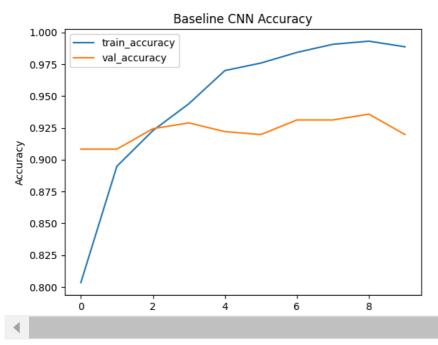
```
1 # Step 1:
 2 from google.colab import drive
 3 drive.mount('/content/drive')
→ Mounted at /content/drive
 1 # Step 2:
 2 import os
 3 import numpy as np
 4 import cv2
 5 from tensorflow.keras.preprocessing.image import ImageDataGenerator
 6 from sklearn.model_selection import train_test_split
 7 import matplotlib.pyplot as plt
 9 import tensorflow as tf
10 from tensorflow.keras.models import Sequential
11 from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
12 from sklearn.metrics import classification_report, confusion_matrix
13 from tensorflow.keras.applications import VGG16
 1 dataset_path = '/content/drive/MyDrive/Data-Science-Projects/
     Facial-Emotion-andBody-Language/Datasets/Master-Dataset-Body/Master-Dataset'
 1 # Step 3: Define the function to load the dataset
 2 def load_images_from_folder(folder):
      images = []
 3
      labels = []
      for class_name in os.listdir(folder):
 5
          class_folder = os.path.join(folder, class_name)
 6
 7
           if os.path.isdir(class_folder):
               for filename in os.listdir(class_folder):
 8
                   img path = os.path.join(class folder, filename)
10
                   img = cv2.imread(img_path)
                   if img is not None:
11
12
                       img = cv2.resize(img, (224, 224))
13
                       images.append(img)
                       labels.append(class_name)
14
      return np.array(images), np.array(labels)
 1 # Step 4: Load the body posture dataset (active/lazy)
 2 X, y = load_images_from_folder(dataset_path)
 4 # Encode labels (0 = Active, 1 = Lazy)
 5 y = np.where(y == 'Active', 0, 1)
 1 # Step 5: Normalize the images
 2 X = X / 255.0
 1
 2 # Step 6: Split into train, validation, and test sets
 3 X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.3, random_state=42)
 4 X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, random_state=42)
 1 print("Training set shape:", X_train.shape)
 2 print("Validation set shape:", X_val.shape)
 3 print("Test set shape:", X_test.shape)
→ Training set shape: (2034, 224, 224, 3)
     Validation set shape: (436, 224, 224, 3)
     Test set shape: (436, 224, 224, 3)
 1 # Step 7: Define the baseline CNN model
 2 def build_baseline_cnn(input_shape):
      model = Sequential()
 3
 5
       # Convolutional layers
      model.add(Conv2D(32, (3, 3), activation='relu', input_shape=input_shape))
 6
       model.add(MaxPooling2D(pool_size=(2, 2)))
```

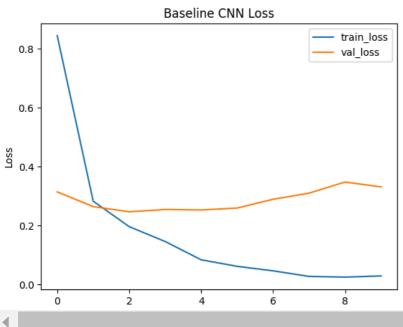
```
9
       model.add(Conv2D(64, (3, 3), activation='relu'))
10
       model.add(MaxPooling2D(pool_size=(2, 2)))
11
12
       model.add(Flatten())
13
14
       # Fully connected layers
15
       model.add(Dense(128, activation='relu'))
       model.add(Dropout(0.5))
16
17
18
       model.add(Dense(1, activation='sigmoid'))
19
       model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
20
21
22
       return model
 1 # Step 8: Build and compile the model
 2 baseline_cnn_model = build_baseline_cnn(input_shape=(224, 224, 3))
🚁 /usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`inp
       super().__init__(activity_regularizer=activity_regularizer, **kwargs)
 1
 2 # Step 9: Train the baseline CNN model
 3 history = baseline_cnn_model.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=10, batch_size=32)

→ Epoch 1/10
     64/64 -
                              – 16s 139ms/step - accuracy: 0.7484 - loss: 1.7214 - val_accuracy: 0.9083 - val_loss: 0.3143
    Epoch 2/10
     64/64 -
                              — 3s 41ms/step - accuracy: 0.8829 - loss: 0.3121 - val_accuracy: 0.9083 - val_loss: 0.2642
     Epoch 3/10
                              - 3s 41ms/step - accuracy: 0.9226 - loss: 0.2139 - val_accuracy: 0.9243 - val_loss: 0.2466
     64/64 ·
     Epoch 4/10
    64/64
                              - 3s 41ms/step - accuracy: 0.9384 - loss: 0.1552 - val_accuracy: 0.9289 - val_loss: 0.2545
    Epoch 5/10
     64/64 -
                              – 3s 41ms/step - accuracy: 0.9722 - loss: 0.0807 - val_accuracy: 0.9220 - val_loss: 0.2528
     Epoch 6/10
                               - 3s 41ms/step - accuracy: 0.9802 - loss: 0.0579 - val_accuracy: 0.9197 - val_loss: 0.2594
    64/64 ·
     Epoch 7/10
    64/64
                               - 3s 41ms/step - accuracy: 0.9846 - loss: 0.0495 - val_accuracy: 0.9312 - val_loss: 0.2892
    Epoch 8/10
     64/64 ·
                              - 3s 42ms/step - accuracy: 0.9911 - loss: 0.0234 - val_accuracy: 0.9312 - val_loss: 0.3100
    Epoch 9/10
                              - 3s 41ms/step - accuracy: 0.9945 - loss: 0.0246 - val_accuracy: 0.9358 - val_loss: 0.3478
    64/64 ·
     Epoch 10/10
     64/64
                               - 3s 41ms/step - accuracy: 0.9864 - loss: 0.0331 - val accuracy: 0.9197 - val loss: 0.3311
 1
 2 # Step 10: Visualize the training results
 3 plt.plot(history.history['accuracy'], label='train_accuracy')
 4 plt.plot(history.history['val_accuracy'], label='val_accuracy')
 5 plt.xlabel('Epochs')
 6 plt.ylabel('Accuracy')
 7 plt.legend()
 8 plt.title('Baseline CNN Accuracy')
 9 plt.show()
```



```
1 plt.plot(history.history['loss'], label='train_loss')
2 plt.plot(history.history['val_loss'], label='val_loss')
3 plt.xlabel('Epochs')
4 plt.ylabel('Loss')
5 plt.legend()
6 plt.title('Baseline CNN Loss')
7 plt.show()

Baseline CNN Loss
```



```
1 # Step 11: Evaluate the baseline model on test set
2 test_loss, test_accuracy = baseline_cnn_model.evaluate(X_test, y_test)
3 print(f"Test Accuracy: {test_accuracy * 100:.2f}%")
                              - 0s 17ms/step - accuracy: 0.9197 - loss: 0.3516
\overline{z}
   14/14 ·
    Test Accuracy: 93.58%
1 y_pred = baseline_cnn_model.predict(X_test)
2 y_pred = (y_pred > 0.5).astype(int)
4 print("Classification Report:\n", classification_report(y_test, y_pred))
5 print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
→ 14/14 ·
                              - 1s 29ms/step
    Classification Report:
                   precision
                                 recall f1-score
                                                    support
               0
                       0.95
                                  0.97
                                            0.96
                                                       337
```

0.83

0.85

99

1

0.88

```
0.94
                                                      436
       accuracy
                                 0.90
      macro avg
                       0.92
                                           0.91
                                                      436
    weighted avg
                       0.93
                                 0.94
                                           0.94
                                                      436
    Confusion Matrix:
    [[326 11]
    [ 17 82]]
1 # Save the baseline CNN model for body posture
2 cnn_model_save_path = '/content/drive/MyDrive/Data-Science-Projects/Facial-Emotion-andBody-Language/Models/body_posture_cnn_model.h5'
3 baseline_cnn_model.save(cnn_model_save_path)
4 print("Baseline CNN model for body posture saved successfully!")
   WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is cons
    Baseline CNN model for body posture saved successfully!
1 # Step 1: Import the VGG16 model
3 def build_fine_tuned_vgg(input_shape):
     base_model = VGG16(weights='imagenet', include_top=False, input_shape=input_shape)
     base_model.trainable = False
     model = Sequential([
         base_model,
         Flatten(),
         Dense(128, activation='relu'),
         Dropout(0.5),
         Dense(1, activation='sigmoid')
     model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
     return model
1 fine_tuned_vgg_model = build_fine_tuned_vgg(input_shape=(224, 224, 3))
   Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop
    58889256/58889256
                                           0s Ous/sten
1 history_vgg = fine_tuned_vgg_model.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=10, batch_size=32)
  Epoch 1/10
    64/64
                              - 45s 491ms/step - accuracy: 0.8035 - loss: 0.7154 - val_accuracy: 0.9220 - val_loss: 0.2103
    Epoch 2/10
    64/64
                             - 10s 160ms/step - accuracy: 0.9286 - loss: 0.1865 - val_accuracy: 0.9564 - val_loss: 0.1277
   Epoch 3/10
    64/64
                             - 10s 164ms/step - accuracy: 0.9558 - loss: 0.1227 - val_accuracy: 0.9564 - val_loss: 0.1076
    Epoch 4/10
    64/64
                              - 10s 162ms/step - accuracy: 0.9751 - loss: 0.0737 - val accuracy: 0.9564 - val loss: 0.1157
    Epoch 5/10
    64/64
                              - 10s 160ms/step - accuracy: 0.9674 - loss: 0.0897 - val_accuracy: 0.9610 - val_loss: 0.1056
   Epoch 6/10
    64/64
                              - 10s 158ms/step - accuracy: 0.9806 - loss: 0.0605 - val_accuracy: 0.9564 - val_loss: 0.1082
    Epoch 7/10
    64/64
                              - 10s 156ms/step - accuracy: 0.9837 - loss: 0.0579 - val_accuracy: 0.9587 - val_loss: 0.1178
    Epoch 8/10
    64/64
                              - 10s 156ms/step - accuracy: 0.9782 - loss: 0.0612 - val_accuracy: 0.9610 - val_loss: 0.1181
   Epoch 9/10
    64/64
                              - 10s 157ms/step - accuracy: 0.9740 - loss: 0.0578 - val_accuracy: 0.9610 - val_loss: 0.0990
    Epoch 10/10
    64/64
                              - 10s 157ms/step - accuracy: 0.9837 - loss: 0.0467 - val accuracy: 0.9541 - val loss: 0.1330
1 plt.plot(history_vgg.history['accuracy'], label='train_accuracy')
2 plt.plot(history_vgg.history['val_accuracy'], label='val_accuracy')
3 plt.xlabel('Epochs')
4 plt.ylabel('Accuracy')
5 plt.legend()
6 plt.title('Fine-tuned VGG Accuracy')
7 plt.show()
```

2

4 5

6

8

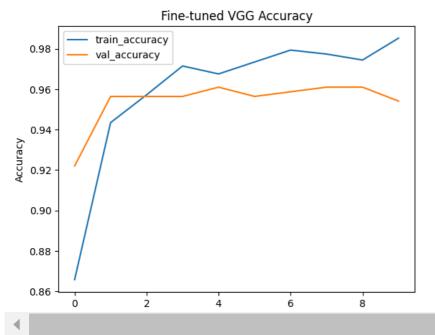
9

10

11

12 13

14 15 16



```
1 model_save_path = '/content/drive/MyDrive/Data-Science-Projects/Facial-Emotion-andBody-Language/Models/body_posture_vgg_model.h5'
2 fine_tuned_vgg_model.save(model_save_path)
3 print("Model saved successfully!")
```

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is cons Model saved successfully!

```
1 def build_yolo_like_model(input_shape):
2
      model = Sequential()
3
      # YOLO-like Convolutional layers
 4
      model.add(Conv2D(16, (3, 3), activation='relu', input_shape=input_shape))
5
6
      model.add(MaxPooling2D(pool_size=(2, 2)))
      model.add(Conv2D(32, (3, 3), activation='relu'))
8
9
      model.add(MaxPooling2D(pool_size=(2, 2)))
10
      model.add(Conv2D(64, (3, 3), activation='relu'))
11
12
      model.add(MaxPooling2D(pool_size=(2, 2)))
13
      model.add(Flatten())
14
15
16
      # Fully connected layers
      model.add(Dense(256, activation='relu'))
17
18
      model.add(Dropout(0.5))
19
      model.add(Dense(128, activation='relu'))
20
      model.add(Dropout(0.5))
21
      model.add(Dense(1, activation='sigmoid'))
22
23
      model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
24
25
      return model
```

```
1 yolo_like_model = build_yolo_like_model(input_shape=(224, 224, 3))
```

/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`inpsuper().__init__(activity_regularizer=activity_regularizer, **kwargs)

```
→
```

1 history_yolo = yolo_like_model.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=10, batch_size=32)

```
Epoch 1/10
64/64 — 16s 170ms/step - accuracy: 0.6989 - loss: 0.7672 - val_accuracy: 0.8945 - val_loss: 0.3648
Epoch 2/10
64/64 — 2s 30ms/step - accuracy: 0.8722 - loss: 0.4059 - val_accuracy: 0.8968 - val_loss: 0.2998
Epoch 3/10
64/64 — 2s 29ms/step - accuracy: 0.9073 - loss: 0.2797 - val_accuracy: 0.9312 - val_loss: 0.2394
```

```
Epoch 4/10
    64/64
                               2s 29ms/step - accuracy: 0.9142 - loss: 0.2076 - val_accuracy: 0.9312 - val_loss: 0.2084
    Epoch 5/10
                               2s 29ms/step - accuracy: 0.9372 - loss: 0.1557 - val_accuracy: 0.9427 - val_loss: 0.2365
    64/64
    Epoch 6/10
                               2s 29ms/step - accuracy: 0.9497 - loss: 0.1123 - val_accuracy: 0.9564 - val_loss: 0.1910
    64/64
    Epoch 7/10
                              - 2s 30ms/step - accuracy: 0.9811 - loss: 0.0579 - val accuracy: 0.9450 - val loss: 0.2371
    64/64
    Epoch 8/10
                               2s 30ms/step - accuracy: 0.9796 - loss: 0.0622 - val_accuracy: 0.9587 - val_loss: 0.2360
    64/64 ·
    Epoch 9/10
                               2s 30ms/step - accuracy: 0.9869 - loss: 0.0397 - val_accuracy: 0.9495 - val_loss: 0.2492
    64/64
    Epoch 10/10
    64/64
                              · 2s 29ms/step - accuracy: 0.9915 - loss: 0.0340 - val_accuracy: 0.9610 - val_loss: 0.2304
1
2 plt.plot(history_yolo.history['accuracy'], label='train_accuracy')
3 plt.plot(history_yolo.history['val_accuracy'], label='val_accuracy')
4 plt.xlabel('Epochs')
5 plt.ylabel('Accuracy')
6 plt.legend()
7 plt.title('YOLO-like Model Accuracy for Body Posture')
8 plt.show()
₹
                      YOLO-like Model Accuracy for Body Posture
```

0.95 - val_accuracy val_accuracy 0.95 - 0.85 - 0.85 - 0.80 -

4

6

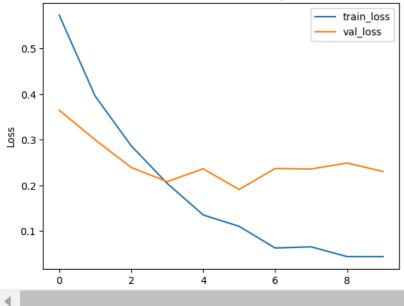
8

```
1
2 plt.plot(history_yolo.history['loss'], label='train_loss')
3 plt.plot(history_yolo.history['val_loss'], label='val_loss')
4 plt.xlabel('Epochs')
5 plt.ylabel('Loss')
6 plt.legend()
7 plt.title('YOLO-like Model Loss for Body Posture')
8 plt.show()
```

2

0

YOLO-like Model Loss for Body Posture



1 yolo_model_save_path = '/content/drive/MyDrive/Data-Science-Projects/Facial-Emotion-andBody-Language/Models/body_posture_yolo_model.h5'
2 yolo_like_model.save(yolo_model_save_path)
3 print("YOLO-like model saved successfully!")

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is cons YOLO-like model saved successfully!

1 cnn_test_loss, cnn_test_accuracy = baseline_cnn_model.evaluate(X_test, y_test)
2 print(f"CNN Test Accuracy: {cnn_test_accuracy * 100:.2f}%")

14/14 ______ 0s 17ms/step - accuracy: 0.9197 - loss: 0.3516 CNN Test Accuracy: 93.58%

1 vgg_test_loss, vgg_test_accuracy = fine_tuned_vgg_model.evaluate(X_test, y_test)
2 print(f"VGG Test Accuracy: {vgg_test_accuracy * 100:.2f}%")

14/14 2s 121ms/step - accuracy: 0.9619 - loss: 0.1162 VGG Test Accuracy: 96.33%

1 yolo_test_loss, yolo_test_accuracy = yolo_like_model.evaluate(X_test, y_test)
2 print(f"YOLO-like Test Accuracy: {yolo_test_accuracy * 100:.2f}%")

14/14 — 0s 14ms/step - accuracy: 0.9539 - loss: 0.3515 YOLO-like Test Accuracy: 95.64%

1 models = ['CNN', 'VGG', 'YOLO']

2 accuracies = [cnn_test_accuracy, vgg_test_accuracy, yolo_test_accuracy]

1 plt.bar(models, accuracies)

2 plt.xlabel('Models')

3 plt.ylabel('Accuracy')

4 plt.title('Comparison of CNN, VGG, and YOLO Models for Body Posture Detection')

5 plt.show()

```
Comparison of CNN, VGG, and YOLO Models for Body Posture Detection

1.0

0.8
```

```
> 0.6
     plt.figure(figsize=(10, 6))
 1
     plt.plot(history.history['accuracy'], label='CNN Train Accuracy',
     linestyle='-', marker='o', color='blue')
     plt.plot(history.history['val_accuracy'], label='CNN Val Accuracy',
     linestyle='--', marker='o', color='blue')
     plt.plot(history_vgg.history['accuracy'], label='VGG Train Accuracy',
     linestyle='-', marker='s', color='green')
     plt.plot(history_vgg.history['val_accuracy'], label='VGG Val Accuracy',
     linestyle='--', marker='s', color='green')
     plt.plot(history_yolo.history['accuracy'], label='YOLO Train Accuracy',
 9
     linestyle='-', marker='x', color='red')
     plt.plot(history_yolo.history['val_accuracy'], label='YOLO Val Accuracy',
     linestyle='--', marker='x', color='red')
11
12
     plt.title('Model Accuracy over Epochs')
     plt.xlabel('Epochs')
13
    plt.ylabel('Accuracy')
14
15
    plt.legend(loc='best')
16
     plt.grid(True)
17
18
     plt.show()
19
```

