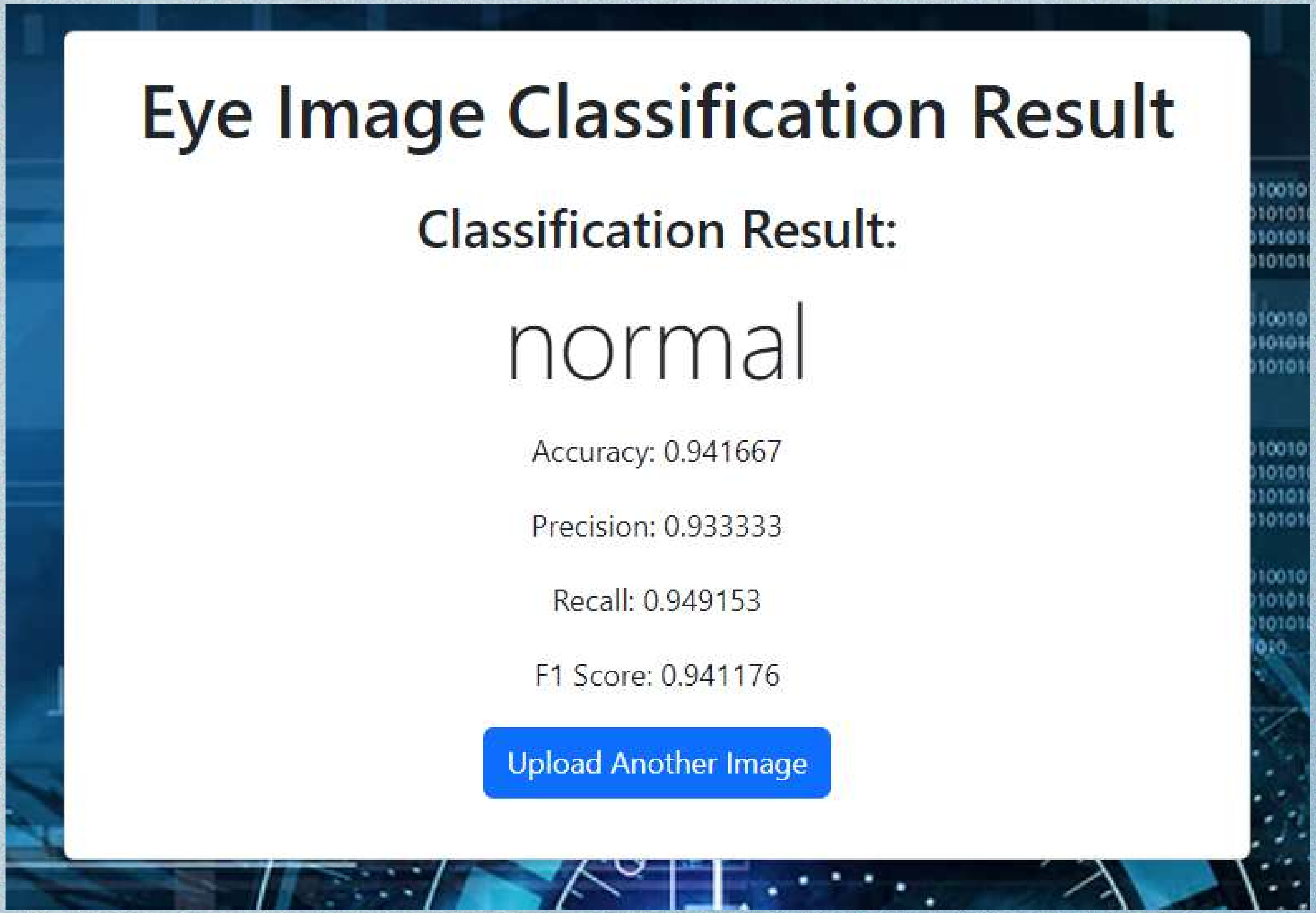

Fig 8:
the result of image upload

CONCLUSION

- The CNN model shows strong performance in classifying eye images, demonstrating the potential of deep learning for automated analysis of medical images.

- The results highlight the viability of CNNs to assist diagnosis through medical image classification. With refinement, such AI systems could be deployed for accessible, large-scale screening.

- This work serves as proof-of-concept for the value of deep learning in ophthalmology, representing an important step towards AI systems for earlier identification and treatment of visual impairments.

- Future work involves improving the model with more data, adding multi-class classification capabilities, real-world deployment and evaluation. Overall, this work shows the promise of AI in enhancing healthcare accessibility, accuracy and consistency.

REFERENCES

- [1] Daniel S Kermany, Michael Goldbaum, Wenjia Cai, Carolina C S Valentim. Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning. Cell. 2018.
- [2] Varun Gulshan, PhD, Lily Peng, MD, PhD, Marc Coram, PhD. Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs. JAMA. 2016.
- [3] Muhammad Waqas Nadeem, Hock Guan Goh, Muzammil Hussain, Soung-Yue Liew, Ivan Andonovic, Muhammad Adnan Khan. Deep Learning for Diabetic Retinopathy Analysis: A Review, Research Challenges, and Future Directions. Diagnostics. 2021.
- [4] Roxane Bunod, Mélanie Lubrano, Antoine Pirovano, Géraldine Chotard, Emmanuelle Brasnu, Sylvain Berlemont, Antoine Labbé, Edouard Augstburger, Christophe Baudouin. A Deep Learning System Using Optical Coherence Tomography Angiography to Detect Glaucoma and Anterior Ischemic Optic Neuropathy. Translational Vision Science & Technology. 2022.
- [5] Zhixi Li, Yifan He, Stuart Keel, Wei Meng, Robert T Chang, Mingguang He. Efficacy of a Deep Learning System for Detecting Glaucomatous Optic Neuropathy Based on Color Fundus Photographs. Ophthalmology. 2018.

Thank You