Final Project 2 - Diabetic Retinopathy Classification

April 28, 2025

1 1. Importing Libraries

[98]:
```
#Basic libraries
import os
import numpy as np
import tensorflow as tf
import pandas as pd

#Visualization
import matplotlib.pyplot as plt
import seaborn as sns

#Tensor Flow Packages
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras import layers, models

#DL/CNN Model
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.applications import VGG16
from tensorflow.keras.applications import InceptionV3

#ML Classification Model
from sklearn.ensemble import RandomForestClassifier

#Metrics
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score, classification_report
```

2 2. Loading and Preprocessing Images

[100]:
```
# Set up directories for images
image_dir = 'Desktop/My Courses/Spring 2025/Machine Learning/Final Project/
 ↪retinopathy_3Classes'  # path to images
labels = []  # List to hold labels (0, 1, 2 for healthy, moderate DR, severe DR)
image_paths = []  # List to hold image paths
```

```
# Collect image paths and corresponding labels
for filename in os.listdir(image_dir):
    if filename.endswith('.jpeg'):
        id_side_class = filename.split('_')  # ID_Side_Class.jpeg
        label = int(id_side_class[-1].split('.')[0])  # Last part is the class
        image_paths.append(os.path.join(image_dir, filename))
        labels.append(label)

# Convert labels to numpy array
labels = np.array(labels)

# Load and preprocess images
images = []
for path in image_paths:
    img = tf.keras.preprocessing.image.load_img(path, target_size=(224, 224))
    img_array = tf.keras.preprocessing.image.img_to_array(img) / 255.0  #␣
 ↪Normalize
    images.append(img_array)

images = np.array(images)

# Split into training and testing sets (80% / 20%)
X_train, X_test, y_train, y_test = train_test_split(images, labels, test_size=0.
 ↪2, stratify=labels, random_state=42)
```

3 3. Build Models

3.1 i. ResNet-50 Model

[103]:
```
# Load ResNet50 model
base_model_resnet = ResNet50(weights='imagenet', include_top=False,␣
↪input_shape=(224, 224, 3))

# Freeze the base model layers
base_model_resnet.trainable = False

# Create the model
model_resnet = models.Sequential([
    base_model_resnet,  # Pre-trained ResNet50 base
    layers.GlobalAveragePooling2D(),  # Global average pooling to reduce the␣
↪output to a vector
    layers.Dense(3, activation='softmax')  # Output layer with 3 classes
])

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

3.2 ii. VGG-16 Model

[105]:
```
# Load VGG-16 model
base_model_vgg = VGG16(weights='imagenet', include_top=False, input_shape=(224,␣
↪224, 3))

# Freeze the base model layers
base_model_vgg.trainable = False

# Create the model
model_vgg = models.Sequential([
    base_model_vgg,  # Pre-trained VGG16 base
    layers.GlobalAveragePooling2D(),  # Global average pooling to reduce the␣
↪output to a vector
    layers.Dense(3, activation='softmax')  # Output layer with 3 classes
])

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

3.3 iii. InceptionV3 Model

[107]:
```
# Load InceptionV3 model
base_model_inception = InceptionV3(weights='imagenet', include_top=False,␣
↪input_shape=(224, 224, 3))

# Freeze the base model layers
```

```
base_model_inception.trainable = False

# Create the model
model_inception = models.Sequential([
    base_model_inception,  # Pre-trained InceptionV3 base
    layers.GlobalAveragePooling2D(),  # Global average pooling to reduce the␣
 ↪output to a vector
    layers.Dense(3, activation='softmax')  # Output layer with 3 classes
])

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

4 4. ML Classification Model

[109]:
```
# Flatten the images so they can be used in traditional ML models (Random␣
 ↪Forest)
X_train_flattened = X_train.reshape(X_train.shape[0], -1)  # Flatten the images␣
 ↪into 1D vectors
X_test_flattened = X_test.reshape(X_test.shape[0], -1)

# Train a Random Forest model
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train_flattened, y_train)

# Predictions on the test set
rf_pred = rf_model.predict(X_test_flattened)

# Calculate Accuracy and F1-score
rf_accuracy = accuracy_score(y_test, rf_pred)
rf_f1 = f1_score(y_test, rf_pred, average='weighted')

print(f"Random Forest Accuracy: {rf_accuracy:.4f}")
print(f"Random Forest F1 Score: {rf_f1:.4f}")
```

```
Random Forest Accuracy: 0.5837
Random Forest F1 Score: 0.4876
```

5 5. Training Models

[111]:
```
# Train the ResNet-50 model
history_resnet = model_resnet.fit(X_train, y_train, validation_data=(X_test,␣
 ↪y_test), epochs=10, batch_size=32)

# Train the VGG-16 model
```

```
history_vgg = model_vgg.fit(X_train, y_train, validation_data=(X_test, y_test),␣
 ↪epochs=10, batch_size=32)

# Train the InceptionV3 model
history_inception = model_inception.fit(X_train, y_train,␣
 ↪validation_data=(X_test, y_test), epochs=10, batch_size=32)
```

```
Epoch 1/10
53/53             50s 900ms/step -
accuracy: 0.5361 - loss: 0.9871 - val_accuracy: 0.5837 - val_loss: 0.9479
Epoch 2/10
53/53             44s 836ms/step -
accuracy: 0.5895 - loss: 0.9496 - val_accuracy: 0.5837 - val_loss: 0.9529
Epoch 3/10
53/53             44s 839ms/step -
accuracy: 0.5972 - loss: 0.9525 - val_accuracy: 0.5837 - val_loss: 0.9503
Epoch 4/10
53/53             44s 832ms/step -
accuracy: 0.5843 - loss: 0.9612 - val_accuracy: 0.5837 - val_loss: 0.9480
Epoch 5/10
53/53             55s 1s/step -
accuracy: 0.5806 - loss: 0.9669 - val_accuracy: 0.5837 - val_loss: 0.9457
Epoch 6/10
53/53             44s 840ms/step -
accuracy: 0.5808 - loss: 0.9619 - val_accuracy: 0.5837 - val_loss: 0.9513
Epoch 7/10
53/53             45s 860ms/step -
accuracy: 0.5896 - loss: 0.9510 - val_accuracy: 0.5837 - val_loss: 0.9582
Epoch 8/10
53/53             45s 853ms/step -
accuracy: 0.5601 - loss: 0.9616 - val_accuracy: 0.5837 - val_loss: 0.9459
Epoch 9/10
53/53             49s 921ms/step -
accuracy: 0.6046 - loss: 0.9281 - val_accuracy: 0.5837 - val_loss: 0.9472
Epoch 10/10
53/53             47s 888ms/step -
accuracy: 0.5822 - loss: 0.9601 - val_accuracy: 0.5837 - val_loss: 0.9496
Epoch 1/10
53/53             161s 3s/step -
accuracy: 0.5941 - loss: 0.9398 - val_accuracy: 0.5837 - val_loss: 0.9419
Epoch 2/10
53/53             160s 3s/step -
accuracy: 0.5990 - loss: 0.9220 - val_accuracy: 0.5837 - val_loss: 0.9214
Epoch 3/10
53/53             161s 3s/step -
accuracy: 0.5749 - loss: 0.9310 - val_accuracy: 0.5766 - val_loss: 0.9261
Epoch 4/10
53/53             154s 3s/step -
```

```
accuracy: 0.5854 - loss: 0.9111 - val_accuracy: 0.5837 - val_loss: 0.9077
Epoch 5/10
53/53            157s 3s/step -
accuracy: 0.5852 - loss: 0.9153 - val_accuracy: 0.5813 - val_loss: 0.9144
Epoch 6/10
53/53            153s 3s/step -
accuracy: 0.5730 - loss: 0.9146 - val_accuracy: 0.5837 - val_loss: 0.8992
Epoch 7/10
53/53            154s 3s/step -
accuracy: 0.5847 - loss: 0.8910 - val_accuracy: 0.5837 - val_loss: 0.8967
Epoch 8/10
53/53            163s 3s/step -
accuracy: 0.5856 - loss: 0.8977 - val_accuracy: 0.5837 - val_loss: 0.8938
Epoch 9/10
53/53            156s 3s/step -
accuracy: 0.5856 - loss: 0.8892 - val_accuracy: 0.5837 - val_loss: 0.8916
Epoch 10/10
53/53            163s 3s/step -
accuracy: 0.5854 - loss: 0.8987 - val_accuracy: 0.5861 - val_loss: 0.8906
Epoch 1/10
53/53            37s 655ms/step -
accuracy: 0.5226 - loss: 1.0444 - val_accuracy: 0.5933 - val_loss: 0.8864
Epoch 2/10
53/53            34s 639ms/step -
accuracy: 0.6023 - loss: 0.8548 - val_accuracy: 0.6268 - val_loss: 0.9165
Epoch 3/10
53/53            36s 675ms/step -
accuracy: 0.6290 - loss: 0.8201 - val_accuracy: 0.6268 - val_loss: 0.8429
Epoch 4/10
53/53            34s 634ms/step -
accuracy: 0.6831 - loss: 0.7238 - val_accuracy: 0.6364 - val_loss: 0.8334
Epoch 5/10
53/53            33s 627ms/step -
accuracy: 0.6982 - loss: 0.7001 - val_accuracy: 0.5861 - val_loss: 0.8628
Epoch 6/10
53/53            33s 619ms/step -
accuracy: 0.7064 - loss: 0.6859 - val_accuracy: 0.5789 - val_loss: 0.8776
Epoch 7/10
53/53            33s 629ms/step -
accuracy: 0.7171 - loss: 0.6681 - val_accuracy: 0.6077 - val_loss: 0.8487
Epoch 8/10
53/53            36s 677ms/step -
accuracy: 0.6907 - loss: 0.6990 - val_accuracy: 0.5933 - val_loss: 0.8604
Epoch 9/10
53/53            34s 639ms/step -
accuracy: 0.7062 - loss: 0.6734 - val_accuracy: 0.6483 - val_loss: 0.8220
Epoch 10/10
53/53            32s 610ms/step -
```

```
accuracy: 0.7302 - loss: 0.6337 - val_accuracy: 0.6459 - val_loss: 0.8146
```

6 6. Evaluation and Metrics

[113]:
```
# Get Accuracy and F1-Score for each model
resnet_acc = history_resnet.history['val_accuracy'][-1]
vgg_acc = history_vgg.history['val_accuracy'][-1]
inception_acc = history_inception.history['val_accuracy'][-1]

# Random Forest metrics computed above
rf_acc = rf_accuracy
rf_f1 = rf_f1

# Create a summary table with F1-scores computed
results = {
    'Model': ['ResNet-50', 'VGG-16', 'InceptionV3', 'Random Forest'],
    'Accuracy': [resnet_acc, vgg_acc, inception_acc, rf_acc],
    'F1 Score': [
        f1_score(y_test, model_resnet.predict(X_test).argmax(axis=1),␣
 ↪average='weighted'),
        f1_score(y_test, model_vgg.predict(X_test).argmax(axis=1),␣
 ↪average='weighted'),
        f1_score(y_test, model_inception.predict(X_test).argmax(axis=1),␣
 ↪average='weighted'),
        rf_f1
    ]
}
# Convert to DataFrame for easy viewing
results_df = pd.DataFrame(results)
print(results_df)
```

```
14/14            11s 730ms/step
14/14            32s 2s/step
14/14            10s 639ms/step
           Model  Accuracy  F1 Score
0      ResNet-50  0.583732  0.430304
1         VGG-16  0.586124  0.436243
2    InceptionV3  0.645933  0.613259
3  Random Forest  0.583732  0.487595
```

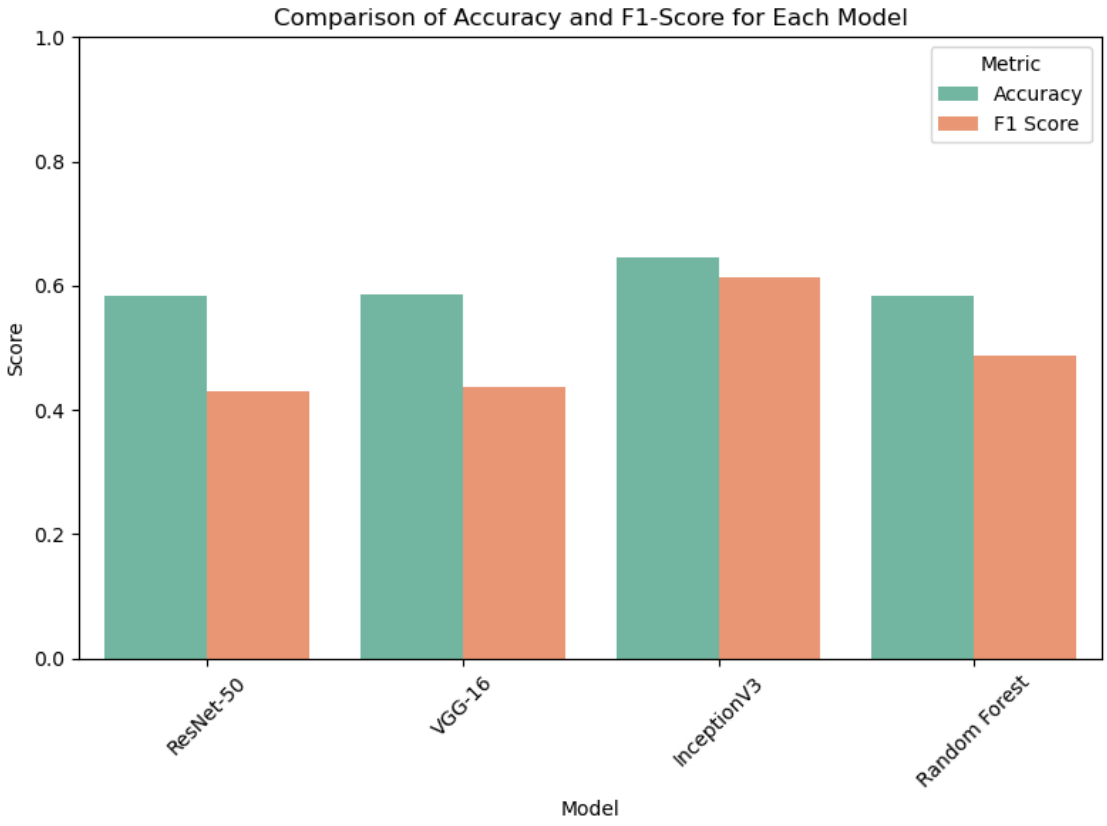
7 7. Visualizing Scores

[115]:
```
# Reshape the DataFrame for easier plotting
results_df_melted = results_df.melt(id_vars="Model", value_vars=["Accuracy",␣
 ↪"F1 Score"],
                                    var_name="Metric", value_name="Score")
```

```
# Create the combined bar plot
plt.figure(figsize=(8, 6))
sns.barplot(x="Model", y="Score", hue="Metric", data=results_df_melted,␣
 ↪palette="Set2")

# Titles and labels
plt.title('Comparison of Accuracy and F1-Score for Each Model')
plt.xticks(rotation=45)
plt.ylim(0, 1)
plt.ylabel('Score')

# Show plot
plt.tight_layout()
plt.show()
```



8 8. Classification Reports for each Model

[129]:
```
# Classification Reports for each model
print("Classification Report for ResNet-50:") #ResNet-50
print(classification_report(y_test, model_resnet.predict(X_test).
 ↪argmax(axis=1), zero_division=0))

print("Classification Report for VGG-16:") #VGG-16
print(classification_report(y_test, model_vgg.predict(X_test).argmax(axis=1),␣
 ↪zero_division=0))

print("Classification Report for InceptionV3:") #InceptionV3
print(classification_report(y_test, model_inception.predict(X_test).
 ↪argmax(axis=1), zero_division=0))

print("Classification Report for Random Forest:") #Random Forest
print(classification_report(y_test, rf_pred, zero_division=0))
```

```
Classification Report for ResNet-50:
14/14             9s 630ms/step
              precision    recall  f1-score   support

           0       0.58      1.00      0.74       244
           1       0.00      0.00      0.00       112
           2       0.00      0.00      0.00        62

    accuracy                           0.58       418
   macro avg       0.19      0.33      0.25       418
weighted avg       0.34      0.58      0.43       418

Classification Report for VGG-16:
14/14             33s 2s/step
              precision    recall  f1-score   support

           0       0.59      1.00      0.74       244
           1       0.00      0.00      0.00       112
           2       0.50      0.02      0.03        62

    accuracy                           0.59       418
   macro avg       0.36      0.34      0.26       418
weighted avg       0.42      0.59      0.44       418

Classification Report for InceptionV3:
14/14             7s 466ms/step
              precision    recall  f1-score   support

           0       0.70      0.86      0.77       244
```

```
              1       0.44      0.21      0.29       112
              2       0.57      0.60      0.58        62

       accuracy                           0.65       418
      macro avg       0.57      0.56      0.55       418
   weighted avg       0.61      0.65      0.61       418

   Classification Report for Random Forest:
                 precision    recall  f1-score   support

              0       0.61      0.94      0.74       244
              1       0.33      0.12      0.17       112
              2       0.40      0.03      0.06        62

       accuracy                           0.58       418
      macro avg       0.45      0.36      0.32       418
   weighted avg       0.51      0.58      0.49       418
```

[ ]: