oko

June 6, 2024

1 Importy

[6]:
```
from __future__ import division
import matplotlib as matplotlib
import sys
from pylab import *
import skimage as ski
import cv2
from skimage import data, io, filters, exposure, measure
from skimage.filters import rank
from skimage import img_as_float, img_as_ubyte
from skimage.morphology import disk
import skimage.morphology as mp
from skimage import util
from skimage.color import rgb2hsv, hsv2rgb, rgb2gray
from skimage.filters.edges import convolve
from skimage.data import camera
from skimage.filters import frangi
from sklearn.metrics import accuracy_score
from matplotlib import pylab as plt
import numpy as np
from numpy import array
from IPython.display import display, clear_output
from ipywidgets import interact, interactive, fixed
from ipywidgets import *
from ipykernel.pylab.backend_inline import flush_figures
from PIL import Image
from scipy import ndimage as ndi
from scipy.stats import gmean
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
from skimage.feature import graycomatrix, graycoprops
import numpy as np
import cv2
import pandas as pd
import math
```

```
from skimage.transform import rescale
from matplotlib import pyplot as plt
from imblearn.under_sampling import RandomUnderSampler
from joblib import dump, load
from skimage import filters
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
```

```
/var/folders/5r/11qk23vn76gfnnsn277vd_4w0000gn/T/ipykernel_1449/2720367253.py:24
: DeprecationWarning: `ipykernel.pylab.backend_inline` is deprecated, directly
use `matplotlib_inline.backend_inline`
  from ipykernel.pylab.backend_inline import flush_figures
```

2 Statystyka

[11]:
```
def show_statistics(predicted, model):
    false_positive = 0
    false_negative = 0
    true_positive = 0
    true_negative = 0

    true_positive = np.sum((predicted > 0) & (model > 0))
    true_negative = np.sum((predicted == 0) & (model == 0))

    false_positive = np.sum((predicted > 0) & (model == 0))
    false_negative = np.sum((predicted == 0) & (model > 0))

    ␣
  ↪print(confusion_matrix(true_positive,true_negative,false_positive,false_negative))
    print()

    total = true_positive + true_negative + false_negative + false_positive

    accuracy = round((true_positive + true_negative) / (total), 4)
    sensitivity = round(true_positive / (true_positive + false_negative + 1), 4)
    specificity = round(true_negative / (false_positive + true_negative + 1), 4)
    precision = round(true_positive / (true_positive + false_positive + 1), 4)
    mean_sensitivity_specificity = round((sensitivity + specificity) / 2, 4)

    print("Accuracy: ", accuracy)
    print("Sensitivity: ", sensitivity)
    print("Specificity: ", specificity)
    print("Precision: ", precision)
    print("Mean Sensitivity-Specificity: ", mean_sensitivity_specificity)
```

[12]:
```python
def confusion_matrix(TP, TN, FP, FN):
    names = {
        'My Results' : ['Positive', 'Negative', 'Sum'],
        'Actually - Positive' : [TP, FN, TP + FN],
        'Actually - Negative' : [FP, TN, FP + TN],
        'Sum' : [TP + FP, FN + TN, TP + FP + FN + TN]
    }

    df = pd.DataFrame(names, columns=['My Results', 'Actually - Positive',␣
↪'Actually - Negative', 'Sum' ]).set_index('My Results')
    return df
```

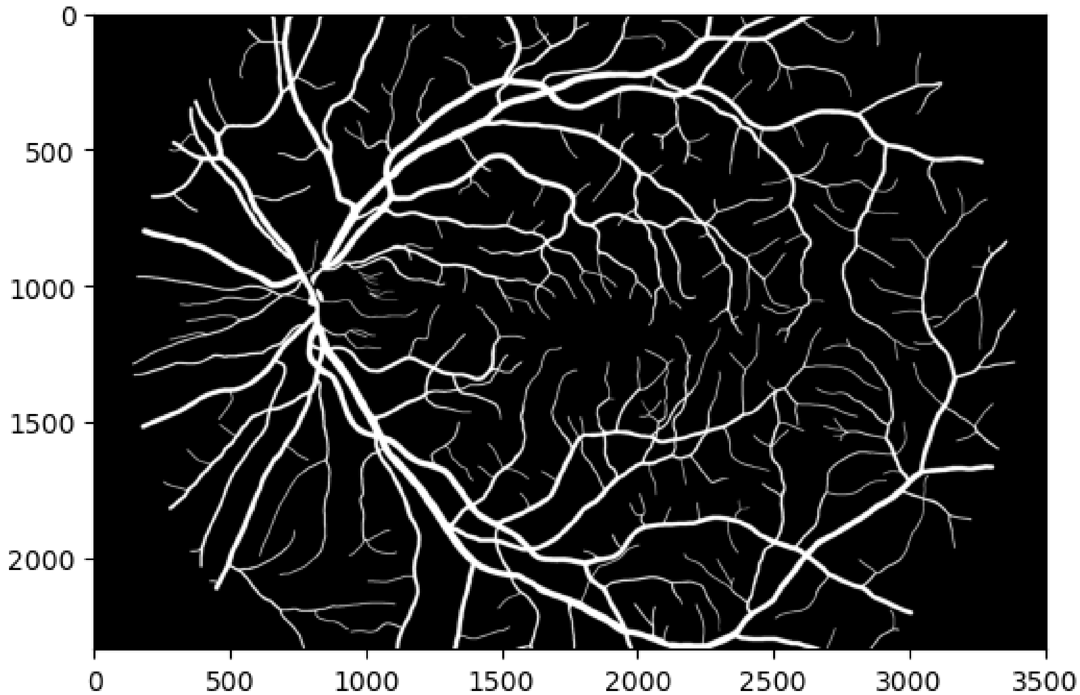
3 Filtr Frangi

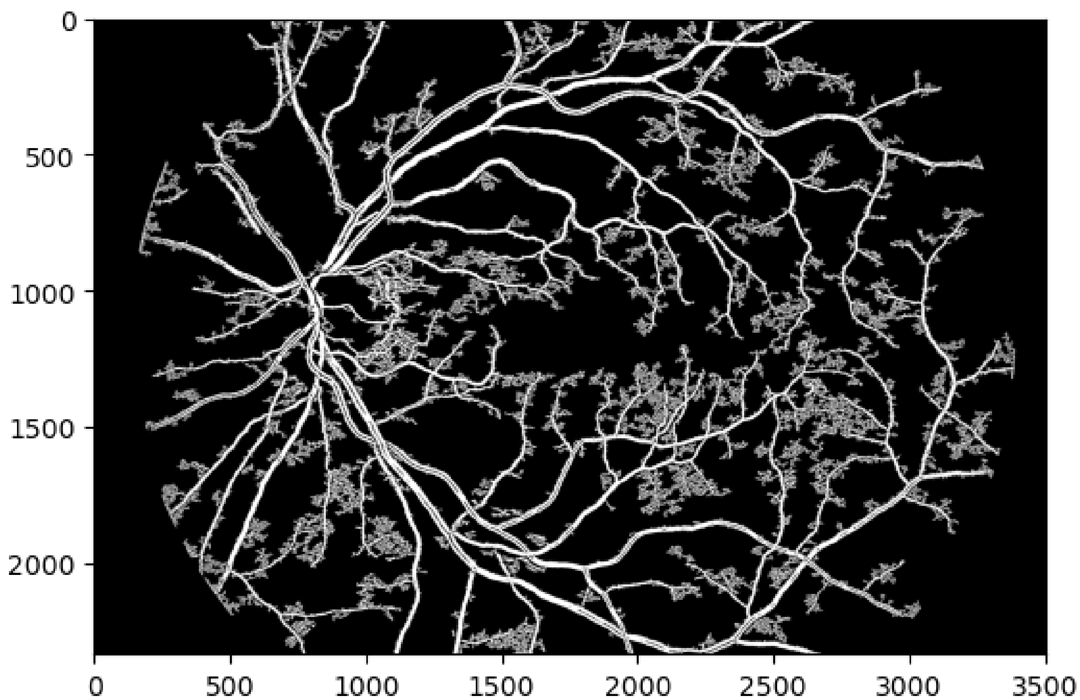
[13]:
```python
def image_processing(image):
    # Wczytuje obraz z pliku .jpg
    img = cv2.imread('images/' + image + '.jpg')

    # Wybiera zielony kanał z obrazu (kanal G w formacie RGB)
    img_green = img[:, :, 1]

    # Stosuje filtr Frangi do zielonego kanału, który jest używany do␣
↪wykrywania naczyń krwionośnych w obrazie
    img_frangi = frangi(img_green)

    # Przekształca wartości w obrazie filtrowanym Frangi do binarnej maski
    for i in range(len(img_frangi)):
        for j in range(len(img_frangi[i])):
            if img_frangi[i][j] > 0.0005:
                img_frangi[i][j] = 255
            else:
                img_frangi[i][j] = 0

    # Konwertuje oryginalny obraz do skali szarości
    img_mask = cv2.cvtColor(img, cv2.COLOR_RGB2GRAY)

    # Tworzy binarną maskę z obrazu w skali szarości, gdzie piksele powyżej␣
↪progu 1 są ustawione na 255 (biały), a poniżej na 0 (czarny)
    (thresh, blackAndWhiteImage) = cv2.threshold(img_mask, 1, 255, cv2.
↪THRESH_BINARY)

    # Definiuje prosty kernel do operacji erozji
    kernel = np.ones((5, 5), np.uint8)

    # Stosuje erozję do binarnej maski, co pomaga usunąć drobne szumy
    blackAndWhiteImage = cv2.erode(blackAndWhiteImage, kernel)
```

```
    # Mnoży maskę frangi przez binarną maskę, aby uzyskać finalny obraz
    final = img_frangi * blackAndWhiteImage

    # Ponownie definiuje kernel do późniejszej operacji
    kernel = np.ones((5, 5), np.uint8)

    # Tworzy binarną maskę, gdzie wartości większe niż 0 są ustawione na True␣
↪(białe), a reszta na False (czarne)
    x = final > 0

    # Usuwa małe obiekty
    end = mp.remove_small_objects(x, 5000)

    # Wczytuje obraz maski z pliku .tif i wybiera zielony kanał
    mask = cv2.cvtColor(cv2.imread('images/' + image + '.tif'), cv2.
↪COLOR_BGR2RGB)[:, :, 1]

    # Wyświetla wczytaną maskę w kolorze RGB
    plt.imshow(cv2.cvtColor(mask, cv2.COLOR_BGR2RGB))
    plt.show()

    # Wyświetla finalną maskę w skali szarości
    plt.imshow(end, cmap=cm.Greys_r)
    plt.show()

    # Wywołuje funkcję, która wyświetla statystyki porównujące finalną maskę z␣
↪maską ekspercką
    show_statistics(end, mask)
```

[14]:

```
image_processing('08_h')
image_processing('09_h')
image_processing('10_h')
image_processing('11_h')
image_processing('12_h')
```



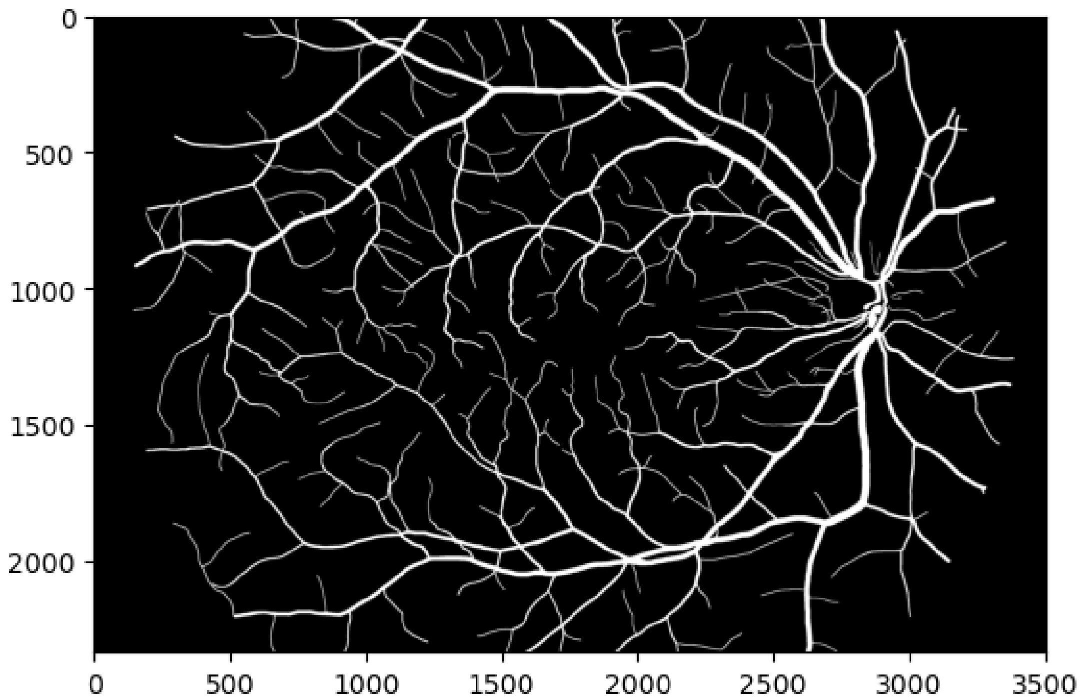


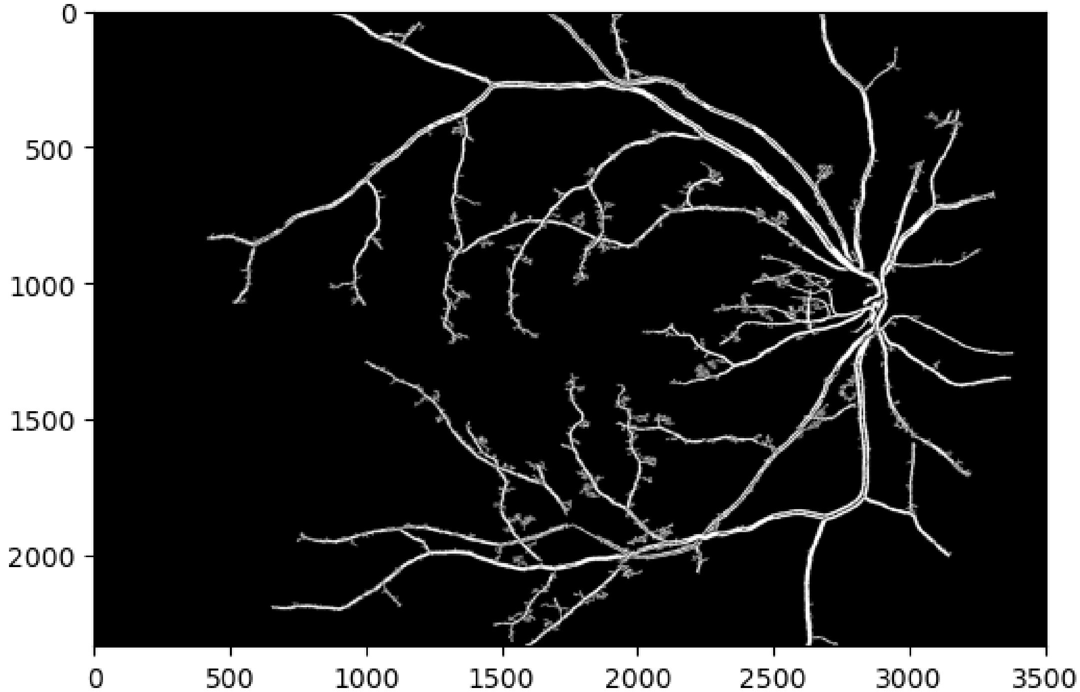
Actually - Positive   Actually - Negative   Sum

My Results

Positive	580956	442914	1023870
Negative	240671	6920803	7161474
Sum	821627	7363717	8185344

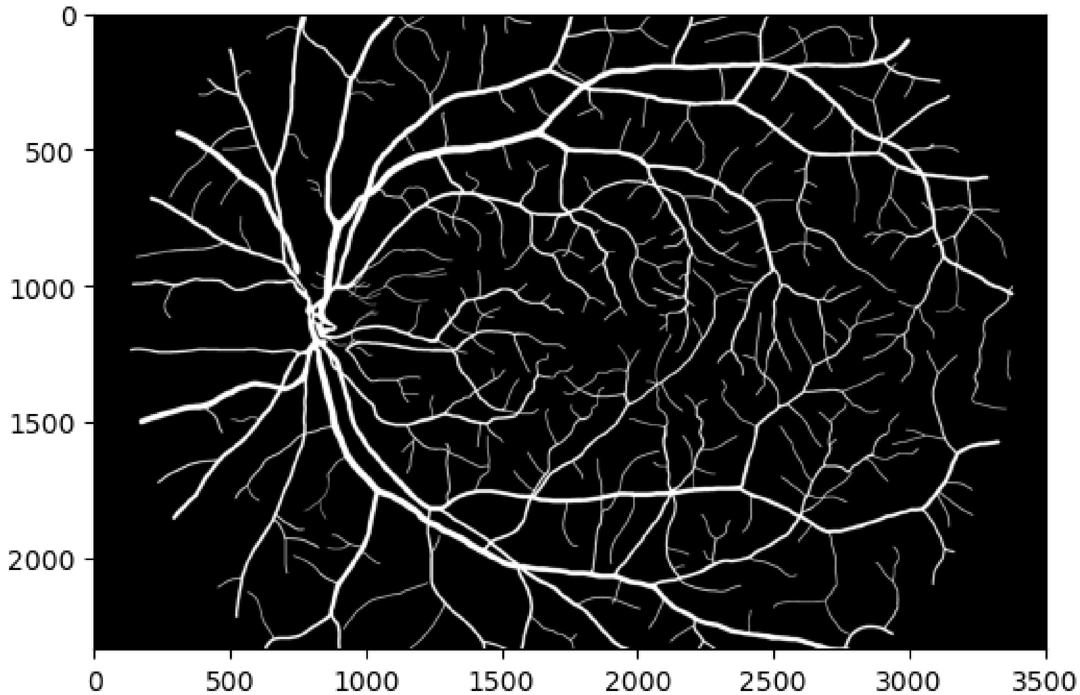
Accuracy: 0.9165
Sensitivity: 0.7071
Specificity: 0.9399
Precision: 0.5674
Mean Sensitivity-Specificity: 0.8235

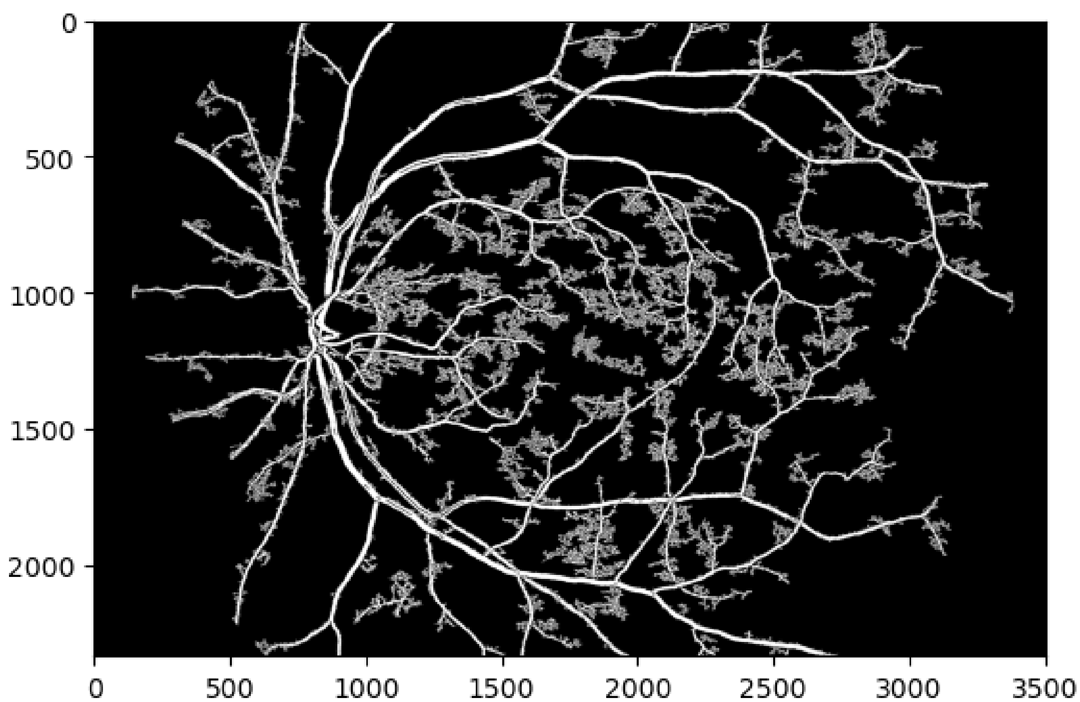




	Actually - Positive	Actually - Negative	Sum
My Results			
Positive	301221	69599	370820
Negative	335247	7479277	7814524
Sum	636468	7548876	8185344

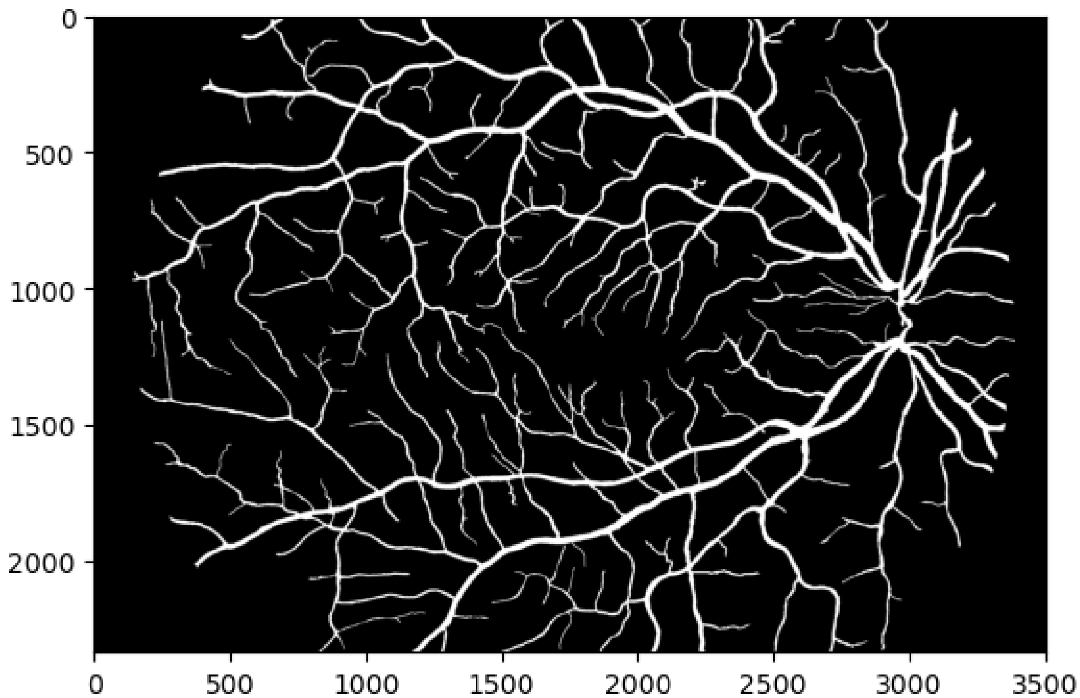
Accuracy: 0.9505
Sensitivity: 0.4733
Specificity: 0.9908
Precision: 0.8123
Mean Sensitivity-Specificity: 0.732

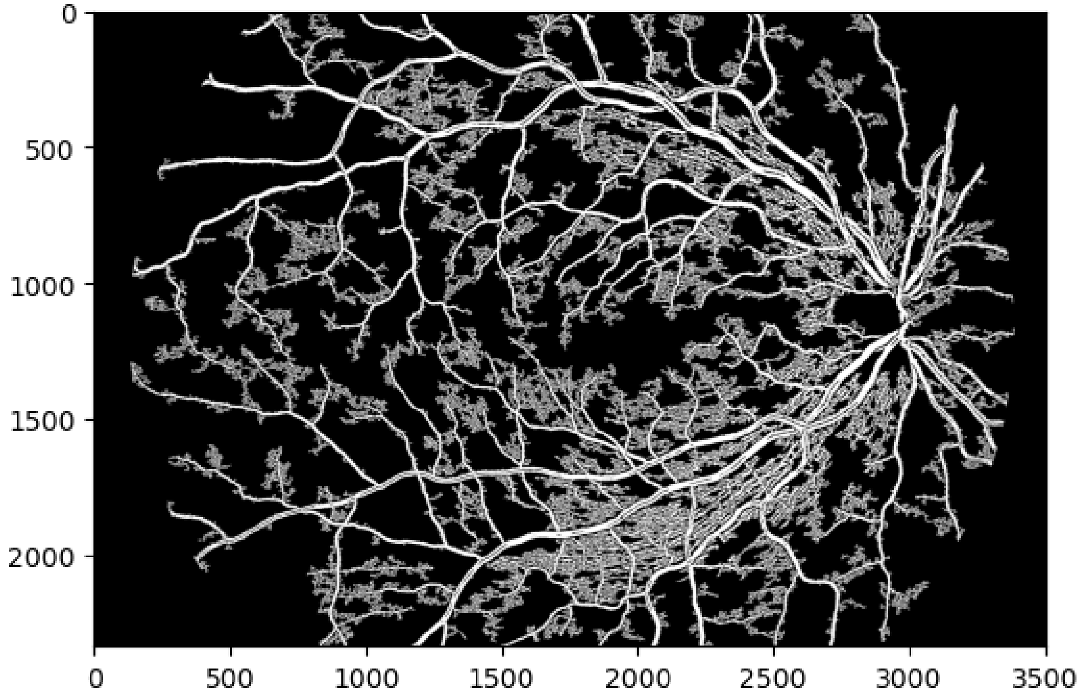





```
Actually - Positive  Actually - Negative      Sum
```

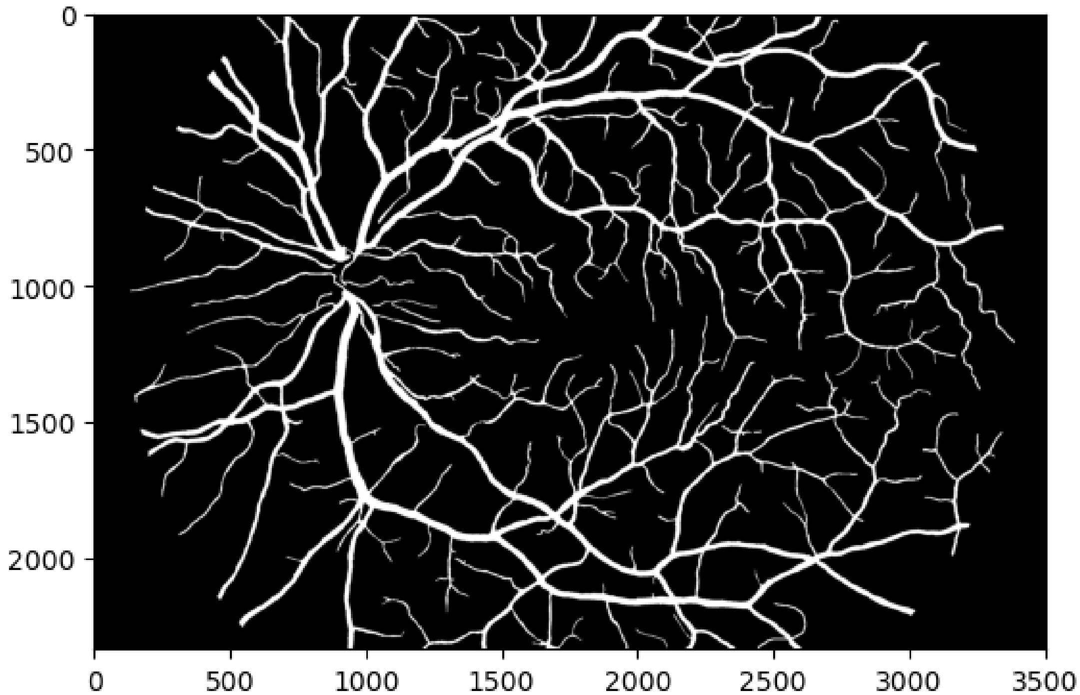
```
My Results
Positive            468746            381359   850105
Negative            236692           7098547  7335239
Sum                 705438           7479906  8185344

Accuracy:  0.9245
Sensitivity:  0.6645
Specificity:  0.949
Precision:  0.5514
Mean Sensitivity-Specificity:  0.8068
```

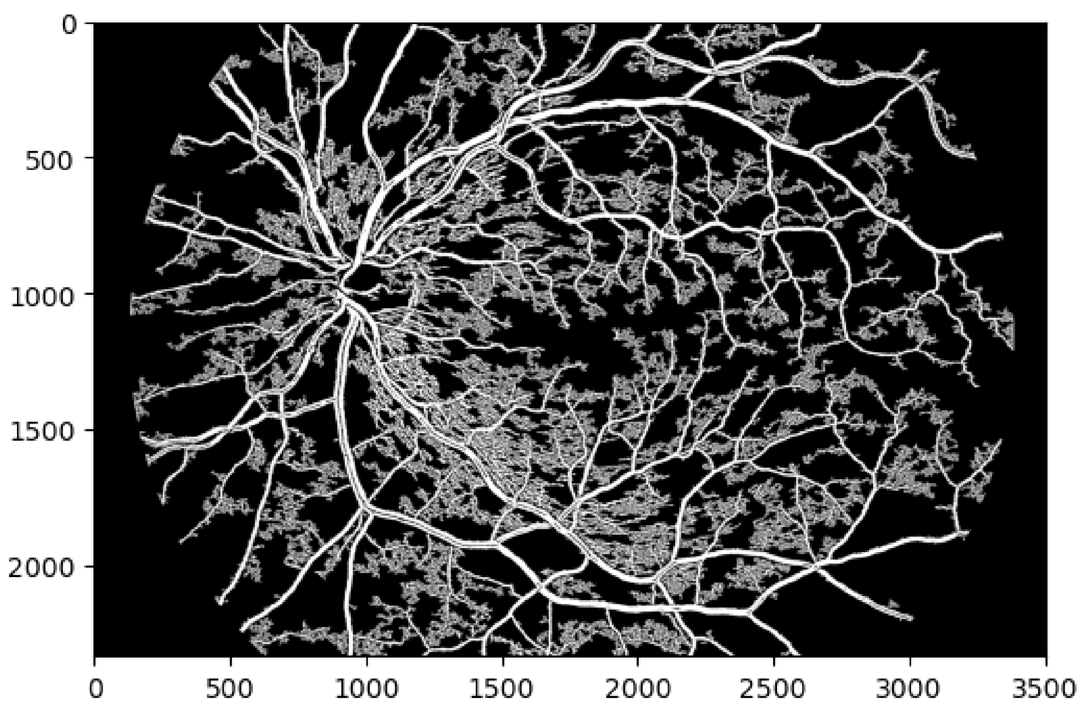




	Actually - Positive	Actually - Negative	Sum
My Results			
Positive	606585	759996	1366581
Negative	158770	6659993	6818763
Sum	765355	7419989	8185344

Accuracy: 0.8878
Sensitivity: 0.7926
Specificity: 0.8976
Precision: 0.4439
Mean Sensitivity-Specificity: 0.8451





Actually - Positive	Actually - Negative	Sum

```
My Results
Positive                698853              827239   1526092
Negative                160442             6498810   6659252
Sum                     859295             7326049   8185344

Accuracy:  0.8793
Sensitivity:  0.8133
Specificity:  0.8871
Precision:  0.4579
Mean Sensitivity-Specificity:  0.8502
```

4 Las decyzyjny

[11]:
```python
SCALE = 0.5

def scaleImage(image):
    height, width = image.shape[:2]
    new_height = int(height * SCALE)
    new_width = int(width * SCALE)
    scaled_image = cv2.resize(image, (new_width, new_height))
    return scaled_image
```

[1]:
```python
PATCH_SIZE = 5  # Ustalony rozmiar fragmentu obrazu do analizy; mniejsze␣
 ↪fragmenty mogą dostarczać bardziej szczegółowych informacji o lokalnych␣
 ↪cechach obrazu

# Funkcja do ekstrakcji cech z obrazu
def get_features(image, gray):
    features = []  # Lista do przechowywania wektorów cech
    height, width = gray.shape  # Pobiera wysokość i szerokość obrazu w skali␣
 ↪szarości

    # Przechodzi przez obraz, dzieląc go na małe fragmenty o rozmiarze␣
 ↪PATCH_SIZE x PATCH_SIZE
    for y in range(0, height - PATCH_SIZE + 1):
        for x in range(0, width - PATCH_SIZE + 1):
            patch = image[y:y + PATCH_SIZE, x:x + PATCH_SIZE]  # Wybiera␣
 ↪fragment obrazu
            patch_gray = gray[y:y + PATCH_SIZE, x:x + PATCH_SIZE]  # Odpowiedni␣
 ↪fragment obrazu w skali szarości

            # Oblicza momenty dla fragmentu obrazu w skali szarości
            moments = cv2.moments(patch_gray)
            # Oblicza Hu-moments, które są niezmienne na obrót, skalowanie i␣
 ↪translację
            hu_moments = cv2.HuMoments(moments).flatten()
```

```
            # Oblicza średnią i odchylenie standardowe dla każdego kanału␣
 ↪kolorów w fragmencie obrazu
            # Te cechy pomagają scharakteryzować kolory i ich zmienność w␣
 ↪analizowanym fragmencie
            mean = np.mean(patch.reshape(-1, 3), axis=0)
            std = np.std(patch.reshape(-1, 3), axis=0)

            # Tworzy wektor cech, łącząc średnią, odchylenie standardowe i␣
 ↪hu_moments
            feature_vector = np.hstack([mean, std, hu_moments])
            features.append(feature_vector)  # Dodaje wektor cech do listy

    return features

# Funkcja do pobierania etykiet (wartości pikseli centralnych) dla każdego␣
 ↪fragmentu obrazu
def get_labels(image):
    labels = []  # Lista do przechowywania etykiet
    height, width = image.shape  # Pobiera wysokość i szerokość obrazu

    # Przechodzi przez obraz i wybiera wartość piksela centralnego dla każdego␣
 ↪fragmentu
    for y in range(0, height - PATCH_SIZE + 1):
        for x in range(0, width - PATCH_SIZE + 1):
            patch = image[y:y + PATCH_SIZE, x:x + PATCH_SIZE]  # Wybiera␣
 ↪fragment obrazu
            label = patch[PATCH_SIZE // 2, PATCH_SIZE // 2]  # Wybiera wartość␣
 ↪piksela centralnego fragmentu
            # Wybór piksela centralnego jest ważny, ponieważ reprezentuje on␣
 ↪wartość dla całego fragmentu
            labels.append(label)  # Dodaje etykietę do listy

    return labels

# Funkcja do tworzenia obrazu z wartościami przewidywanymi przez model
def get_predicted_image(image, predicted):
    height, width = image.shape  # Pobiera wysokość i szerokość obrazu
    new_image = np.zeros((height, width))  # Tworzy nowy obraz o tych samych␣
 ↪wymiarach, wypełniony zerami
    for y in range(0, height - PATCH_SIZE + 1):
        for x in range(0, width - PATCH_SIZE + 1):
            # Wstawia przewidywaną wartość do nowego obrazu
            # Używamy przewidywanej wartości dla całego fragmentu
            new_image[y:y + PATCH_SIZE, x:x + PATCH_SIZE] = predicted[0]
```

```
            predicted = predicted[1:]  # Przechodzi do kolejnej przewidywanej␣
↪wartości
    return new_image
```

[20]:
```
features = []  # Lista do przechowywania cech z wszystkich obrazów treningowych
labels = []  # Lista do przechowywania etykiet z wszystkich obrazów treningowych

train_data = ["01", "02", "03"]  # Lista identyfikatorów obrazów treningowych

for train_image in train_data:
    print(f"Processing image: {train_image}")
    # Wczytuje obraz do analizy
    image = cv2.imread("images/" + train_image + "_h.jpg")
    # Skaluje obraz do odpowiedniego rozmiaru
    image = scaleImage(image)
    # Konwertuje obraz na skalę szarości
    gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
    # Stosuje filtr wyostrzający, który może poprawić widoczność drobnych␣
↪szczegółów
    gray = filters.unsharp_mask(gray)

    # Wczytuje odpowiadający model obrazu (np. maska ekspercka)
    model = cv2.imread("images/" + train_image + "_h.tif")
    # Skaluje model do odpowiedniego rozmiaru
    model = scaleImage(model)
    # Konwertuje model do skali szarości
    model = cv2.cvtColor(model, cv2.COLOR_BGR2GRAY)
    # Tworzy binarną maskę, gdzie piksele powyżej wartości 50 są ustawione na␣
↪True
    model = model > 50
    print("Features and labels")
    # Dodaje cechy i etykiety do odpowiednich list
    features.extend(get_features(image, gray))
    labels.extend(get_labels(model))
```

```
Processing image: 01
Features and labels
Processing image: 02
Features and labels
Processing image: 03
Features and labels
Processing image: 04
Features and labels
Processing image: 05
Features and labels
```

[21]:
```
features = np.array(features)  # Konwertuje listę cech na tablicę numpy
labels = np.array(labels)  # Konwertuje listę etykiet na tablicę numpy

print("Creating and fitting sampler")
# Tworzy i dopasowuje próbkę losową, aby zrównoważyć liczbę próbek w każdej␣
 ↪klasie
sampler = RandomUnderSampler(sampling_strategy=1)
features, labels = sampler.fit_resample(features, labels)

print("Train test split")
# Dzieli dane na zestawy treningowe i testowe w celu oceny wydajności modelu
X_train, X_test, y_train, y_test = train_test_split(features, labels,␣
 ↪test_size=0.2, random_state=42)

classifier = RandomForestClassifier(n_estimators=500, n_jobs=-1)  #␣
 ↪Inicjalizuje klasyfikator lasu losowego z 500 drzewami
print("Classifier fitting")
classifier.fit(X_train, y_train)  # Dopasowuje model do danych treningowych

print("Classifier scoring")
# Ocena wydajności klasyfikatora na danych testowych
accuracy = classifier.score(X_test, y_test)
print("Accuracy:", accuracy)

dump(classifier, "test.joblib")  # Zapisuje wytrenowany klasyfikator do pliku␣
 ↪"test.joblib"
```

```
Creating and fitiing sampler
Train test split
Classifier fitting
Classifier scoring
Accuracy: 0.901937398836933
```

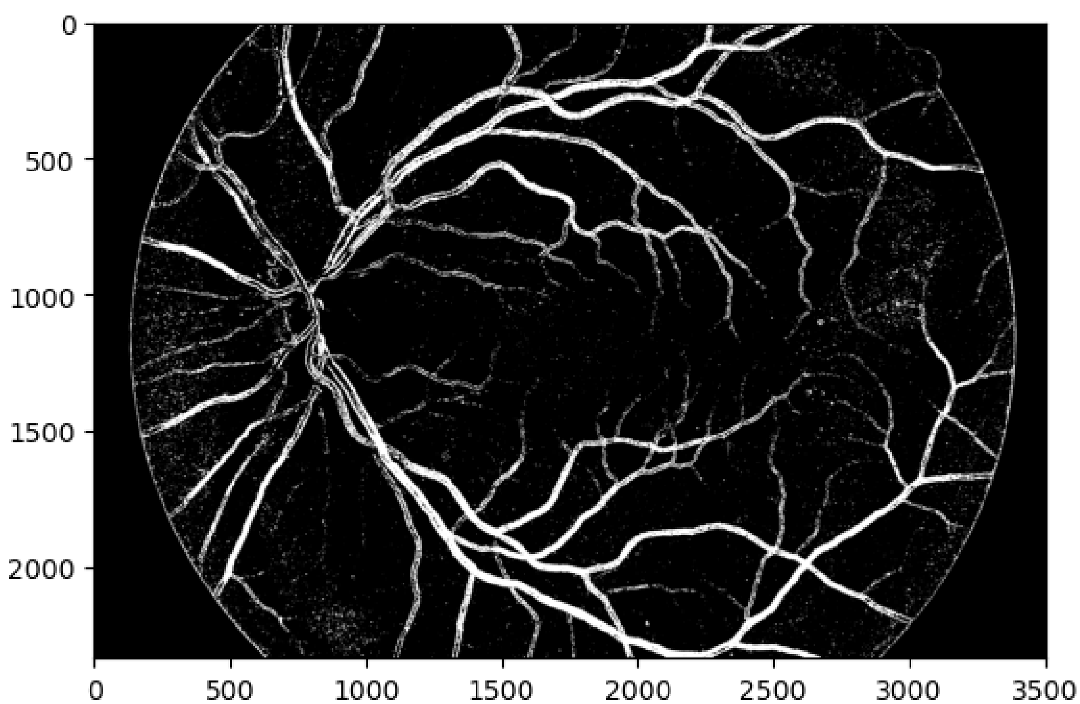
[21]:
```
['test2.joblib']
```

[58]:
```
def load_classifier():
  return load("test.joblib")

loaded_classifier = load_classifier()
```

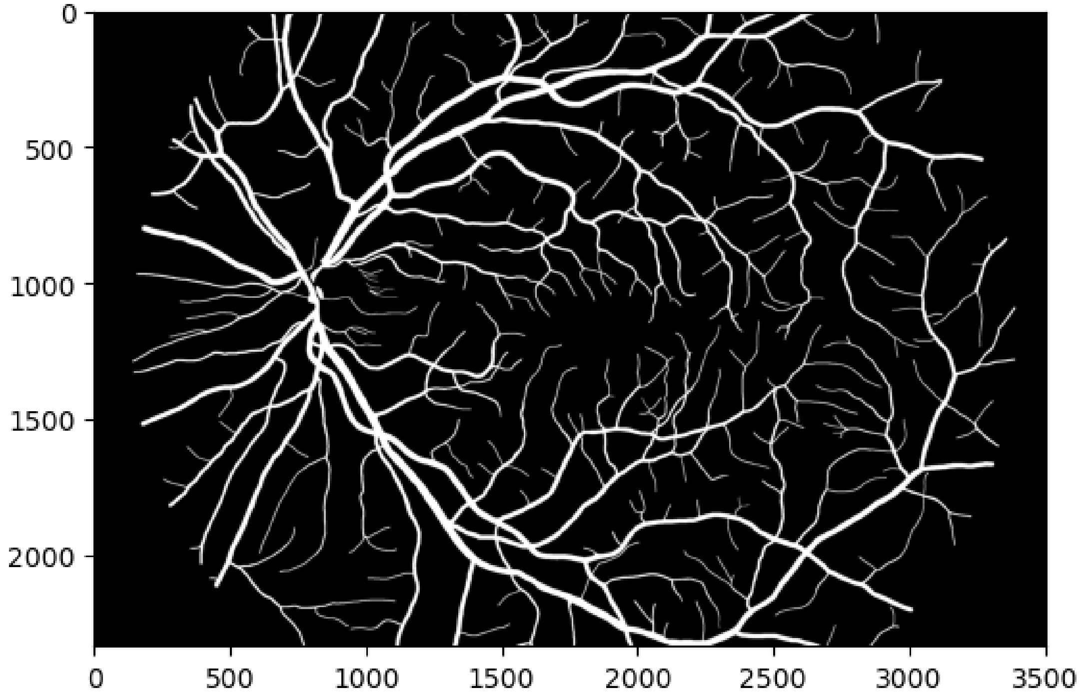
[59]:
```
test_data = ["08","09","10","11","12"]



for train_image in test_data:
    image = cv2.imread("images/" + train_image + "_h.jpg")
    plt.imshow(image)
```

```
gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
gray = filters.unsharp_mask(gray)


model = cv2.imread("images/" + train_image + "_h.tif")
model = cv2.cvtColor(model, cv2.COLOR_BGR2GRAY)
model = model > 50

classifier = loaded_classifier
predictions = classifier.predict(get_features(image, gray))

print()
print(f"Processed image: {train_image}")
predicted_image = get_predicted_image(gray, predictions)
plt.imshow(predicted_image, cmap='gray')
plt.show()
print(f"Expert image: {train_image}")
plt.imshow(model, cmap='gray')
plt.show()


show_statistics(predicted_image, model)
```

```
Processed image: 08
```



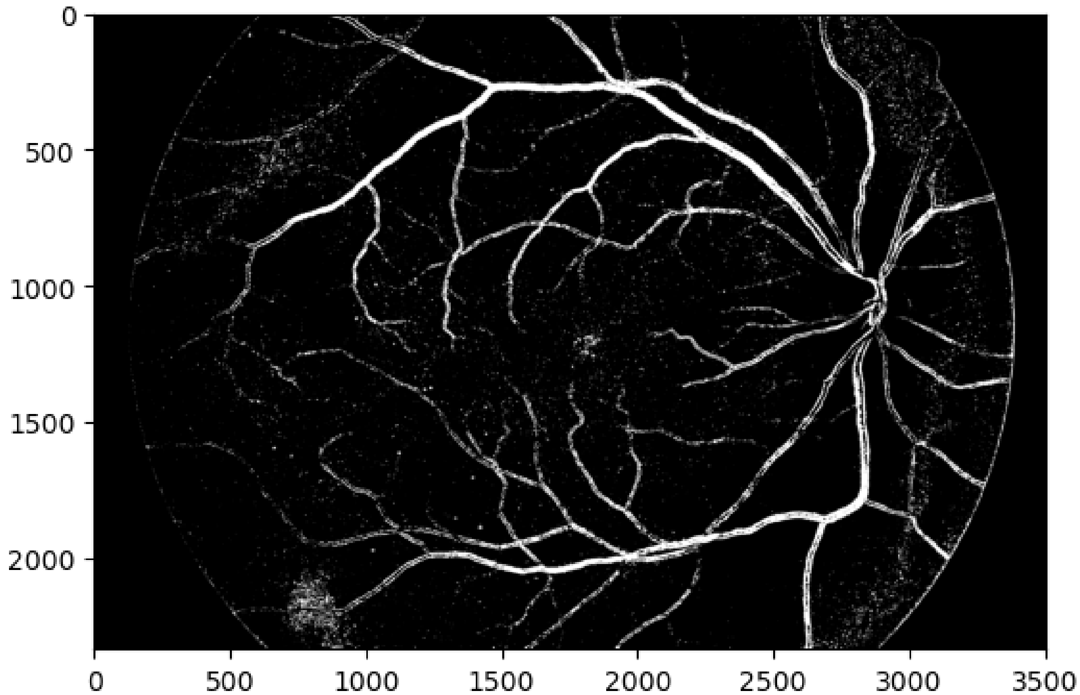
Expert image: 08



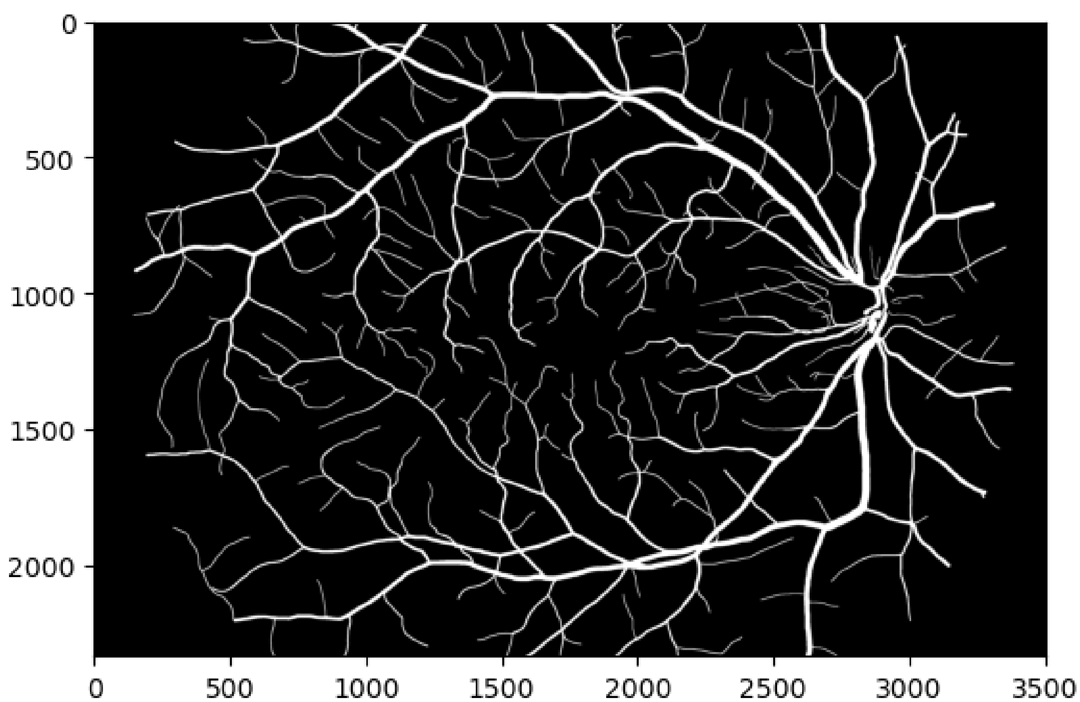
	Actually - Positive	Actually - Negative	Sum
My Results			
Positive	464057	233225	697282
Negative	357570	7130492	7488062
Sum	821627	7363717	8185344

Accuracy: 0.9278
Sensitivity: 0.5648
Specificity: 0.9683
Precision: 0.6655
Mean Sensitivity-Specificity: 0.7666

Processed image: 09



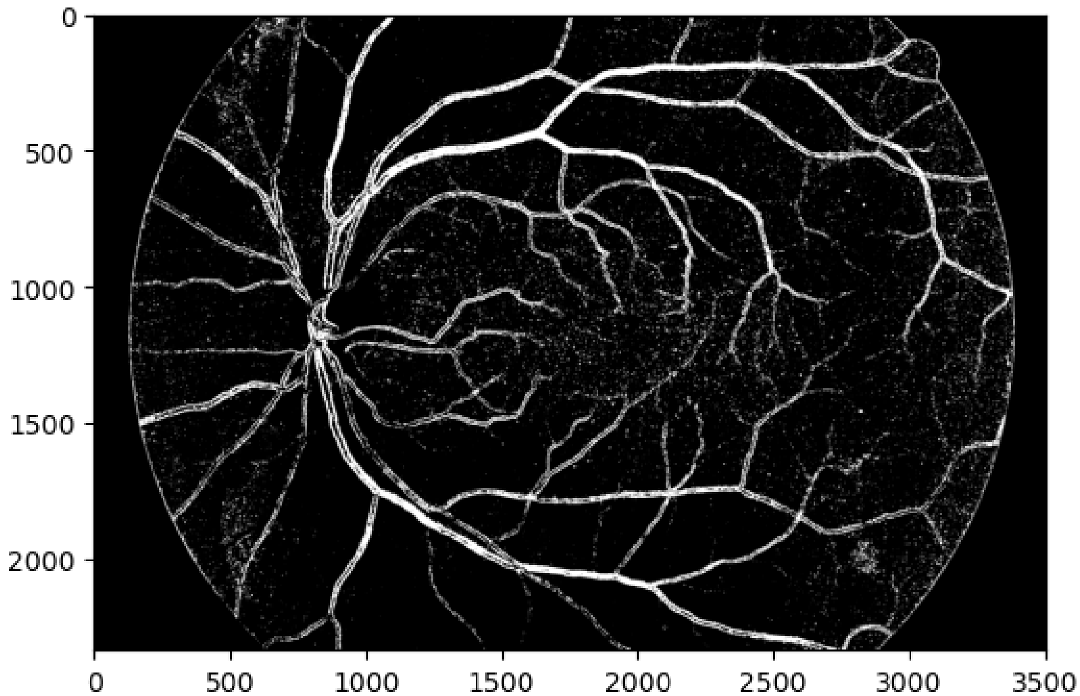
Expert image: 09



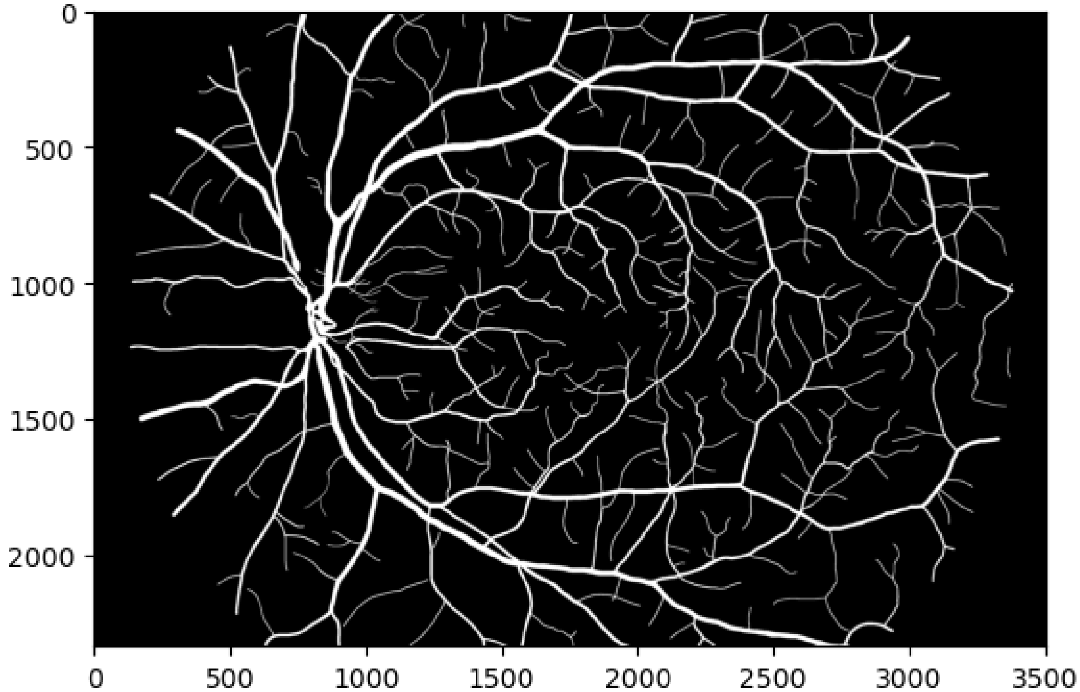
	Actually - Positive	Actually - Negative	Sum
My Results			
Positive	278973	180296	459269
Negative	357495	7368580	7726075
Sum	636468	7548876	8185344

Accuracy: 0.9343
Sensitivity: 0.4383
Specificity: 0.9761
Precision: 0.6074
Mean Sensitivity-Specificity: 0.7072

Processed image: 10

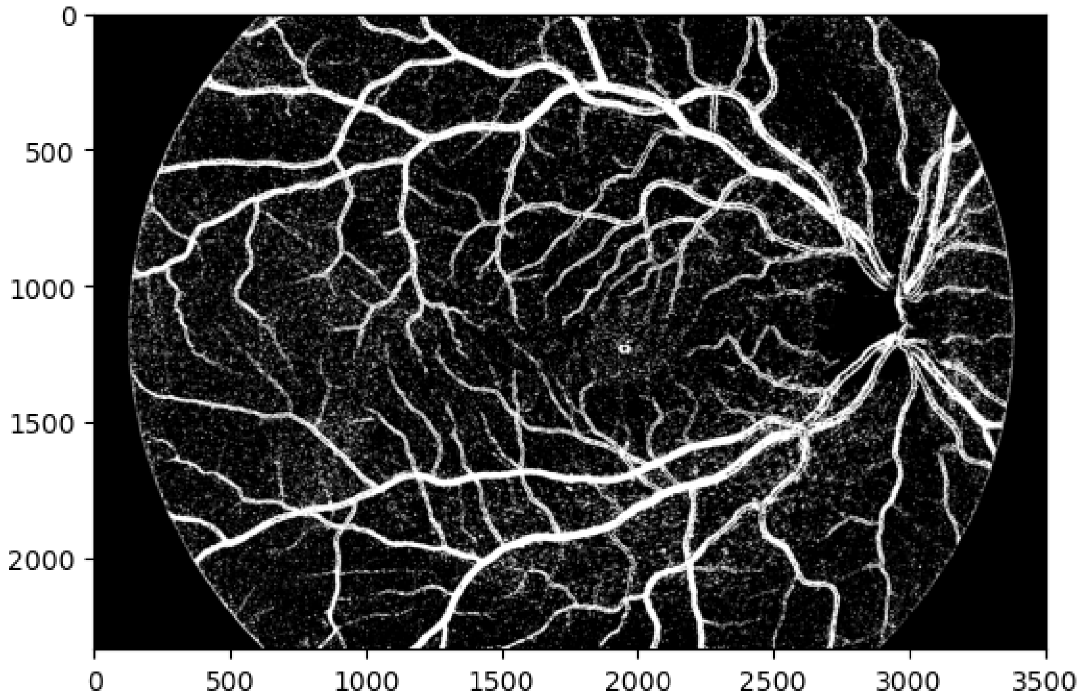


Expert image: 10

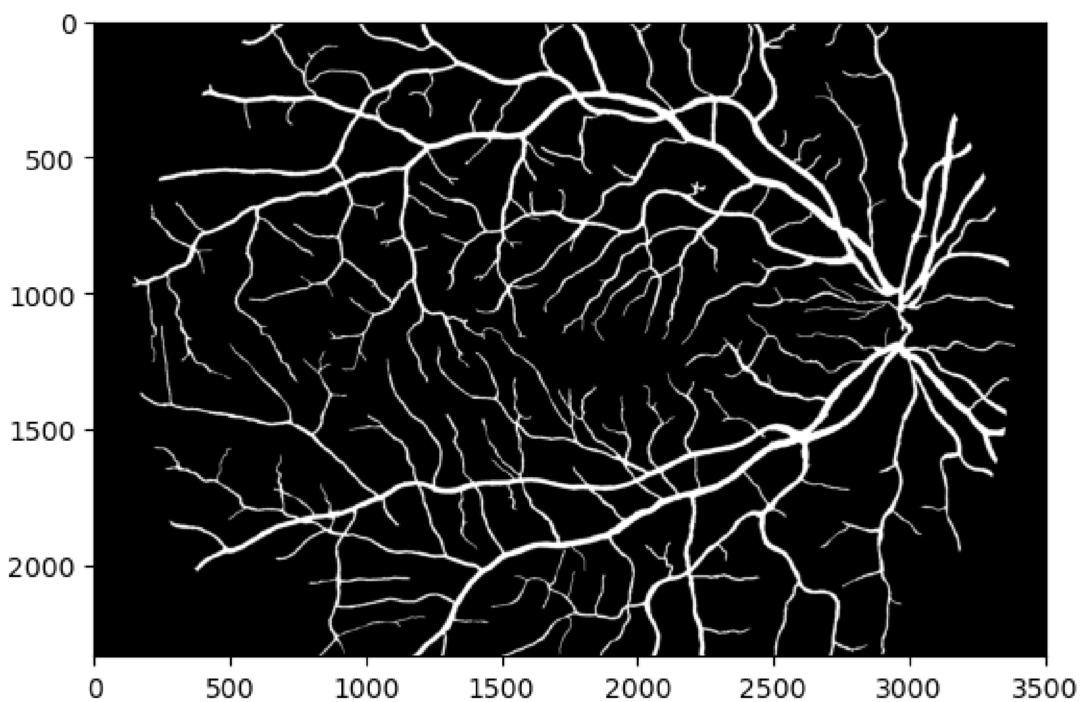


	Actually - Positive	Actually - Negative	Sum
My Results			
Positive	348529	295166	643695
Negative	356909	7184740	7541649
Sum	705438	7479906	8185344

```
Accuracy:  0.9203
Sensitivity:  0.4941
Specificity:  0.9605
Precision:  0.5414
Mean Sensitivity-Specificity:  0.7273

Processed image: 11
```



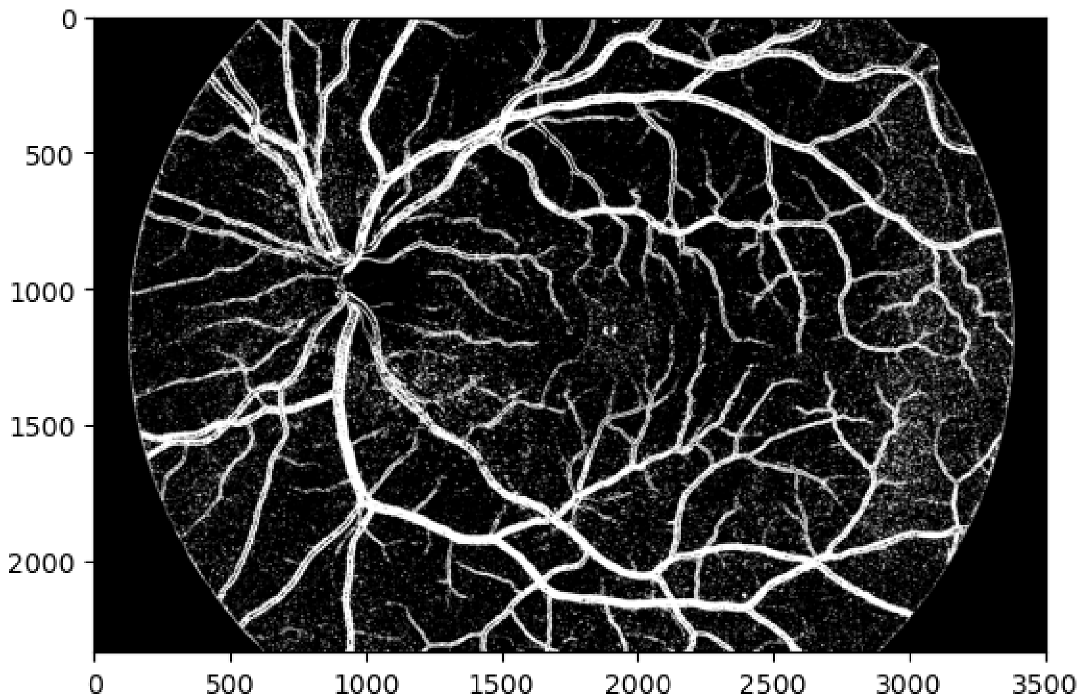
Expert image: 11



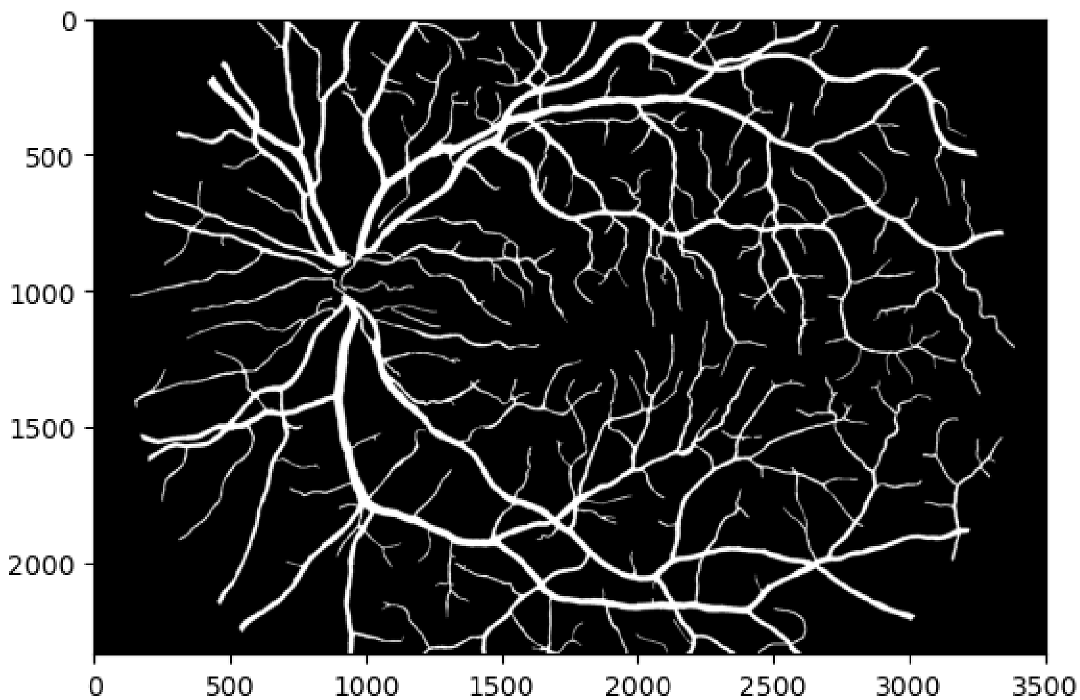
	Actually - Positive	Actually - Negative	Sum
My Results			
Positive	575123	782845	1357968
Negative	190004	6637372	6827376
Sum	765127	7420217	8185344

```
Accuracy:  0.8811
Sensitivity:  0.7517
Specificity:  0.8945
Precision:  0.4235
Mean Sensitivity-Specificity:  0.8231
```

Processed image: 12



Expert image: 12



My Results	Actually - Positive	Actually - Negative	Sum
Positive	642459	678284	1320743
Negative	216198	6648403	6864601
Sum	858657	7326687	8185344

```
Accuracy:  0.8907
Sensitivity:  0.7482
Specificity:  0.9074
Precision:  0.4864
Mean Sensitivity-Specificity:  0.8278
```

5 Głęboka sieć neuronowa

[43]:
```
import cv2
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from imblearn.under_sampling import RandomUnderSampler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.utils import to_categorical
```

```python
PATCH_SIZE = 5  # Rozmiar fragmentu (patrz) wykorzystywanego do ekstrakcji cech

# Funkcja do ekstrakcji cech i etykiet z obrazu
def get_features_and_labels(image, gray, model):
    features = []
    labels = []
    height, width = gray.shape

    # Przechodzi przez obraz w krokach równych PATCH_SIZE
    for y in range(0, height - PATCH_SIZE + 1, PATCH_SIZE):
        for x in range(0, width - PATCH_SIZE + 1, PATCH_SIZE):
            # Wycinanie fragmentów obrazu
            patch = image[y:y + PATCH_SIZE, x:x + PATCH_SIZE]
            patch_gray = gray[y:y + PATCH_SIZE, x:x + PATCH_SIZE]
            label_patch = model[y:y + PATCH_SIZE, x:x + PATCH_SIZE]

            # Oblicza momenty dla fragmentu w skali szarości
            moments = cv2.moments(patch_gray)
            hu_moments = cv2.HuMoments(moments).flatten()

            # Oblicza średnią i odchylenie standardowe dla każdego kanału kolorów
            mean = np.mean(patch.reshape(-1, 3), axis=0)
            std = np.std(patch.reshape(-1, 3), axis=0)

            # Tworzy wektor cech, łącząc średnią, odchylenie standardowe i momenty Hu
            feature_vector = np.hstack([mean, std, hu_moments])
            features.append(feature_vector)

            # Etykieta to wartość piksela centralnego
            label = label_patch[PATCH_SIZE // 2, PATCH_SIZE // 2]
            labels.append(label)

    return np.array(features), np.array(labels)

features = []
labels = []

# Lista nazw plików obrazów treningowych
train_data = ["01", "02", "03", "04", "05", "06", "07"]

for train_image in train_data:
    print(f"Processing image: {train_image}")
    image = cv2.imread("images/" + train_image + "_h.jpg")
    image = scaleImage(image)  # Skaluje obraz do odpowiedniego rozmiaru
```

```
    # Konwersja do skali szarości
    gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
    gray = filters.unsharp_mask(gray)  # Zastosowanie maski wyostrzającej

    model = cv2.imread("images/" + train_image + "_h.tif")
    model = scaleImage(model)  # Skaluje obraz maski do odpowiedniego rozmiaru

    model = cv2.cvtColor(model, cv2.COLOR_BGR2GRAY)  # Konwersja do skali␣
 ↪szarości
    model = model > 25  # Próg binarny do stworzenia maski binarnej

    print("Extracting features and labels")
    feats, lbls = get_features_and_labels(image, gray, model)  # Ekstrakcja␣
 ↪cech i etykiet
    features.extend(feats)
    labels.extend(lbls)

features = np.array(features)
labels = np.array(labels)

print("Balancing data")
# Balansowanie danych za pomocą losowego próbkowania
sampler = RandomUnderSampler(sampling_strategy=1)
features, labels = sampler.fit_resample(features, labels)

print("Splitting data")
# Dzieli dane na zestawy treningowe i testowe w proporcji 80/20
X_train, X_test, y_train, y_test = train_test_split(features, labels,␣
 ↪test_size=0.2, random_state=42)

# Konwertuje etykiety na postać kategoryczną (one-hot encoding)
y_train = to_categorical(y_train, num_classes=2)
y_test = to_categorical(y_test, num_classes=2)

# Definicja modelu sekwencyjnego
model = Sequential([
    Dense(64, activation='relu', input_shape=(features.shape[1],)),  # Warstwa␣
 ↪wejściowa z 64 neuronami
    Dense(128, activation='relu'),  # Warstwa ukryta z 128 neuronami
    Dense(64, activation='relu'),   # Kolejna warstwa ukryta z 64 neuronami
    Dense(2, activation='softmax')  # Warstwa wyjściowa z 2 neuronami dla␣
 ↪klasyfikacji binarnej
])

# Kompilacja modelu z użyciem optymalizatora Adam, funkcji straty kategorii i␣
 ↪metryki dokładności,
```

```python
#Funkcja straty kategorii została wybrana, ponieważ mamy do czynienia z␣
↪problemem klasyfikacji binarnej i wyjście modelu jest kodowane w postaci␣
↪kategorialnej
model.compile(optimizer='adam', loss='categorical_crossentropy',␣
↪metrics=['accuracy'])

print("Training model")
# Trening modelu przez 100 epok, z rozmiarem batcha 5 i 20% danymi walidacyjnymi
model.fit(X_train, y_train, epochs=100, batch_size=5, validation_split=0.2)

print("Evaluating model")
# Ocena modelu na danych testowych
accuracy = model.evaluate(X_test, y_test)[1]
print("Accuracy:", accuracy)

model.save("newmodel.h5")  # Zapisuje wytrenowany model do pliku "newmodel.h5"
```

```
Processing image: 01
Extracting features and labels
Processing image: 02
Extracting features and labels
Processing image: 03
Extracting features and labels
Processing image: 04
Extracting features and labels
Processing image: 05
Extracting features and labels
Processing image: 06
Extracting features and labels
Processing image: 07
Extracting features and labels
Balancing data
Splitting data
Training model
Epoch 1/100
```

```
/opt/anaconda3/lib/python3.11/site-packages/keras/src/layers/core/dense.py:87:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
15852/15852            7s 445us/step
- accuracy: 0.7922 - loss: 27.8201 - val_accuracy: 0.8598 - val_loss: 0.3401
Epoch 2/100
15852/15852            7s 432us/step
- accuracy: 0.8528 - loss: 0.5048 - val_accuracy: 0.8572 - val_loss: 0.3433
Epoch 3/100
```

```
15852/15852            7s 428us/step
- accuracy: 0.8529 - loss: 0.3507 - val_accuracy: 0.8478 - val_loss: 0.3503
Epoch 4/100
15852/15852            7s 427us/step
- accuracy: 0.8585 - loss: 1102.9467 - val_accuracy: 0.8624 - val_loss: 0.3338
Epoch 5/100
15852/15852            7s 429us/step
- accuracy: 0.8599 - loss: 0.3379 - val_accuracy: 0.8529 - val_loss: 0.3513
Epoch 6/100
15852/15852            7s 436us/step
- accuracy: 0.8590 - loss: 0.3392 - val_accuracy: 0.8596 - val_loss: 0.3351
Epoch 7/100
15852/15852            7s 432us/step
- accuracy: 0.8617 - loss: 0.3396 - val_accuracy: 0.8616 - val_loss: 0.3375
Epoch 8/100
15852/15852            7s 437us/step
- accuracy: 0.8615 - loss: 0.3374 - val_accuracy: 0.8592 - val_loss: 0.3413
Epoch 9/100
15852/15852            7s 438us/step
- accuracy: 0.8581 - loss: 0.3416 - val_accuracy: 0.8623 - val_loss: 0.3296
Epoch 10/100
15852/15852            7s 443us/step
- accuracy: 0.8614 - loss: 0.3372 - val_accuracy: 0.8626 - val_loss: 0.3358
Epoch 11/100
15852/15852            7s 438us/step
- accuracy: 0.8605 - loss: 0.3351 - val_accuracy: 0.8653 - val_loss: 0.3358
Epoch 12/100
15852/15852            7s 445us/step
- accuracy: 0.8621 - loss: 0.3347 - val_accuracy: 0.8611 - val_loss: 0.3343
Epoch 13/100
15852/15852            7s 440us/step
- accuracy: 0.8631 - loss: 0.3385 - val_accuracy: 0.8653 - val_loss: 0.3269
Epoch 14/100
15852/15852            7s 442us/step
- accuracy: 0.8629 - loss: 0.3334 - val_accuracy: 0.8644 - val_loss: 0.3275
Epoch 15/100
15852/15852            7s 445us/step
- accuracy: 0.8657 - loss: 0.3276 - val_accuracy: 0.8627 - val_loss: 0.3298
Epoch 16/100
15852/15852            7s 442us/step
- accuracy: 0.8646 - loss: 0.3308 - val_accuracy: 0.8638 - val_loss: 0.3348
Epoch 17/100
15852/15852            7s 448us/step
- accuracy: 0.8668 - loss: 0.3251 - val_accuracy: 0.8663 - val_loss: 0.3266
Epoch 18/100
15852/15852            7s 443us/step
- accuracy: 0.8659 - loss: 0.3275 - val_accuracy: 0.8618 - val_loss: 0.3447
Epoch 19/100
```

```
15852/15852              7s 444us/step
- accuracy: 0.8640 - loss: 0.3290 - val_accuracy: 0.8517 - val_loss: 0.3459
Epoch 20/100
15852/15852              7s 443us/step
- accuracy: 0.8621 - loss: 0.3277 - val_accuracy: 0.8661 - val_loss: 0.3224
Epoch 21/100
15852/15852              7s 443us/step
- accuracy: 0.8640 - loss: 0.3283 - val_accuracy: 0.8645 - val_loss: 0.3247
Epoch 22/100
15852/15852              7s 446us/step
- accuracy: 0.8644 - loss: 0.3254 - val_accuracy: 0.8625 - val_loss: 0.3304
Epoch 23/100
15852/15852              7s 444us/step
- accuracy: 0.8654 - loss: 0.3270 - val_accuracy: 0.8642 - val_loss: 0.3253
Epoch 24/100
15852/15852              7s 446us/step
- accuracy: 0.8643 - loss: 0.3270 - val_accuracy: 0.8622 - val_loss: 0.3269
Epoch 25/100
15852/15852              7s 440us/step
- accuracy: 0.8662 - loss: 0.3245 - val_accuracy: 0.8660 - val_loss: 0.3227
Epoch 26/100
15852/15852              7s 445us/step
- accuracy: 0.8629 - loss: 0.3294 - val_accuracy: 0.8658 - val_loss: 0.3218
Epoch 27/100
15852/15852              7s 447us/step
- accuracy: 0.8654 - loss: 0.3264 - val_accuracy: 0.8589 - val_loss: 0.3662
Epoch 28/100
15852/15852              7s 448us/step
- accuracy: 0.8655 - loss: 0.3293 - val_accuracy: 0.8644 - val_loss: 0.3264
Epoch 29/100
15852/15852              7s 446us/step
- accuracy: 0.8666 - loss: 0.3282 - val_accuracy: 0.8609 - val_loss: 0.3378
Epoch 30/100
15852/15852              7s 445us/step
- accuracy: 0.8679 - loss: 0.3242 - val_accuracy: 0.8620 - val_loss: 0.3350
Epoch 31/100
15852/15852              7s 445us/step
- accuracy: 0.8650 - loss: 0.3270 - val_accuracy: 0.8634 - val_loss: 0.3389
Epoch 32/100
15852/15852              7s 446us/step
- accuracy: 0.8665 - loss: 0.3374 - val_accuracy: 0.8665 - val_loss: 0.3206
Epoch 33/100
15852/15852              7s 446us/step
- accuracy: 0.8684 - loss: 0.3240 - val_accuracy: 0.8667 - val_loss: 0.3200
Epoch 34/100
15852/15852              7s 445us/step
- accuracy: 0.8639 - loss: 0.3261 - val_accuracy: 0.8660 - val_loss: 0.3208
Epoch 35/100
```

```
15852/15852             7s 445us/step
- accuracy: 0.8653 - loss: 0.3366 - val_accuracy: 0.8646 - val_loss: 0.3321
Epoch 36/100
15852/15852             7s 446us/step
- accuracy: 0.8666 - loss: 0.3263 - val_accuracy: 0.8640 - val_loss: 0.3397
Epoch 37/100
15852/15852             7s 450us/step
- accuracy: 0.8673 - loss: 0.3270 - val_accuracy: 0.8672 - val_loss: 0.3231
Epoch 38/100
15852/15852             7s 446us/step
- accuracy: 0.8671 - loss: 0.3261 - val_accuracy: 0.8650 - val_loss: 0.3255
Epoch 39/100
15852/15852             7s 448us/step
- accuracy: 0.8669 - loss: 0.3261 - val_accuracy: 0.8675 - val_loss: 0.3210
Epoch 40/100
15852/15852             7s 449us/step
- accuracy: 0.8666 - loss: 0.3317 - val_accuracy: 0.8673 - val_loss: 0.3219
Epoch 41/100
15852/15852             7s 449us/step
- accuracy: 0.8684 - loss: 0.3235 - val_accuracy: 0.8675 - val_loss: 0.3223
Epoch 42/100
15852/15852             7s 448us/step
- accuracy: 0.8664 - loss: 0.3247 - val_accuracy: 0.8676 - val_loss: 0.3215
Epoch 43/100
15852/15852             7s 447us/step
- accuracy: 0.8670 - loss: 0.3236 - val_accuracy: 0.8618 - val_loss: 0.3383
Epoch 44/100
15852/15852             7s 437us/step
- accuracy: 0.8652 - loss: 0.3255 - val_accuracy: 0.8689 - val_loss: 0.3247
Epoch 45/100
15852/15852             7s 437us/step
- accuracy: 0.8675 - loss: 0.3249 - val_accuracy: 0.8677 - val_loss: 0.3193
Epoch 46/100
15852/15852             7s 437us/step
- accuracy: 0.8665 - loss: 0.3222 - val_accuracy: 0.8671 - val_loss: 0.3907
Epoch 47/100
15852/15852             7s 436us/step
- accuracy: 0.8669 - loss: 0.4207 - val_accuracy: 0.8650 - val_loss: 0.3248
Epoch 48/100
15852/15852             7s 439us/step
- accuracy: 0.8672 - loss: 0.3226 - val_accuracy: 0.8691 - val_loss: 0.3200
Epoch 49/100
15852/15852             7s 446us/step
- accuracy: 0.8685 - loss: 0.3217 - val_accuracy: 0.8695 - val_loss: 0.3216
Epoch 50/100
15852/15852             7s 445us/step
- accuracy: 0.8679 - loss: 0.3194 - val_accuracy: 0.8667 - val_loss: 0.3288
Epoch 51/100
```

```
15852/15852             7s 447us/step
- accuracy: 0.8677 - loss: 0.3239 - val_accuracy: 0.8619 - val_loss: 0.3283
Epoch 52/100
15852/15852             7s 443us/step
- accuracy: 0.8671 - loss: 0.3238 - val_accuracy: 0.8662 - val_loss: 0.3283
Epoch 53/100
15852/15852             7s 446us/step
- accuracy: 0.8661 - loss: 0.3248 - val_accuracy: 0.8690 - val_loss: 0.3286
Epoch 54/100
15852/15852             7s 443us/step
- accuracy: 0.8690 - loss: 0.3196 - val_accuracy: 0.8663 - val_loss: 0.3188
Epoch 55/100
15852/15852             7s 446us/step
- accuracy: 0.8662 - loss: 0.3244 - val_accuracy: 0.8663 - val_loss: 0.3196
Epoch 56/100
15852/15852             7s 445us/step
- accuracy: 0.8690 - loss: 0.3191 - val_accuracy: 0.8689 - val_loss: 0.3175
Epoch 57/100
15852/15852             7s 442us/step
- accuracy: 0.8658 - loss: 0.3242 - val_accuracy: 0.8684 - val_loss: 0.3249
Epoch 58/100
15852/15852             7s 446us/step
- accuracy: 0.8661 - loss: 0.3256 - val_accuracy: 0.8643 - val_loss: 0.3246
Epoch 59/100
15852/15852             7s 445us/step
- accuracy: 0.8672 - loss: 0.3246 - val_accuracy: 0.8665 - val_loss: 0.3229
Epoch 60/100
15852/15852             7s 443us/step
- accuracy: 0.8648 - loss: 0.3261 - val_accuracy: 0.8622 - val_loss: 0.3331
Epoch 61/100
15852/15852             7s 444us/step
- accuracy: 0.8688 - loss: 0.3197 - val_accuracy: 0.8669 - val_loss: 0.3195
Epoch 62/100
15852/15852             7s 445us/step
- accuracy: 0.8674 - loss: 0.3247 - val_accuracy: 0.8683 - val_loss: 0.3189
Epoch 63/100
15852/15852             7s 445us/step
- accuracy: 0.8693 - loss: 0.3205 - val_accuracy: 0.8666 - val_loss: 0.3276
Epoch 64/100
15852/15852             7s 446us/step
- accuracy: 0.8655 - loss: 0.3273 - val_accuracy: 0.8690 - val_loss: 0.3194
Epoch 65/100
15852/15852             7s 447us/step
- accuracy: 0.8652 - loss: 0.3280 - val_accuracy: 0.8704 - val_loss: 0.3151
Epoch 66/100
15852/15852             7s 445us/step
- accuracy: 0.8670 - loss: 0.3242 - val_accuracy: 0.8689 - val_loss: 0.3191
Epoch 67/100
```

```
15852/15852             7s 448us/step
- accuracy: 0.8681 - loss: 0.3213 - val_accuracy: 0.8667 - val_loss: 0.3239
Epoch 68/100
15852/15852             7s 445us/step
- accuracy: 0.8671 - loss: 0.3213 - val_accuracy: 0.8654 - val_loss: 0.3219
Epoch 69/100
15852/15852             7s 444us/step
- accuracy: 0.8681 - loss: 0.3203 - val_accuracy: 0.8644 - val_loss: 0.3297
Epoch 70/100
15852/15852             7s 444us/step
- accuracy: 0.8699 - loss: 0.3191 - val_accuracy: 0.8686 - val_loss: 0.3207
Epoch 71/100
15852/15852             7s 443us/step
- accuracy: 0.8674 - loss: 0.3213 - val_accuracy: 0.8656 - val_loss: 0.3231
Epoch 72/100
15852/15852             7s 444us/step
- accuracy: 0.8662 - loss: 0.3265 - val_accuracy: 0.8677 - val_loss: 0.3239
Epoch 73/100
15852/15852             7s 446us/step
- accuracy: 0.8687 - loss: 0.3237 - val_accuracy: 0.8657 - val_loss: 0.3212
Epoch 74/100
15852/15852             7s 448us/step
- accuracy: 0.8671 - loss: 0.3239 - val_accuracy: 0.8644 - val_loss: 0.3231
Epoch 75/100
15852/15852             7s 443us/step
- accuracy: 0.8675 - loss: 0.3243 - val_accuracy: 0.8631 - val_loss: 0.3291
Epoch 76/100
15852/15852             7s 445us/step
- accuracy: 0.8679 - loss: 0.3225 - val_accuracy: 0.8657 - val_loss: 0.3242
Epoch 77/100
15852/15852             7s 444us/step
- accuracy: 0.8674 - loss: 0.3230 - val_accuracy: 0.8667 - val_loss: 0.3203
Epoch 78/100
15852/15852             7s 446us/step
- accuracy: 0.8672 - loss: 0.3249 - val_accuracy: 0.8677 - val_loss: 0.3233
Epoch 79/100
15852/15852             7s 444us/step
- accuracy: 0.8674 - loss: 0.3241 - val_accuracy: 0.8622 - val_loss: 0.3293
Epoch 80/100
15852/15852             7s 445us/step
- accuracy: 0.8677 - loss: 0.3239 - val_accuracy: 0.8683 - val_loss: 0.3263
Epoch 81/100
15852/15852             7s 443us/step
- accuracy: 0.8700 - loss: 0.3168 - val_accuracy: 0.8648 - val_loss: 0.3316
Epoch 82/100
15852/15852             7s 443us/step
- accuracy: 0.8675 - loss: 0.3244 - val_accuracy: 0.8664 - val_loss: 0.3245
Epoch 83/100
```

```
15852/15852              7s 452us/step
- accuracy: 0.8659 - loss: 0.3245 - val_accuracy: 0.8663 - val_loss: 0.3194
Epoch 84/100
15852/15852              7s 444us/step
- accuracy: 0.8665 - loss: 0.3234 - val_accuracy: 0.8640 - val_loss: 0.3283
Epoch 85/100
15852/15852              7s 446us/step
- accuracy: 0.8670 - loss: 0.3249 - val_accuracy: 0.8687 - val_loss: 0.3227
Epoch 86/100
15852/15852              7s 446us/step
- accuracy: 0.8651 - loss: 0.3261 - val_accuracy: 0.8679 - val_loss: 0.3188
Epoch 87/100
15852/15852              7s 447us/step
- accuracy: 0.8665 - loss: 0.3259 - val_accuracy: 0.8641 - val_loss: 0.3326
Epoch 88/100
15852/15852              7s 444us/step
- accuracy: 0.8666 - loss: 0.3296 - val_accuracy: 0.8691 - val_loss: 0.3205
Epoch 89/100
15852/15852              7s 445us/step
- accuracy: 0.8694 - loss: 0.3205 - val_accuracy: 0.8637 - val_loss: 0.3292
Epoch 90/100
15852/15852              7s 446us/step
- accuracy: 0.8657 - loss: 0.3422 - val_accuracy: 0.8672 - val_loss: 0.3339
Epoch 91/100
15852/15852              7s 445us/step
- accuracy: 0.8673 - loss: 0.3296 - val_accuracy: 0.8653 - val_loss: 0.3309
Epoch 92/100
15852/15852              7s 448us/step
- accuracy: 0.8671 - loss: 0.3244 - val_accuracy: 0.8658 - val_loss: 0.3220
Epoch 93/100
15852/15852              7s 447us/step
- accuracy: 0.8670 - loss: 0.3242 - val_accuracy: 0.8683 - val_loss: 0.3275
Epoch 94/100
15852/15852              7s 448us/step
- accuracy: 0.8689 - loss: 0.3221 - val_accuracy: 0.8693 - val_loss: 0.3197
Epoch 95/100
15852/15852              7s 445us/step
- accuracy: 0.8699 - loss: 0.3220 - val_accuracy: 0.8686 - val_loss: 0.3174
Epoch 96/100
15852/15852              7s 447us/step
- accuracy: 0.8639 - loss: 0.3284 - val_accuracy: 0.8690 - val_loss: 0.3178
Epoch 97/100
15852/15852              7s 447us/step
- accuracy: 0.8649 - loss: 0.3260 - val_accuracy: 0.8672 - val_loss: 0.3281
Epoch 98/100
15852/15852              7s 446us/step
- accuracy: 0.8653 - loss: 0.3310 - val_accuracy: 0.8691 - val_loss: 0.3224
Epoch 99/100
```

```
15852/15852             7s 456us/step
- accuracy: 0.8682 - loss: 0.3228 - val_accuracy: 0.8672 - val_loss: 0.3219
Epoch 100/100
15852/15852             7s 456us/step
- accuracy: 0.8674 - loss: 0.3240 - val_accuracy: 0.8660 - val_loss: 0.3258
Evaluating model
774/774             0s 281us/step -
accuracy: 0.8619 - loss: 0.3308
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
`keras.saving.save_model(model)`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')` or `keras.saving.save_model(model,
'my_model.keras')`.
```

```
Accuracy: 0.8618378639221191
```

[36]:

```
def get_predicted_image(gray, predictions, patch_size):
    predicted_image = np.zeros_like(gray)
    height, width = gray.shape
    index = 0

    for y in range(0, height - patch_size + 1, patch_size):
        for x in range(0, width - patch_size + 1, patch_size):
            predicted_image[y:y + patch_size, x:x + patch_size] =␣
 ↪predictions[index]
            index += 1

    return predicted_image
```

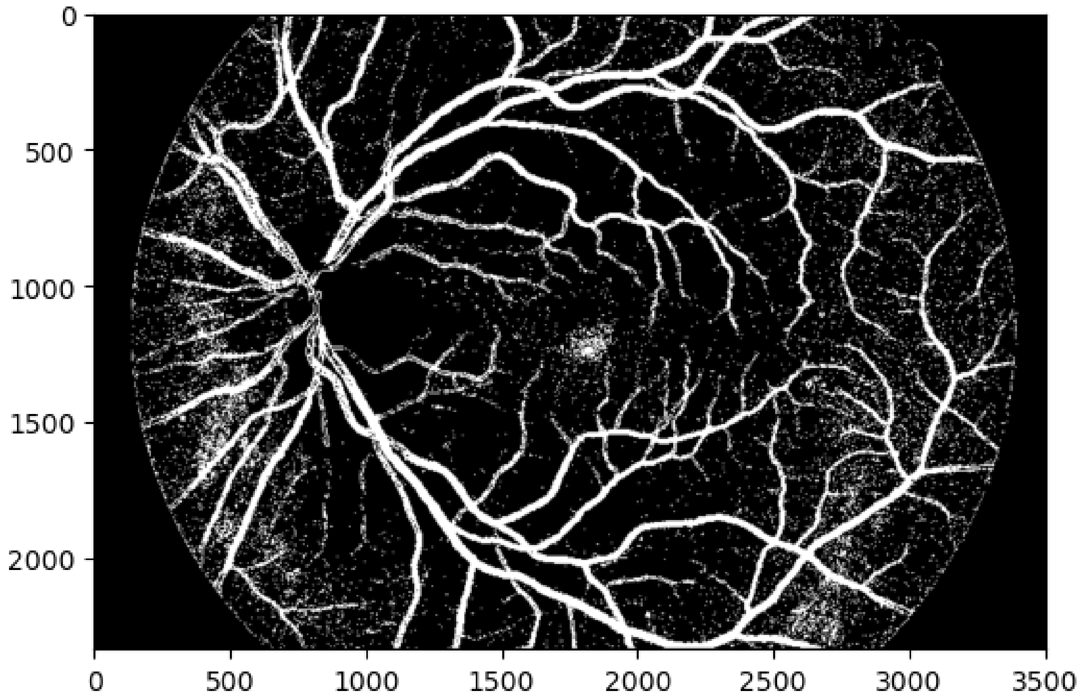
[45]:

```
import cv2
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.models import load_model
from skimage import filters
from tensorflow.keras.utils import to_categorical

model = load_model("newmodel.h5")

test_data = ["08","09","10", "11", "12"]

for test_image in test_data:
    print(f"Processing image: {test_image}")
    image = cv2.imread("images/" + test_image + "_h.jpg")


    gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
    gray = filters.unsharp_mask(gray)
```

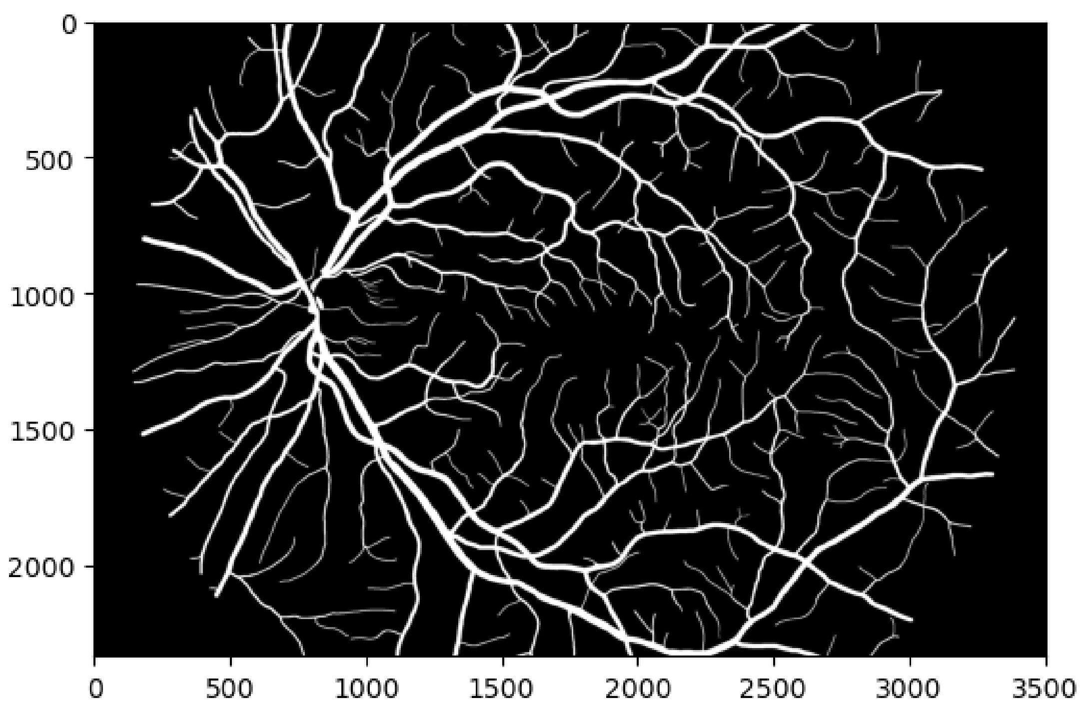
```
ground_truth = cv2.imread("images/" + test_image + "_h.tif")
ground_truth = cv2.cvtColor(ground_truth, cv2.COLOR_BGR2GRAY)
ground_truth = ground_truth > 25

print("Extracting features for prediction")
features, _ = get_features_and_labels(image, gray, ground_truth)

print("Making predictions")
predictions = model.predict(features)
predictions = np.argmax(predictions, axis=1)

predicted_image = get_predicted_image(gray, predictions.reshape(-1, 1),␣
↪PATCH_SIZE)

print("Predicted image:")
plt.imshow(predicted_image, cmap='gray')
plt.show()

print("Ground truth image:")
plt.imshow(ground_truth, cmap='gray')
plt.show()

print("Statistics:")
show_statistics(predicted_image, ground_truth)
```

```
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be
built. `model.compile_metrics` will be empty until you train or evaluate the
model.
```

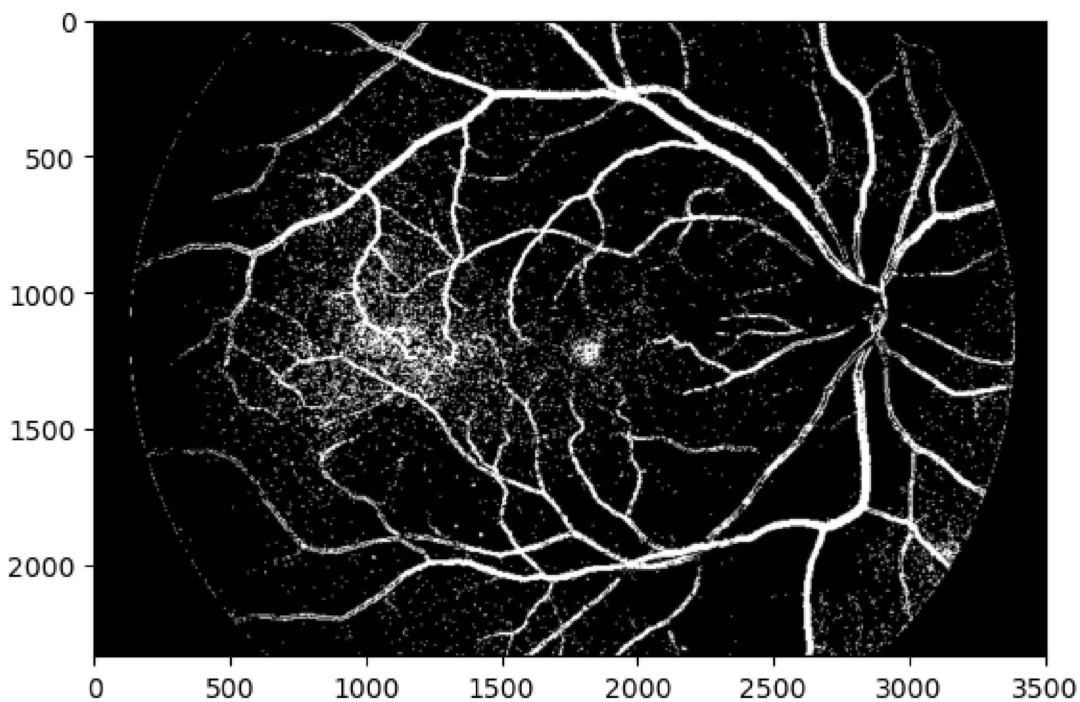
```
Processing image: 08
Extracting features for prediction
Making predictions
10216/10216            3s 251us/step
Predicted image:
```



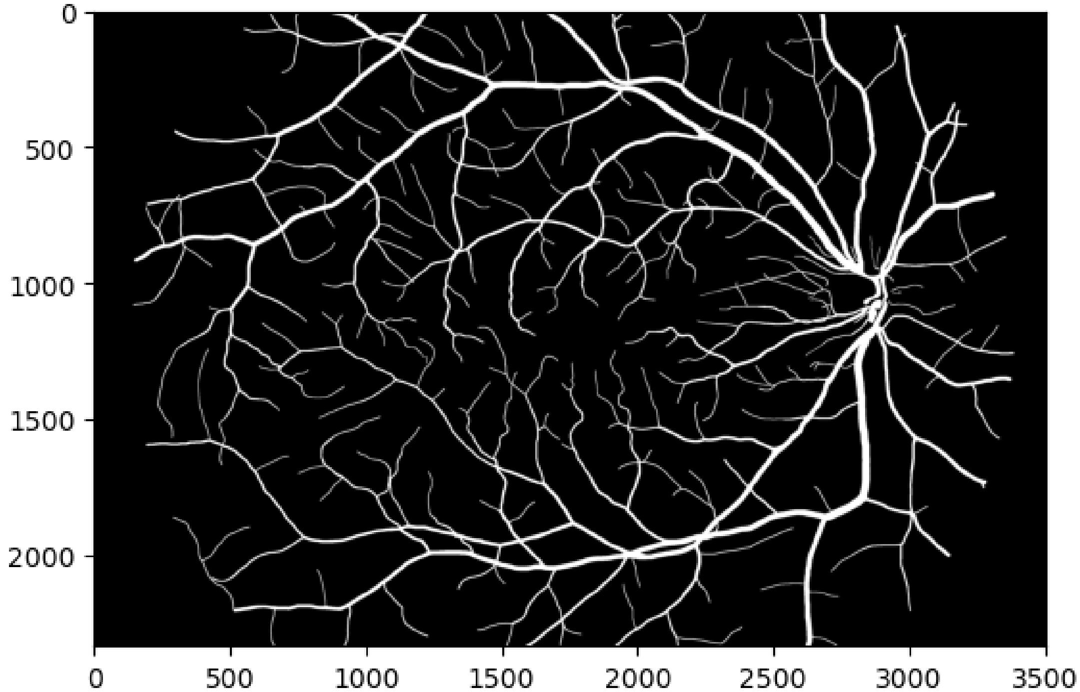
Ground truth image:



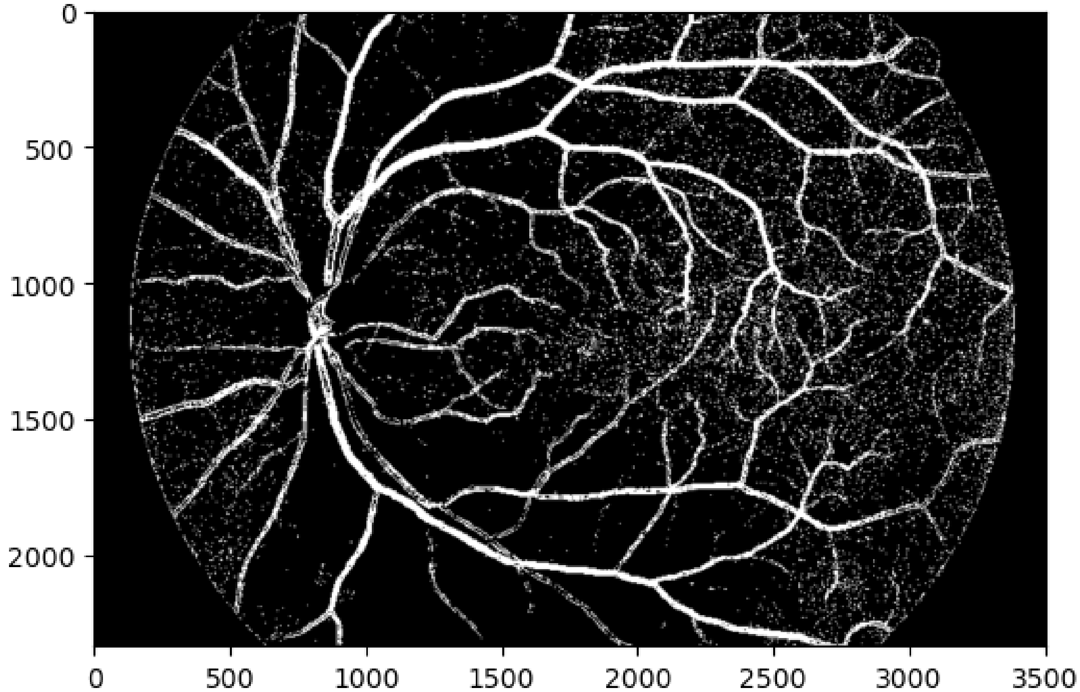
```
Statistics:
            Actually - Positive  Actually - Negative      Sum
My Results
Positive                646359               621641  1268000
Negative                175268              6742076  6917344
Sum                     821627              7363717  8185344

Accuracy:  0.9026
Sensitivity:  0.7867
Specificity:  0.9156
Precision:  0.5097
Mean Sensitivity-Specificity:  0.8512
Processing image: 09
Extracting features for prediction
Making predictions
10216/10216            3s 261us/step
Predicted image:
```



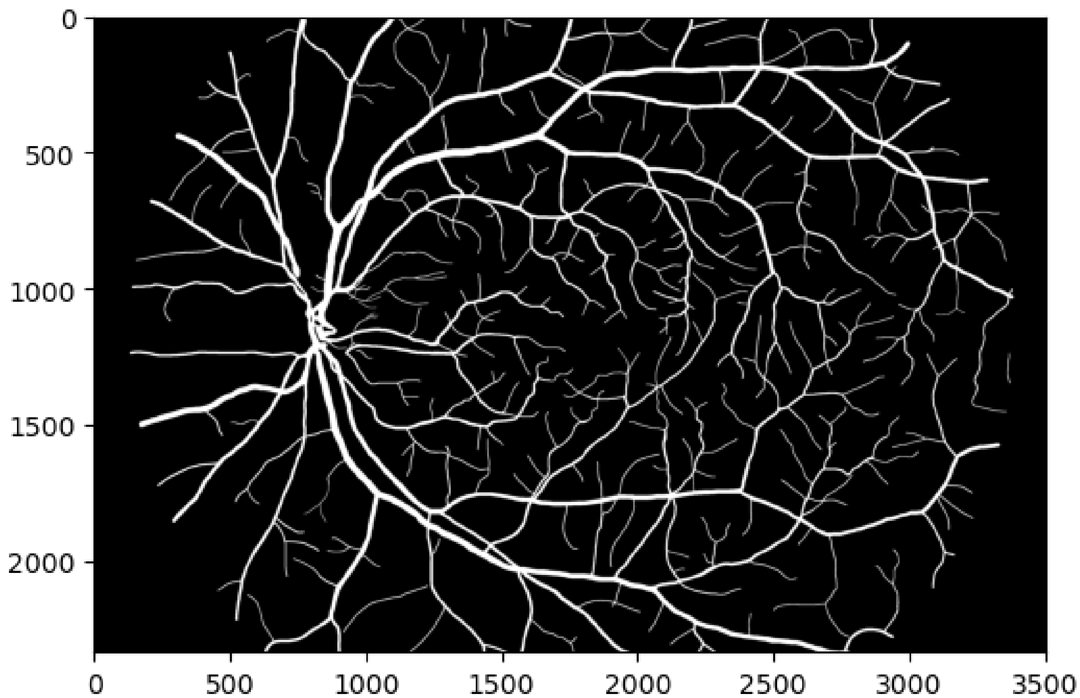

```
Ground truth image:
```



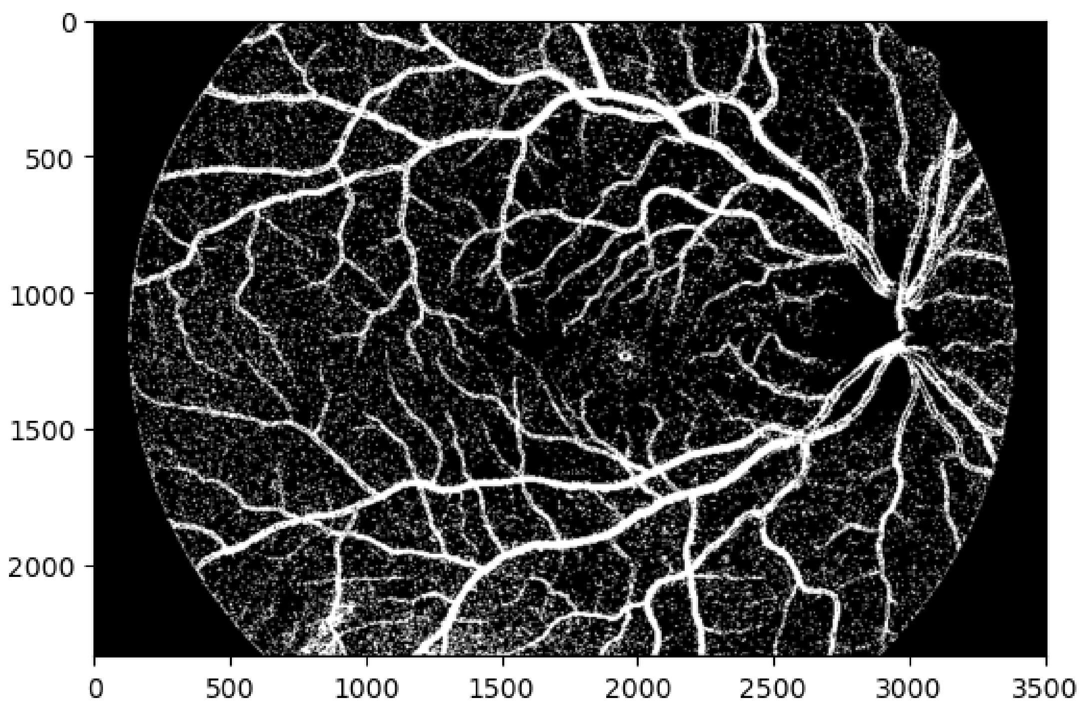

```
Statistics:
            Actually - Positive  Actually - Negative      Sum
My Results
Positive                 405824               402426   808250
Negative                 230644              7146450  7377094
Sum                      636468              7548876  8185344

Accuracy:  0.9227
Sensitivity:  0.6376
Specificity:  0.9467
Precision:  0.5021
Mean Sensitivity-Specificity:  0.7921
Processing image: 10
Extracting features for prediction
Making predictions
10216/10216            3s 255us/step
Predicted image:
```



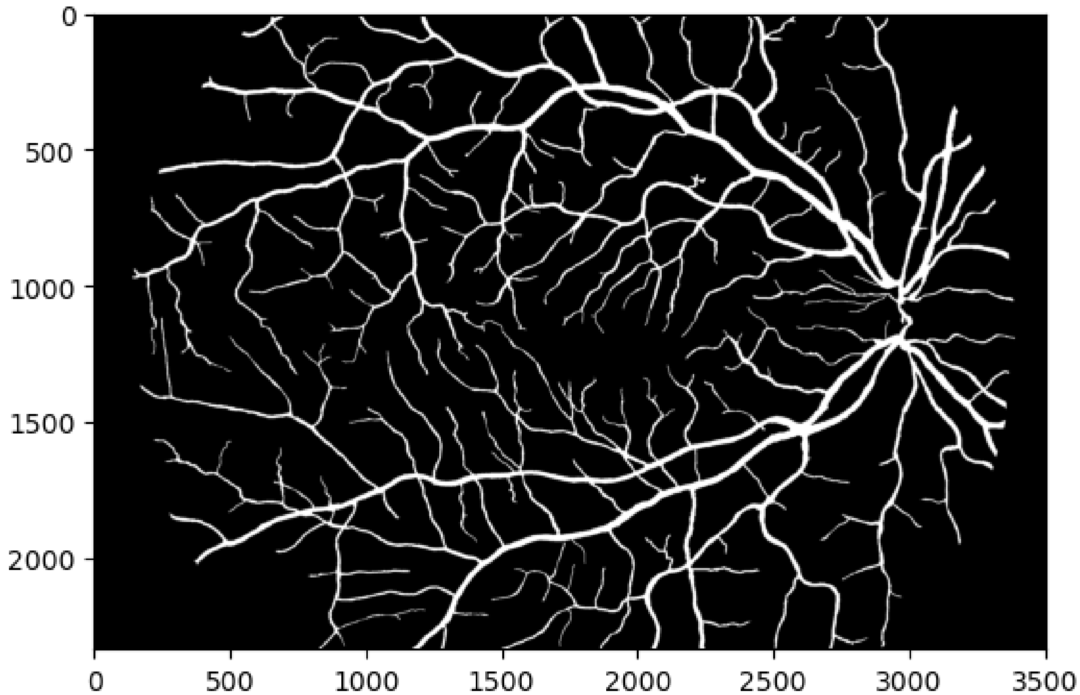
Ground truth image:



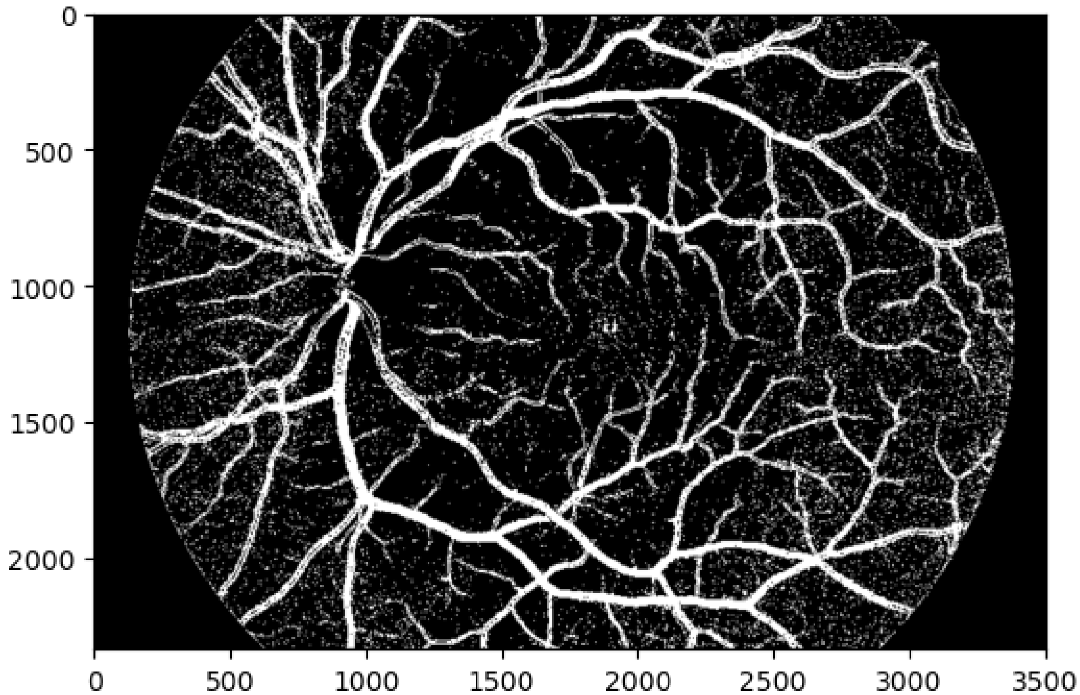
```
Statistics:
            Actually - Positive  Actually - Negative      Sum
My Results
Positive                 461246               504379   965625
Negative                 244192              6975527  7219719
Sum                      705438              7479906  8185344

Accuracy:  0.9085
Sensitivity:  0.6538
Specificity:  0.9326
Precision:  0.4777
Mean Sensitivity-Specificity:  0.7932
Processing image: 11
Extracting features for prediction
Making predictions
10216/10216              3s 252us/step
Predicted image:
```



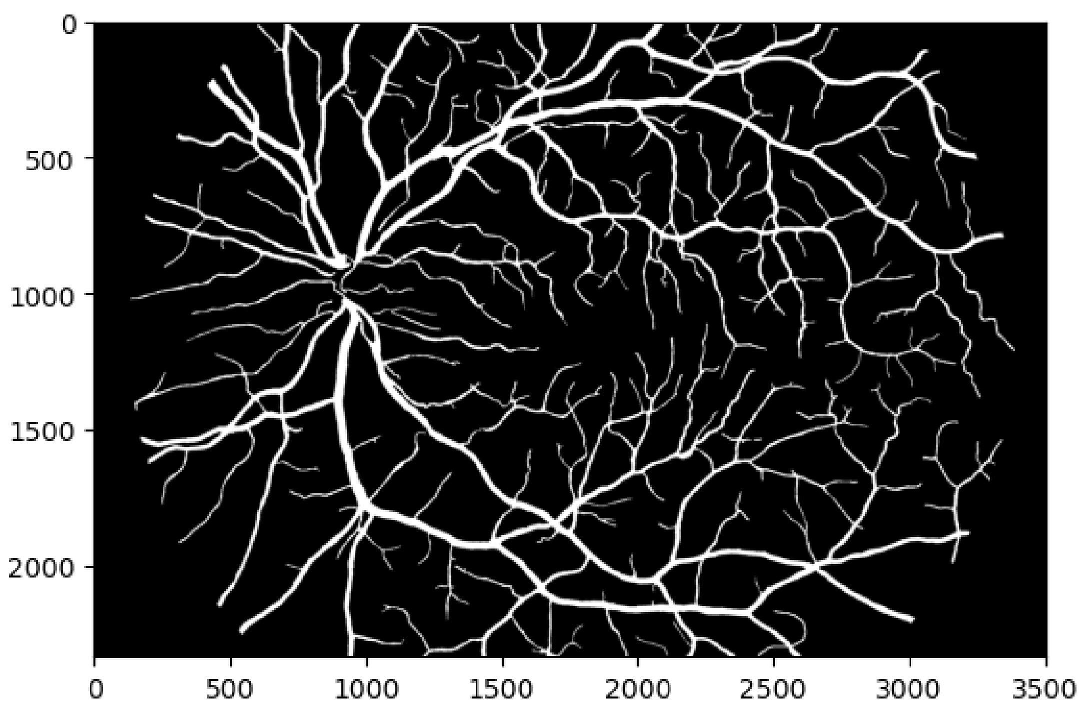

```
Ground truth image:
```




```
Statistics:
            Actually - Positive  Actually - Negative      Sum
My Results
Positive                 594674               880776  1475450
Negative                 170509              6539385  6709894
Sum                      765183              7420161  8185344

Accuracy:  0.8716
Sensitivity:  0.7772
Specificity:  0.8813
Precision:  0.403
Mean Sensitivity-Specificity:  0.8292
Processing image: 12
Extracting features for prediction
Making predictions
10216/10216            3s 260us/step
Predicted image:
```



Ground truth image:



```
Statistics:
            Actually - Positive  Actually - Negative      Sum
My Results
Positive                 660176               683824  1344000
Negative                 198649              6642695  6841344
Sum                      858825              7326519  8185344

Accuracy:  0.8922
Sensitivity:  0.7687
Specificity:  0.9067
Precision:  0.4912
Mean Sensitivity-Specificity:  0.8377
```

6 Porównanie wyników

6.1 zdjęcie nr 8

6.1.1 Frangi:

Accuracy: 0.9165

Sensitivity: 0.7071

Specificity: 0.9399

Precision: 0.5674

Mean Sensitivity-Specificity: 0.8235

6.1.2 Las decyzyjny:

Accuracy: 0.9278

Sensitivity: 0.5648

Specificity: 0.9683

Precision: 0.6655

Mean Sensitivity-Specificity: 0.7666

6.1.3 Sieć neuronowa:

Accuracy: 0.9026

Sensitivity: 0.7867

Specificity: 0.9156

Precision: 0.5097

Mean Sensitivity-Specificity: 0.8512

6.2 zdjęcie nr 9

6.2.1 Frangi:

Accuracy: 0.9505

Sensitivity: 0.4733

Specificity: 0.9908

Precision: 0.8123

Mean Sensitivity-Specificity: 0.732

6.2.2 Las decyzyjny:

Accuracy: 0.9343

Sensitivity: 0.4383

Specificity: 0.9761

Precision: 0.6074

Mean Sensitivity-Specificity: 0.7072

6.2.3 Sieć neuronowa:

Accuracy: 0.9227

Sensitivity: 0.6376

Specificity: 0.9467

Precision: 0.5021

Mean Sensitivity-Specificity: 0.7921

6.3 zdjęcie nr 10

6.3.1 Frangi:

Accuracy: 0.8878

Sensitivity: 0.7926

Specificity: 0.8976

Precision: 0.4439

Mean Sensitivity-Specificity: 0.8451

6.3.2 Las decyzyjny:

Accuracy: 0.8811

Sensitivity: 0.7517

Specificity: 0.8945

Precision: 0.4235

Mean Sensitivity-Specificity: 0.8231

6.3.3 Sieć neuronowa:

Accuracy: 0.9085

Sensitivity: 0.6538

Specificity: 0.9326

Precision: 0.4777

Mean Sensitivity-Specificity: 0.7932

6.4 zdjęcie nr 11

6.4.1 Frangi:

Accuracy: 0.9245

Sensitivity: 0.6645

Specificity: 0.949

Precision: 0.5514

Mean Sensitivity-Specificity: 0.8068

6.4.2 Las decyzyjny:

Accuracy: 0.8811

Sensitivity: 0.7517

Specificity: 0.8945

Precision: 0.4235

Mean Sensitivity-Specificity: 0.8231

6.4.3 Sieć neuronowa:

Accuracy: 0.8716

Sensitivity: 0.7772

Specificity: 0.8813

Precision: 0.403

Mean Sensitivity-Specificity: 0.8292

6.5 zdjęcie nr 12

6.5.1 Frangi

Accuracy: 0.8793

Sensitivity: 0.8133

Specificity: 0.8871

Precision: 0.4579

Mean Sensitivity-Specificity: 0.8502

6.5.2 Las decyzyjny:

Accuracy: 0.8907

Sensitivity: 0.7482

Specificity: 0.9074

Precision: 0.4864

Mean Sensitivity-Specificity: 0.8278

6.5.3 Sieć neuronowa:

Accuracy: 0.8922

Sensitivity: 0.7687

Specificity: 0.9067

Precision: 0.4912

Mean Sensitivity-Specificity: 0.8377

6.6 Podsumowanie:

Metoda z wykorzystaniem filtru Frangi - wykazuje dobrą równowagę między czułością i swoistością, ale jest mniej precyzyjna niż sieć neuronowa, co sugeruje większą liczbę fałszywych pozytywów. Wyniki wskazują na wysoką dokładność, co oznacza, że metoda ta jest efektywna w klasyfikacji obrazów i minimalizacji błędów ogólnych. Wymaga ręcznego dostosowania.

Las Decyzyjny - ogólnie charakteryzuje się wyższą dokładnością i swoistością niż sieć neuronowa, ale niższą czułością. Oznacza to, że lepiej identyfikuje negatywne przypadki, ale ma trudności z identyfikacją pozytywnych przypadków.

Sieć Neuronowa - ogólnie charakteryzuje się wyższą czułością i średnią wartością czułości i swoistości, co wskazuje na lepszą równowagę między wykrywaniem pozytywnych i negatywnych przypadków. Dokładność i swoistość są zazwyczaj nieco niższe niż w przypadku lasu decyzyjnego, ale czułość jest wyraźnie wyższa. Wizualnie lepiej przypomina maskę ekspercką niż las decyzyjny.

[ ]:

```

```