

#COMPUTER VISION CAPSTONE PROJECT AIML OBJECT DETECTION - CAR

```
from prettytable import PrettyTable

# Create a PrettyTable object
table = PrettyTable()

# Define the columns
table.field_names = ["S.NO", "Contents", "Cell Number"]

# Add rows
table.add_row([1, "Problem Statement", 8 ])
table.add_row([2, "Introduction", 10])
table.add_row([3, "Libraries Used", 12])
table.add_row([4, "Data Handling", 14 ])
table.add_row(["4A", "Data Handling - Import Data", 15 ])
table.add_row(["4B", "Data Handling - Map Images w.r.t Classes", 14 ])
table.add_row(["4C", "Data Handling - Map Images w.r.t Annotations",
14 ])
table.add_row([5, "Display Result - bounding box", 16 ])
table.add_row([6, "Design Basic CNN Models", 17 ])
table.add_row(["6A", "VGGNet CNN Model", 17 ])
table.add_row(["6B", "Google CNN Model", 17 ])
table.add_row(["6C", "AlexNet CNN Model", 17 ])
table.add_row(["6D", "U-Net CNN Model", 17 ])
table.add_row(["7", "Summary", 17 ])
```

```
# Print the table
print(table)
```

S.NO	Contents	Cell Number
1	Problem Statement	8
2	Introduction	10
3	Libraries Used	12
4	Data Handling	14
4A	Data Handling - Import Data	15
4B	Data Handling - Map Images w.r.t Classes	14
4C	Data Handling - Map Images w.r.t Annotations	14
5	Display Result - bounding box	16
6	Design Basic CNN Models	17
6A	VGGNet CNN Model	17
6B	Google CNN Model	17
6C	AlexNet CNN Model	17
6D	U-Net CNN Model	17
7	Summary	17

1. Problem Statement

Computer vision can be used to automate supervision and generate action appropriate action trigger if the event is predicted from the image of interest. For example a car moving on the road can be easily identified by a camera as make of the car, type, colour, number plates etc.

Design a DL based car identification model.

1. Introduction

The Cars dataset contains 16,185 images of 196 classes of cars. The data is split into 8,144 training images and 8,041 testing images, where each class has been split roughly in a 50-50 split. Classes are typically at the level of Make, Model, Year, e.g. 2012 Tesla Model S or 2012 BMW M3 coupe.

Data description:

- ▶ Train Images: Consists of real images of cars as per the make and year of the car.
- ▶ Test Images: Consists of real images of cars as per the make and year of the car.
- ▶ Train Annotation: Consists of bounding box region for training images.
- ▶ Test Annotation: Consists of bounding box region for testing images.

1. Libraries Used

```

import os
import zipfile
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import cv2
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten,
Dense, Dropout, GlobalAveragePooling2D, BatchNormalization
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import matplotlib.patches as patches
import glob # for file path handling
from PIL import Image # For image loading and manipulation
import xml.etree.ElementTree as ET # For handling XML annotations
(common for object detection datasets)
import matplotlib.pyplot as plt # For visualization
from sklearn.model_selection import train_test_split # For potential
data splitting if needed
from sklearn.preprocessing import LabelEncoder
from tensorflow import keras
from tensorflow.keras import layers

from tensorflow.keras.applications import VGG16, VGG19
from tensorflow.keras.optimizers import Adam

from tensorflow.keras.applications import InceptionV3
from tensorflow.keras.preprocessing.image import load_img,
img_to_array

```

1. Data Handling

4A. Data Handling - Import Data

```

# Define file paths
car_names_file = 'Car names and make.csv'
annotations_zip_file = 'Annotations.zip'
images_zip_file = 'Car Images.zip'

# Step 1: Load the car names and make data
car_names_df = pd.read_csv(car_names_file)

# Display the first few rows of the DataFrame

```

```

print("Car Names and Makes:")
print(car_names_df.head())

# Step 2: Extract Annotations.zip
with zipfile.ZipFile(annotations_zip_file, 'r') as zip_ref:
    zip_ref.extractall('Annotations')

# List the extracted files
print("\nExtracted Annotations:")
print(os.listdir('Annotations'))

# Step 3: Extract Car Images.zip
with zipfile.ZipFile(images_zip_file, 'r') as zip_ref:
    zip_ref.extractall('Car_Images')

# List the extracted files
print("\nExtracted Car Images:")
print(os.listdir('Car_Images'))

Car Names and Makes:
  AM General Hummer SUV 2000
0      Acura RL Sedan 2012
1      Acura TL Sedan 2012
2      Acura TL Type-S 2008
3      Acura TSX Sedan 2012
4  Acura Integra Type R 2001

Extracted Annotations:
['Annotations']

Extracted Car Images:
['Car Images']

# Load the training annotations
train_annotations_path = r'Train Annotations.csv' # Adjust the path
as necessary
train_annotations_df = pd.read_csv(train_annotations_path)
print("Training Annotations Columns:")
print(train_annotations_df.columns)
train_annotations_df.head(5)

Training Annotations Columns:
Index(['Image Name', 'Bounding Box coordinates', 'Unnamed: 2',
      'Unnamed: 3',
      'Unnamed: 4', 'Image class'],
      dtype='object')

  Image Name  Bounding Box coordinates  Unnamed: 2  Unnamed: 3
Unnamed: 4 \
0  00001.jpg                39          116          569
375

```

```

1 00002.jpg          36          116          868
587
2 00003.jpg          85          109          601
381
3 00004.jpg         621          393         1484
1096
4 00005.jpg          14           36          133
99

```

```

Image class
0          14
1           3
2          91
3         134
4         106

```

Load the Test annotations

```

test_annotations_path = r'Test Annotation.csv' # Adjust the path as
necessary
test_annotations_df = pd.read_csv(test_annotations_path)
print("Test Annotations Columns:")
print(test_annotations_df.columns)
test_annotations_df.head(5)

```

Test Annotations Columns:

```

Index(['Image Name', 'Bounding Box coordinates', 'Unnamed: 2',
      'Unnamed: 3',
      'Unnamed: 4', 'Image class'],
      dtype='object')

```

```

Image Name  Bounding Box coordinates  Unnamed: 2  Unnamed: 3
Unnamed: 4 \
0 00001.jpg          30           52          246
147
1 00002.jpg         100           19          576
203
2 00003.jpg          51          105          968
659
3 00004.jpg          67           84          581
407
4 00005.jpg         140          151          593
339

```

```

Image class
0         181
1         103
2         145
3         187
4         185

```

```
# Renaming column names
```

```
train_annotations_df = train_annotations_df.rename(columns={'Bounding  
Box coordinates': 'Bounding Box coordinates_xmin', 'Unnamed:  
2': 'Bounding Box coordinates_ymin', 'Unnamed: 3': 'Bounding Box  
coordinates_xmax', 'Unnamed: 4': 'Bounding Box coordinates_ymax'})  
train_annotations_df.head(5)
```

	Image Name	Bounding Box coordinates_xmin	Bounding Box coordinates_ymin \
0	00001.jpg	39	116
1	00002.jpg	36	116
2	00003.jpg	85	109
3	00004.jpg	621	393
4	00005.jpg	14	36

	Bounding Box coordinates_xmax	Bounding Box coordinates_ymax	Image class
0	569	375	14
1	868	587	3
2	601	381	91
3	1484	1096	134
4	133	99	106

```
# Renaming column names
```

```
test_annotations_df = test_annotations_df.rename(columns={'Bounding  
Box coordinates': 'Bounding Box coordinates_xmin', 'Unnamed:  
2': 'Bounding Box coordinates_ymin', 'Unnamed: 3': 'Bounding Box  
coordinates_xmax', 'Unnamed: 4': 'Bounding Box coordinates_ymax'})  
test_annotations_df.head(5)
```

	Image Name	Bounding Box coordinates_xmin	Bounding Box coordinates_ymin \
0	00001.jpg	30	52
1	00002.jpg	100	19
2	00003.jpg	51	105
3	00004.jpg	67	84

```

4 00005.jpg 140
151
    Bounding Box coordinates_xmax Bounding Box coordinates_ymax Image
class
0 246 147
181
1 576 203
103
2 968 659
145
3 581 407
187
4 593 339
185

# for images
train_images_path = os.path.join('Car_Images/Car Images/Train Images')
test_images_path = os.path.join('Car_Images/Car Images/Test Images')

```

4B. Data Handling - Map Images w.r.t Classes

```

train_class_folders = [f.path for f in os.scandir(train_images_path)
if f.is_dir()]

train_image_classes = {} # Dictionary to store training image: class
mapping

# Define columns for the Training DataFrame
columns_training = ['Image_Path', 'labels']

# Create an empty DataFrame
df_training = pd.DataFrame(columns=columns_training)

# --- Map filenames in a class for train_image_classes
for class_folder in train_class_folders:
    class_name = os.path.basename(class_folder) # Extract class name
    from folder name
    #labels_train.append(class_name)
    image_files = glob.glob(os.path.join(class_folder, '*.jpg')) #
    images are .jpg
    for image_file in image_files:
        train_image_classes[os.path.basename(image_file)] =
class_name # Map filename to class
        #image_file_path_training.append(image_file)
        df_training.loc[len(df_training)] = [image_file, class_name]

print(df_training.head(10))

```

```
# --- Print a few mappings to verify ---
print("Sample Training Image to Class Mappings:")
count = 0
for img_name, class_label in train_image_classes.items():
    print(f"{img_name}: {class_label}")
    count += 1
    if count > 5: break # Print first few only
```

```

                                Image_Path \
0  Car_Images/Car Images/Train Images\Acura Integ...
1  Car_Images/Car Images/Train Images\Acura Integ...
2  Car_Images/Car Images/Train Images\Acura Integ...
3  Car_Images/Car Images/Train Images\Acura Integ...
4  Car_Images/Car Images/Train Images\Acura Integ...
5  Car_Images/Car Images/Train Images\Acura Integ...
6  Car_Images/Car Images/Train Images\Acura Integ...
7  Car_Images/Car Images/Train Images\Acura Integ...
8  Car_Images/Car Images/Train Images\Acura Integ...
9  Car_Images/Car Images/Train Images\Acura Integ...
```

```

                                labels
0  Acura Integra Type R 2001
1  Acura Integra Type R 2001
2  Acura Integra Type R 2001
3  Acura Integra Type R 2001
4  Acura Integra Type R 2001
5  Acura Integra Type R 2001
6  Acura Integra Type R 2001
7  Acura Integra Type R 2001
8  Acura Integra Type R 2001
9  Acura Integra Type R 2001
Sample Training Image to Class Mappings:
00198.jpg: Acura Integra Type R 2001
00255.jpg: Acura Integra Type R 2001
00308.jpg: Acura Integra Type R 2001
00374.jpg: Acura Integra Type R 2001
00878.jpg: Acura Integra Type R 2001
00898.jpg: Acura Integra Type R 2001
```

```
test_class_folders = [f.path for f in os.scandir(test_images_path) if
f.is_dir()]
test_image_classes = {} # Dictionary to store testing image: class
mapping
```

```
# Define columns for the Testing DataFrame
columns_testing = ['Image_Path', 'labels']
```

```
# Create an empty DataFrame
df_testing = pd.DataFrame(columns=columns_testing)
```



```

# similar logic for test_images_path and test_image_classes
for class_folder in test_class_folders:
    class_name = os.path.basename(class_folder) # Extract class name
    from folder name
    #labels_testing.append(class_name)
    image_files = glob.glob(os.path.join(class_folder, '*.jpg')) #
    images are .jpg
    for image_file in image_files:
        test_image_classes[os.path.basename(image_file)] = class_name
# Map filename to class
    #image_file_path_testing.append(image_file)
    df_testing.loc[len(df_testing)] = [image_file, class_name]

print(df_testing.head(10))

print("Sample Testing Image to Class Mappings:")
count = 0
for img_name, class_label in test_image_classes.items():
    print(f"{img_name}: {class_label}")
    count += 1
    if count > 5: break # Print first few only

```

```

                                Image_Path \
0  Car_Images/Car Images/Test Images\Acura Integr...
1  Car_Images/Car Images/Test Images\Acura Integr...
2  Car_Images/Car Images/Test Images\Acura Integr...
3  Car_Images/Car Images/Test Images\Acura Integr...
4  Car_Images/Car Images/Test Images\Acura Integr...
5  Car_Images/Car Images/Test Images\Acura Integr...
6  Car_Images/Car Images/Test Images\Acura Integr...
7  Car_Images/Car Images/Test Images\Acura Integr...
8  Car_Images/Car Images/Test Images\Acura Integr...
9  Car_Images/Car Images/Test Images\Acura Integr...

```

```

                                labels
0  Acura Integra Type R 2001
1  Acura Integra Type R 2001
2  Acura Integra Type R 2001
3  Acura Integra Type R 2001
4  Acura Integra Type R 2001
5  Acura Integra Type R 2001
6  Acura Integra Type R 2001
7  Acura Integra Type R 2001
8  Acura Integra Type R 2001
9  Acura Integra Type R 2001
Sample Testing Image to Class Mappings:
00128.jpg: Acura Integra Type R 2001
00130.jpg: Acura Integra Type R 2001

```

```
00386.jpg: Acura Integra Type R 2001
00565.jpg: Acura Integra Type R 2001
00711.jpg: Acura Integra Type R 2001
01002.jpg: Acura Integra Type R 2001
```

4C. Data Handling - Map Images w.r.t Annotations

```
# *****Definition of the method *****
def map_images_to_bboxes(annotations_file):
    image_bboxes = {}
    try:
        for index, row in annotations_file.iterrows():
            image_name = row['Image Name']
            x_min = row['Bounding Box coordinates_xmin']
            y_min = row['Bounding Box coordinates_ymin']
            x_max = row['Bounding Box coordinates_xmax']
            y_max = row['Bounding Box coordinates_ymax']
            image_class = row['Image class']

            image_bboxes[image_name] = (x_min, y_min, x_max,
y_max) # Store bbox as tuple

        except FileNotFoundError:
            print(f"Error: Annotation file not found: {annotations_file}")
        except KeyError as e:
            print(f"Error: Column '{e}' not found in CSV file. Check your
CSV column names.")
            print("Expected columns (example): filename, xmin, ymin, xmax,
ymax") # Example expected columns

    return image_bboxes

train_image_bboxes = map_images_to_bboxes(train_annotations_df)
# --- Print a few mappings to verify for Training images ---
print("\nSample Training Image to Bounding Box Mappings (DF):")
count = 0
for img_name, bbox in train_image_bboxes.items():
    print(f"{img_name}: {bbox}")
    count += 1
    if count > 5: break
```

```
Sample Training Image to Bounding Box Mappings (DF):
00001.jpg: (39, 116, 569, 375)
00002.jpg: (36, 116, 868, 587)
00003.jpg: (85, 109, 601, 381)
00004.jpg: (621, 393, 1484, 1096)
```

```

00005.jpg: (14, 36, 133, 99)
00006.jpg: (259, 289, 515, 416)

test_image_bboxes = map_images_to_bboxes(test_annotations_df)
# --- Print a few mappings to verify testing images---
print("\nSample Testing Image to Bounding Box Mappings (DF):")
count = 0
for img_name, bbox in test_image_bboxes.items():
    print(f"{img_name}: {bbox}")
    count += 1
    if count > 5: break

Sample Testing Image to Bounding Box Mappings (DF):
00001.jpg: (30, 52, 246, 147)
00002.jpg: (100, 19, 576, 203)
00003.jpg: (51, 105, 968, 659)
00004.jpg: (67, 84, 581, 407)
00005.jpg: (140, 151, 593, 339)
00006.jpg: (20, 77, 420, 301)

```

1. Display Result - bounding box

```

# Display images with bounding boxes
def display_image_with_bbox(image_path, annotation):
    # Load image
    img = Image.open(image_path)

    # Create plot
    fig, ax = plt.subplots(1)
    ax.imshow(img)

    # Draw bounding box
    x_min = row['Bounding Box coordinates_xmin']
    y_min = row['Bounding Box coordinates_ymin']
    x_max = row['Bounding Box coordinates_xmax']
    y_max = row['Bounding Box coordinates_ymax']
    image_class = row['Image class']
    bbox = annotation['bbox']
    rect = patches.Rectangle(
        (x_min, y_min), # (x_min, y_min) - (bbox[0], bbox[1])
        (x_max - x_min), # width (x_max - x_min) - bbox[2] -
bbox[0]
        (y_max - y_min), # height (y_max - y_min) -- bbox[3] -
bbox[1]
        linewidth=2,
        edgecolor='r',
        facecolor='none'
    )
    ax.add_patch(rect)

```

```

# Add class label
plt.text(
    bbox[0], bbox[1] - 10, # Position of the label
    annotation['image_class'],
    color='red',
    fontsize=12,
    backgroundcolor='white'
)

plt.axis('off')
plt.show()

# for training images
print("For Training Images") # Changed message to "Test Image"
displayed_image_count = 0 # Initialize a counter to track displayed
images

image_paths_details_training=[]
images_paths_details_testing=[]

for index, row in train_annotations_df.iterrows():
    if displayed_image_count >= 5: # Check if we've already displayed
two images
        break # If yes, exit the loop

    image_name = str(row['Image Name']).strip()
    image_path = None # Initialize image_path to None

    for class_folder in train_class_folders:
        potential_image_path = os.path.join(class_folder, image_name)
        if os.path.exists(potential_image_path):
            image_path = potential_image_path
            image_paths_details_training.append(potential_image_path)
            break # Image found, no need to check other class folders

    if image_path: # If image_path is found (not None)
        annotation = {
            'bbox': [row['Bounding Box coordinates_xmin'],
row['Bounding Box coordinates_ymin'], row['Bounding Box
coordinates_xmax'], row['Bounding Box coordinates_ymax']],
            'image_class' : row['Image class']}
        display_image_with_bbox(image_path, annotation)
        displayed_image_count += 1 # Increment the counter
    else:
        # print(f"Training Image not found: {image_name}")

```

```
print(f"Displayed {displayed_image_count} training images with  
bounding boxes.")
```

For Training Images

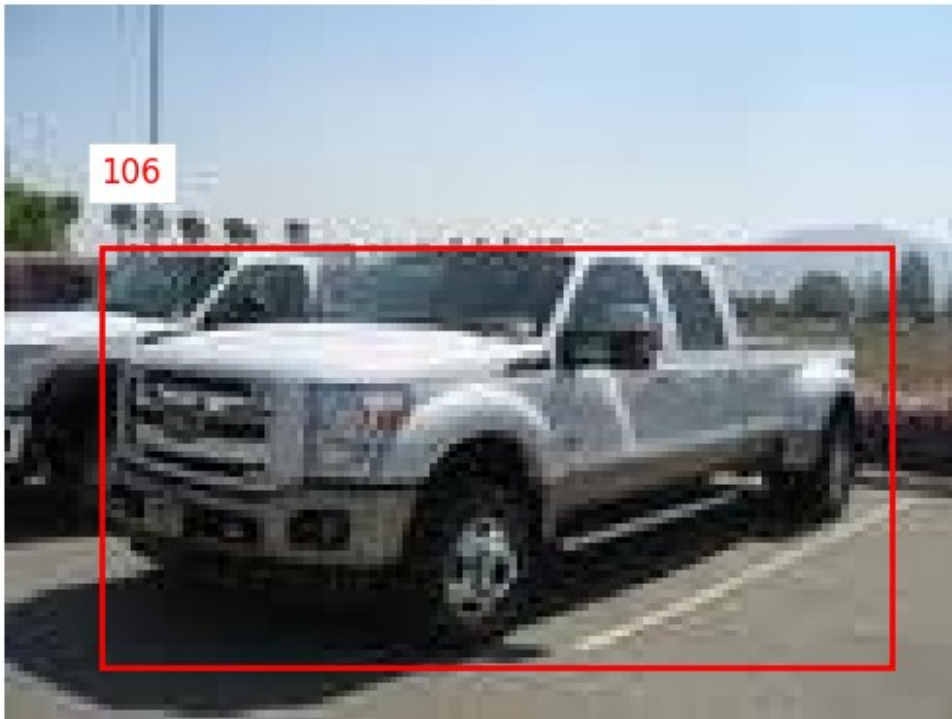


91



134





Displayed 5 training images with bounding boxes.

```
# for test images
print("For Testing Images") # Changed message to "Test Image"
displayed_image_count_test = 0 # Initialize a counter to track
displayed images

for index, row in test_annotations_df.iterrows(): # Use
test_annotations_df DataFrame
    if displayed_image_count_test >= 5: # Check if we've already
displayed two images (adjust number here if you want 5 or more)
        break # If yes, exit the loop

    image_name_test = str(row['Image Name']).strip()
    image_path_test = None # Initialize image_path_test to None

    for class_folder in test_class_folders: # Use test_class_folders
        potential_image_path_test = os.path.join(class_folder,
image_name_test)
        if os.path.exists(potential_image_path_test):
            image_path_test = potential_image_path_test # Assigned to
image_path_test
            images_paths_details_testing.append(potential_image_path)
            break # Image found, no need to check other class folders

    if image_path_test: # If image_path_test is found (not None)
```

```

        annotation_test = {
            'bbox': [row['Bounding Box coordinates_xmin'],
                    row['Bounding Box coordinates_ymin'], row['Bounding Box
                    coordinates_xmax'], row['Bounding Box coordinates_ymax']],
            'image_class' : row['Image class'] # Assuming 'Image
            class' column also exists in test_annotations_df (verify!)
        }
        display_image_with_bbox(image_path_test, annotation_test) #
        Changed here
        displayed_image_count_test += 1 # Increment the counter
    #else:
    #    print(f"Test Image not found: {image_name_test}") # Changed
    message to "Test Image"

print(f"Displayed {displayed_image_count_test} test images with
bounding boxes.") # Changed message to "test images"

```

For Testing Images

181



103



145





Displayed 5 test images with bounding boxes.

1. Design Basic CNN Models

The Models designed are:

1. VGGNet
2. GoogleNet

3. AlexNet
4. U-Net

```
def preprocess_image(image_path, target_size=(224, 224)):
    """
    Load and preprocess an image for CNN input.
    """
    # Check if the image file exists
    if not os.path.exists(image_path):
        print(f"Warning: Image file not found: {image_path}")
        return None # Or handle the missing image in a way that makes
        sense for your application

    image = cv2.imread(image_path) # Load image

    # Check if image loading was successful
    if image is None:
        print(f"Warning: Failed to load image: {image_path}")
        return None # Or handle the loading error as needed

    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB) # Convert to RGB
    image = cv2.resize(image, target_size) # Resize to target size
    image = image / 255.0 # Normalize pixel values to [0, 1]
    return image

def custom_generator(df, batch_size, target_size):
    """
    Custom generator for images and labels.
    """
    num_samples = len(df)
    while True:
        for offset in range(0, num_samples, batch_size):
            batch_samples = df.iloc[offset:offset + batch_size]
            images = []
            labels = []
            for _, row in batch_samples.iterrows():
                image = preprocess_image(row['Image_Path'],
target_size)
                label = row['label_categorical']
                images.append(image)
                labels.append(label)
            X = np.array(images)
            y = np.array(labels)
            yield X, y

# Apply preprocessing to all images
df_testing['image'] = df_testing['Image_Path'].apply(preprocess_image)
df_training['image'] =
df_training['Image_Path'].apply(preprocess_image)

# Check for and handle None values in the 'image' column
```

```

df_testing = df_testing.dropna(subset=['image']) # Remove rows with
None in 'image'
df_training = df_training.dropna(subset=['image']) # Remove rows with
None in 'image'

# Encode labels
label_encoder = LabelEncoder()
df_testing['labels_encoded'] =
label_encoder.fit_transform(df_testing['labels'])
df_training['labels_encoded'] =
label_encoder.fit_transform(df_training['labels'])

# Convert labels to categorical (one-hot encoding)
df_testing['label_categorical'] =
df_testing['labels_encoded'].apply(lambda x: to_categorical(x,
num_classes=len(test_class_folders)))
df_training['label_categorical'] =
df_training['labels_encoded'].apply(lambda x: to_categorical(x,
num_classes=len(test_class_folders)))

# Create generators
batch_size = 32
train_generator = custom_generator(df_training, batch_size,
target_size=(224, 224))
val_generator = custom_generator(df_testing, batch_size,
target_size=(224, 224))

# Check training generator
X_batch, y_batch = next(train_generator)
print("Training batch shape:", X_batch.shape, y_batch.shape)

# Check validation generator
X_batch, y_batch = next(val_generator)
print("Validation batch shape:", X_batch.shape, y_batch.shape)

Training batch shape: (32, 224, 224, 3) (32, 196)
Validation batch shape: (32, 224, 224, 3) (32, 196)

```

6A. VGGNet CNN Model

```

train_images = []
for img_path in df_training['Image_Path'].head(20): # Iterate through
image paths
    img = load_img(img_path, target_size=(224, 224)) # Load the image
    img_array = img_to_array(img) # Convert to NumPy array
    train_images.append(img_array) # Add to the list

train_images = np.array(train_images) # Convert list to NumPy array

# --- Apply resizing if needed ---

```



```

train_images = np.array([cv2.resize(img, (224, 224)) for img in
train_images])

train_labels =
np.stack(df_training['label_categorical'].head(20).values)

# Similarly for test images:
test_images = []
for img_path in df_testing['Image_Path'].head(20): # Iterate through
image paths
    img = load_img(img_path, target_size=(224, 224)) # Load the image
    img_array = img_to_array(img) # Convert to NumPy array
    test_images.append(img_array) # Add to the list

test_images = np.array(test_images) # Convert list to NumPy array

# --- Apply resizing if needed ---
test_images = np.array([cv2.resize(img, (224, 224)) for img in
test_images])

test_labels =
np.stack(df_testing['label_categorical'].head(20).values)

# Check shapes
print(f"train_images shape: {train_images.shape}")
print(f"train_labels shape: {train_labels.shape}")
print(f"test_images shape: {test_images.shape}")
print(f"test_labels shape: {test_labels.shape}")
# Load VGG16 model without the top layer
base_model = VGG16(weights='imagenet', include_top=False,
input_shape=(224, 224, 3))

# Add custom layers on top
x = Flatten()(base_model.output)
x = Dense(256, activation='relu')(x)
predictions = Dense(num_classes, activation='softmax')(x)

# Create the model
model = Model(inputs=base_model.input, outputs=predictions)

# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])

# Data augmentation
datagen = ImageDataGenerator(rescale=1./255, validation_split=0.2)

model.summary()
# Fit the model

```

```

model.fit(datagen.flow(train_images, train_labels, batch_size=32,
subset='training'),
validation_data=datagen.flow(train_images, train_labels,
batch_size=32, subset='validation'),
epochs=10)

```

```

train_images shape: (20, 224, 224, 3)
train_labels shape: (20, 196)
test_images shape: (20, 224, 224, 3)
test_labels shape: (20, 196)

```

Model: "functional_73"

Layer (type) Param #	Output Shape	
input_layer_9 (InputLayer) 0	(None, 224, 224, 3)	
block1_conv1 (Conv2D) 1,792	(None, 224, 224, 64)	
block1_conv2 (Conv2D) 36,928	(None, 224, 224, 64)	
block1_pool (MaxPooling2D) 0	(None, 112, 112, 64)	
block2_conv1 (Conv2D) 73,856	(None, 112, 112, 128)	
block2_conv2 (Conv2D) 147,584	(None, 112, 112, 128)	
block2_pool (MaxPooling2D) 0	(None, 56, 56, 128)	
block3_conv1 (Conv2D) 295,168	(None, 56, 56, 256)	

590,080	block3_conv2 (Conv2D)	(None, 56, 56, 256)	
590,080	block3_conv3 (Conv2D)	(None, 56, 56, 256)	
0	block3_pool (MaxPooling2D)	(None, 28, 28, 256)	
1,180,160	block4_conv1 (Conv2D)	(None, 28, 28, 512)	
2,359,808	block4_conv2 (Conv2D)	(None, 28, 28, 512)	
2,359,808	block4_conv3 (Conv2D)	(None, 28, 28, 512)	
0	block4_pool (MaxPooling2D)	(None, 14, 14, 512)	
2,359,808	block5_conv1 (Conv2D)	(None, 14, 14, 512)	
2,359,808	block5_conv2 (Conv2D)	(None, 14, 14, 512)	
2,359,808	block5_conv3 (Conv2D)	(None, 14, 14, 512)	
0	block5_pool (MaxPooling2D)	(None, 7, 7, 512)	
0	flatten_7 (Flatten)	(None, 25088)	

dense_20 (Dense)	(None, 256)	
6,422,784		
dense_21 (Dense)	(None, 196)	
50,372		

Total params: 21,187,844 (80.83 MB)

Trainable params: 21,187,844 (80.83 MB)

Non-trainable params: 0 (0.00 B)

Epoch 1/10

```
c:\Python\Lib\site-packages\keras\src\trainers\data_adapters\
py_dataset_adapter.py:121: UserWarning: Your `PyDataset` class should
call `super().__init__(**kwargs)` in its constructor. `**kwargs` can
include `workers`, `use_multiprocessing`, `max_queue_size`. Do not
pass these arguments to `fit()`, as they will be ignored.
  self._warn_if_super_not_called()
```

1/1 ————— 8s 8s/step - accuracy: 0.0000e+00 - loss: 4.4485 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 2/10

1/1 ————— 4s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 3/10

1/1 ————— 4s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 4/10

1/1 ————— 4s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 5/10

1/1 ————— 4s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 6/10

1/1 ————— 4s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 7/10

1/1 ————— 4s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 8/10

1/1 ————— 4s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 9/10

1/1 ————— 4s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 10/10


```
1/1 _____ 4s 4s/step - accuracy: 1.0000 - loss:
0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

<keras.src.callbacks.history.History at 0x1abf22fc890>
```

6B. GoogleNet

```
base_model = InceptionV3(weights='imagenet', include_top=False,
input_shape=(224, 224, 3))

# Add custom layers on top of the base model
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(1024, activation='relu')(x)
predictions = Dense(196, activation='softmax')(x)

# Define the complete model
model = Model(inputs=base_model.input, outputs=predictions)

# Freeze the layers of the base model
for layer in base_model.layers:
    layer.trainable = False

# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])

# Convert to numpy arrays
# Ensure all images have the same shape before stacking

# Ensure the model summary is called after defining the model
model.summary()

# Train the model
model.fit(
    train_images, # Preprocessed training images
    train_labels, # One-hot encoded training labels
    epochs=10,
    batch_size=32,
    validation_data=(test_images, test_labels)
)

Model: "functional_74"
```

Layer (type)	Output Shape	Param #	Connected to
--------------	--------------	---------	--------------

input_layer_10	(None, 224, 224,	0	-	
(InputLayer)	3)			
conv2d_129 (Conv2D)	(None, 111, 111,	864		
input_layer_10[0]...	32)			
batch_normalizatio...	(None, 111, 111,	96	conv2d_129[0]	
[0]				
(BatchNormalizatio...	32)			
activation_94	(None, 111, 111,	0		
batch_normalizat...				
(Activation)	32)			
conv2d_130 (Conv2D)	(None, 109, 109,	9,216		
activation_94[0]...				
	32)			
batch_normalizatio...	(None, 109, 109,	96	conv2d_130[0]	
[0]				
(BatchNormalizatio...	32)			
activation_95	(None, 109, 109,	0		
batch_normalizat...				
(Activation)	32)			
conv2d_131 (Conv2D)	(None, 109, 109,	18,432		
activation_95[0]...				
	64)			

batch_normalization_131[0]	(None, 109, 109, 64)	192	conv2d_131[0]
activation_96	(None, 109, 109, 64)	0	
max_pooling2d_19	(None, 54, 54, 64)	0	
conv2d_132	(None, 54, 54, 80)	5,120	
batch_normalization_132[0]	(None, 54, 54, 80)	240	conv2d_132[0]
activation_97	(None, 54, 54, 80)	0	
conv2d_133	(None, 52, 52, 192)	138,240	
batch_normalization_133[0]	(None, 52, 52, 192)	576	conv2d_133[0]

activation_98 batch_normalizat...	(None, 52, 52,	0	
(Activation)	192)		
max_pooling2d_20 activation_98[0]...	(None, 25, 25,	0	
(MaxPooling2D)	192)		
conv2d_137 (Conv2D) max_pooling2d_20...	(None, 25, 25,	12,288	
	64)		
batch_normalizatio... [0]	(None, 25, 25,	192	conv2d_137[0]
(BatchNormalizatio...	64)		
activation_102 batch_normalizat...	(None, 25, 25,	0	
(Activation)	64)		
conv2d_135 (Conv2D) max_pooling2d_20...	(None, 25, 25,	9,216	
	48)		
conv2d_138 (Conv2D) activation_102[0]...	(None, 25, 25,	55,296	
	96)		
batch_normalizatio... [0]	(None, 25, 25,	144	conv2d_135[0]
(BatchNormalizatio...	48)		

batch_normalization_100[0]	(None, 25, 25, 96)	288	conv2d_138[0]
activation_100	(None, 25, 25, 48)	0	
batch_normalization_103	(None, 25, 25, 96)	0	
average_pooling2d_9	(None, 25, 25, 192)	0	
conv2d_134 (Conv2D)	(None, 25, 25, 64)	12,288	
conv2d_136 (Conv2D)	(None, 25, 25, 64)	76,800	
conv2d_139 (Conv2D)	(None, 25, 25, 96)	82,944	
conv2d_140 (Conv2D)	(None, 25, 25, 32)	6,144	
batch_normalization_100	(None, 25, 25, 192)	192	conv2d_134[0]

[0]	(BatchNormalizatio...	64)		
	batch_normalizatio...	(None, 25, 25,	192	conv2d_136[0]
[0]	(BatchNormalizatio...	64)		
	batch_normalizatio...	(None, 25, 25,	288	conv2d_139[0]
[0]	(BatchNormalizatio...	96)		
	batch_normalizatio...	(None, 25, 25,	96	conv2d_140[0]
[0]	(BatchNormalizatio...	32)		
	activation_99	(None, 25, 25,	0	
batch_normalizat...	(Activation)	64)		
	activation_101	(None, 25, 25,	0	
batch_normalizat...	(Activation)	64)		
	activation_104	(None, 25, 25,	0	
batch_normalizat...	(Activation)	96)		
	activation_105	(None, 25, 25,	0	
batch_normalizat...	(Activation)	32)		
	mixed0	(None, 25, 25,	0	
activation_99[0]...				

(Concatenate)	256)		
activation_101[0...			
activation_104[0...			
activation_105[0...			
conv2d_144 (Conv2D)	(None, 25, 25,	16,384	mixed0[0][0]
	64)		
batch_normalizatio...	(None, 25, 25,	192	conv2d_144[0]
[0]			
(BatchNormalizatio...	64)		
activation_109	(None, 25, 25,	0	
batch_normalizat...			
(Activation)	64)		
conv2d_142 (Conv2D)	(None, 25, 25,	12,288	mixed0[0][0]
	48)		
conv2d_145 (Conv2D)	(None, 25, 25,	55,296	
activation_109[0...			
	96)		
batch_normalizatio...	(None, 25, 25,	144	conv2d_142[0]
[0]			
(BatchNormalizatio...	48)		
batch_normalizatio...	(None, 25, 25,	288	conv2d_145[0]
[0]			
(BatchNormalizatio...	96)		

activation_107 batch_normalizat...	(None, 25, 25,	0	
(Activation)	48)		
activation_110 batch_normalizat...	(None, 25, 25,	0	
(Activation)	96)		
average_pooling2d_...	(None, 25, 25,	0	mixed0[0][0]
(AveragePooling2D)	256)		
conv2d_141 (Conv2D)	(None, 25, 25,	16,384	mixed0[0][0]
	64)		
conv2d_143 (Conv2D)	(None, 25, 25,	76,800	
activation_107[0...	64)		
conv2d_146 (Conv2D)	(None, 25, 25,	82,944	
activation_110[0...	96)		
conv2d_147 (Conv2D)	(None, 25, 25,	16,384	
average_pooling2...	64)		
batch_normalizatio...	(None, 25, 25,	192	conv2d_141[0]
[0] (BatchNormalizatio...	64)		

batch_normalization_105[0]	(None, 25, 25, 64)	192	conv2d_143[0]
batch_normalization_106[0]	(None, 25, 25, 96)	288	conv2d_146[0]
batch_normalization_107[0]	(None, 25, 25, 64)	192	conv2d_147[0]
activation_106 batch_normalization_107[0]	(None, 25, 25, 64)	0	
activation_108 batch_normalization_108[0]	(None, 25, 25, 64)	0	
activation_111 batch_normalization_109[0]	(None, 25, 25, 96)	0	
activation_112 batch_normalization_110[0]	(None, 25, 25, 64)	0	
mixed1 activation_106[0] (Concatenate) activation_108[0] activation_111[0]	(None, 25, 25, 288)	0	

activation_112[0...				
conv2d_151 (Conv2D)	(None, 25, 25,	18,432	mixed1[0][0]	
	64)			
batch_normalizatio...	(None, 25, 25,	192	conv2d_151[0]	
[0]	(BatchNormalizatio...	64)		
activation_116	(None, 25, 25,	0		
batch_normalizat...	(Activation)	64)		
conv2d_149 (Conv2D)	(None, 25, 25,	13,824	mixed1[0][0]	
	48)			
conv2d_152 (Conv2D)	(None, 25, 25,	55,296		
activation_116[0...	96)			
batch_normalizatio...	(None, 25, 25,	144	conv2d_149[0]	
[0]	(BatchNormalizatio...	48)		
batch_normalizatio...	(None, 25, 25,	288	conv2d_152[0]	
[0]	(BatchNormalizatio...	96)		
activation_114	(None, 25, 25,	0		
batch_normalizat...	(Activation)	48)		

activation_117 batch_normalizat... (Activation)	(None, 25, 25, 96)	0	
average_pooling2d_... (AveragePooling2D)	(None, 25, 25, 288)	0	mixed1[0][0]
conv2d_148 (Conv2D)	(None, 25, 25, 64)	18,432	mixed1[0][0]
conv2d_150 (Conv2D) activation_114[0...]	(None, 25, 25, 64)	76,800	
conv2d_153 (Conv2D) activation_117[0...]	(None, 25, 25, 96)	82,944	
conv2d_154 (Conv2D) average_pooling2...	(None, 25, 25, 64)	18,432	
batch_normalizatio... [0] (BatchNormalizatio...)	(None, 25, 25, 64)	192	conv2d_148[0]
batch_normalizatio... [0] (BatchNormalizatio...)	(None, 25, 25, 64)	192	conv2d_150[0]

batch_normalization_153[0]	(None, 25, 25, 96)	288	conv2d_153[0]
batch_normalization_154[0]	(None, 25, 25, 64)	192	conv2d_154[0]
activation_113 batch_normalization_153[0]	(None, 25, 25, 64)	0	
activation_115 batch_normalization_154[0]	(None, 25, 25, 64)	0	
activation_118 batch_normalization_153[0]	(None, 25, 25, 96)	0	
activation_119 batch_normalization_154[0]	(None, 25, 25, 64)	0	
mixed2 activation_113[0] (Concatenate) activation_115[0] activation_118[0] activation_119[0]	(None, 25, 25, 288)	0	
conv2d_156 (Conv2D)	(None, 25, 25, 64)	18,432	mixed2[0][0]

batch_normalization_156 [0]	(None, 25, 25, 64)	192	conv2d_156[0]
activation_121	(None, 25, 25, 64)	0	
batch_normalization_157 [0]	(None, 25, 25, 96)	55,296	
conv2d_157 (Conv2D)	(None, 25, 25, 96)		
activation_121 [0]			
batch_normalization_158 [0]	(None, 25, 25, 96)	288	conv2d_157[0]
activation_122	(None, 25, 25, 96)	0	
batch_normalization_159 [0]	(None, 25, 25, 96)		
conv2d_155 (Conv2D)	(None, 12, 12, 384)	995,328	mixed2[0][0]
conv2d_158 (Conv2D)	(None, 12, 12, 96)	82,944	
activation_122 [0]			
batch_normalization_160 [0]	(None, 12, 12, 384)	1,152	conv2d_155[0]

batch_normalization_158[0]	(None, 12, 12, 96)	288	conv2d_158[0]
activation_120 batch_normalization_158[0]	(None, 12, 12, 384)	0	
activation_123 batch_normalization_158[0]	(None, 12, 12, 96)	0	
max_pooling2d_21	(None, 12, 12, 288)	0	mixed2[0][0]
mixed3 activation_120[0]... (Concatenate) activation_123[0]... max_pooling2d_21...	(None, 12, 12, 768)	0	
conv2d_163 (Conv2D)	(None, 12, 12, 128)	98,304	mixed3[0][0]
batch_normalization_163[0]	(None, 12, 12, 128)	384	conv2d_163[0]
activation_128 batch_normalization_163[0]	(None, 12, 12, 128)	0	

conv2d_164 (Conv2D)	(None, 12, 12,	114,688	
activation_128[0]	128)		
batch_normalization_128[0]	(None, 12, 12,	384	conv2d_164[0]
(BatchNormalization)	128)		
activation_129	(None, 12, 12,	0	
batch_normalization_129[0]	128)		
(Activation)			
conv2d_160 (Conv2D)	(None, 12, 12,	98,304	mixed3[0][0]
	128)		
conv2d_165 (Conv2D)	(None, 12, 12,	114,688	
activation_129[0]	128)		
batch_normalization_160[0]	(None, 12, 12,	384	conv2d_160[0]
(BatchNormalization)	128)		
batch_normalization_165[0]	(None, 12, 12,	384	conv2d_165[0]
(BatchNormalization)	128)		
activation_125	(None, 12, 12,	0	
batch_normalization_125[0]	128)		
(Activation)			

activation_130 batch_normalizat...	(None, 12, 12,	0		
(Activation)	128)			
conv2d_161 (Conv2D) activation_125[0...	(None, 12, 12,	114,688		
	128)			
conv2d_166 (Conv2D) activation_130[0...	(None, 12, 12,	114,688		
	128)			
batch_normalizatio... [0]	(None, 12, 12,	384	conv2d_161[0]	
(BatchNormalizatio...	128)			
batch_normalizatio... [0]	(None, 12, 12,	384	conv2d_166[0]	
(BatchNormalizatio...	128)			
activation_126 batch_normalizat...	(None, 12, 12,	0		
(Activation)	128)			
activation_131 batch_normalizat...	(None, 12, 12,	0		
(Activation)	128)			
average_pooling2d_... (AveragePooling2D)	(None, 12, 12,	0	mixed3[0][0]	
	768)			

conv2d_159 (Conv2D)	(None, 12, 12, 192)	147,456	mixed3[0][0]
conv2d_162 (Conv2D)	(None, 12, 12, 192)	172,032	activation_126[0]
conv2d_167 (Conv2D)	(None, 12, 12, 192)	172,032	activation_131[0]
conv2d_168 (Conv2D)	(None, 12, 12, 192)	147,456	average_pooling2d[0]
batch_normalization[0] (Batch Normalization)	(None, 12, 12, 192)	576	conv2d_159[0]
batch_normalization[0] (Batch Normalization)	(None, 12, 12, 192)	576	conv2d_162[0]
batch_normalization[0] (Batch Normalization)	(None, 12, 12, 192)	576	conv2d_167[0]
batch_normalization[0] (Batch Normalization)	(None, 12, 12, 192)	576	conv2d_168[0]

activation_124 batch_normalizat...	(None, 12, 12,	0	
(Activation)	192)		
activation_127 batch_normalizat...	(None, 12, 12,	0	
(Activation)	192)		
activation_132 batch_normalizat...	(None, 12, 12,	0	
(Activation)	192)		
activation_133 batch_normalizat...	(None, 12, 12,	0	
(Activation)	192)		
mixed4 activation_124[0...	(None, 12, 12,	0	
(Concatenate)	768)		
activation_127[0...			
activation_132[0...			
activation_133[0...			
conv2d_173 (Conv2D)	(None, 12, 12,	122,880	mixed4[0][0]
	160)		
batch_normalizatio...	(None, 12, 12,	480	conv2d_173[0]
[0]			
(BatchNormalizatio...	160)		
activation_138 batch_normalizat...	(None, 12, 12,	0	
(Activation)	160)		

conv2d_174 (Conv2D)	(None, 12, 12,	179,200	
activation_138[0...	160)		
batch_normalizatio...	(None, 12, 12,	480	conv2d_174[0]
[0]	(BatchNormalizatio...	160)	
activation_139	(None, 12, 12,	0	
batch_normalizat...	160)		
(Activation)			
conv2d_170 (Conv2D)	(None, 12, 12,	122,880	mixed4[0][0]
	160)		
conv2d_175 (Conv2D)	(None, 12, 12,	179,200	
activation_139[0...	160)		
batch_normalizatio...	(None, 12, 12,	480	conv2d_170[0]
[0]	(BatchNormalizatio...	160)	
batch_normalizatio...	(None, 12, 12,	480	conv2d_175[0]
[0]	(BatchNormalizatio...	160)	
activation_135	(None, 12, 12,	0	
batch_normalizat...	160)		
(Activation)			

activation_140 batch_normalizat...	(None, 12, 12, 160)	0	
conv2d_171 (Conv2D) activation_135[0...	(None, 12, 12, 160)	179,200	
conv2d_176 (Conv2D) activation_140[0...	(None, 12, 12, 160)	179,200	
batch_normalizatio... [0]	(None, 12, 12, 160)	480	conv2d_171[0]
batch_normalizatio... [0]	(None, 12, 12, 160)	480	conv2d_176[0]
activation_136 batch_normalizat...	(None, 12, 12, 160)	0	
activation_141 batch_normalizat...	(None, 12, 12, 160)	0	
average_pooling2d_... (AveragePooling2D)	(None, 12, 12, 768)	0	mixed4[0][0]

conv2d_169 (Conv2D)	(None, 12, 12, 192)	147,456	mixed4[0][0]
conv2d_172 (Conv2D)	(None, 12, 12, 192)	215,040	activation_136[0]
conv2d_177 (Conv2D)	(None, 12, 12, 192)	215,040	activation_141[0]
conv2d_178 (Conv2D)	(None, 12, 12, 192)	147,456	average_pooling2d[0]
batch_normalization[0] (Batch Normalization)	(None, 12, 12, 192)	576	conv2d_169[0]
batch_normalization[0] (Batch Normalization)	(None, 12, 12, 192)	576	conv2d_172[0]
batch_normalization[0] (Batch Normalization)	(None, 12, 12, 192)	576	conv2d_177[0]
batch_normalization[0] (Batch Normalization)	(None, 12, 12, 192)	576	conv2d_178[0]

activation_134 batch_normalizat...	(None, 12, 12,	0	
(Activation)	192)		
activation_137 batch_normalizat...	(None, 12, 12,	0	
(Activation)	192)		
activation_142 batch_normalizat...	(None, 12, 12,	0	
(Activation)	192)		
activation_143 batch_normalizat...	(None, 12, 12,	0	
(Activation)	192)		
mixed5 activation_134[0...	(None, 12, 12,	0	
(Concatenate)	768)		
activation_137[0...			
activation_142[0...			
activation_143[0...			
conv2d_183 (Conv2D)	(None, 12, 12,	122,880	mixed5[0][0]
	160)		
batch_normalizatio...	(None, 12, 12,	480	conv2d_183[0]
[0]	(BatchNormalizatio...	160)	
activation_148 batch_normalizat...	(None, 12, 12,	0	
(Activation)	160)		

conv2d_184 (Conv2D) activation_148[0...]	(None, 12, 12, 160)	179,200	
batch_normalizatio... [0] (BatchNormalizatio...	(None, 12, 12, 160)	480	conv2d_184[0]
activation_149 batch_normalizati... (Activation)	(None, 12, 12, 160)	0	
conv2d_180 (Conv2D)	(None, 12, 12, 160)	122,880	mixed5[0][0]
conv2d_185 (Conv2D) activation_149[0...]	(None, 12, 12, 160)	179,200	
batch_normalizatio... [0] (BatchNormalizatio...	(None, 12, 12, 160)	480	conv2d_180[0]
batch_normalizatio... [0] (BatchNormalizatio...	(None, 12, 12, 160)	480	conv2d_185[0]
activation_145 batch_normalizati... (Activation)	(None, 12, 12, 160)	0	

activation_150 batch_normalizat...	(None, 12, 12,	0	
(Activation)	160)		
conv2d_181 (Conv2D)	(None, 12, 12,	179,200	
activation_145[0...	160)		
conv2d_186 (Conv2D)	(None, 12, 12,	179,200	
activation_150[0...	160)		
batch_normalizatio...	(None, 12, 12,	480	conv2d_181[0]
[0]	(BatchNormalizatio...	160)	
batch_normalizatio...	(None, 12, 12,	480	conv2d_186[0]
[0]	(BatchNormalizatio...	160)	
activation_146 batch_normalizat...	(None, 12, 12,	0	
(Activation)	160)		
activation_151 batch_normalizat...	(None, 12, 12,	0	
(Activation)	160)		
average_pooling2d_...	(None, 12, 12,	0	mixed5[0][0]
(AveragePooling2D)	768)		

conv2d_179 (Conv2D)	(None, 12, 12, 192)	147,456	mixed5[0][0]
conv2d_182 (Conv2D)	(None, 12, 12, 192)	215,040	activation_146[0]
conv2d_187 (Conv2D)	(None, 12, 12, 192)	215,040	activation_151[0]
conv2d_188 (Conv2D)	(None, 12, 12, 192)	147,456	average_pooling2d[0]
batch_normalization_179 (Batch Normalization)	(None, 12, 12, 192)	576	conv2d_179[0]
batch_normalization_182 (Batch Normalization)	(None, 12, 12, 192)	576	conv2d_182[0]
batch_normalization_187 (Batch Normalization)	(None, 12, 12, 192)	576	conv2d_187[0]
batch_normalization_188 (Batch Normalization)	(None, 12, 12, 192)	576	conv2d_188[0]
activation_144	(None, 12, 12, 0)	0	

batch_normalizat...	(Activation)	192)		
activation_147	(None, 12, 12,	0		
batch_normalizat...	(Activation)	192)		
activation_152	(None, 12, 12,	0		
batch_normalizat...	(Activation)	192)		
activation_153	(None, 12, 12,	0		
batch_normalizat...	(Activation)	192)		
mixed6	(None, 12, 12,	0		
activation_144[0...	(Concatenate)	768)		
activation_147[0...				
activation_152[0...				
activation_153[0...				
conv2d_193 (Conv2D)	(None, 12, 12,	147,456	mixed6[0][0]	
	192)			
batch_normalizatio...	(None, 12, 12,	576	conv2d_193[0]	
[0]	(BatchNormalizatio...	192)		
activation_158	(None, 12, 12,	0		
batch_normalizat...	(Activation)	192)		

conv2d_194 (Conv2D)	(None, 12, 12,	258,048	
activation_158[0...	192)		
batch_normalizatio...	(None, 12, 12,	576	conv2d_194[0]
[0]			
(BatchNormalizatio...	192)		
activation_159	(None, 12, 12,	0	
batch_normalizati...			
(Activation)	192)		
conv2d_190 (Conv2D)	(None, 12, 12,	147,456	mixed6[0][0]
	192)		
conv2d_195 (Conv2D)	(None, 12, 12,	258,048	
activation_159[0...	192)		
batch_normalizatio...	(None, 12, 12,	576	conv2d_190[0]
[0]			
(BatchNormalizatio...	192)		
batch_normalizatio...	(None, 12, 12,	576	conv2d_195[0]
[0]			
(BatchNormalizatio...	192)		
activation_155	(None, 12, 12,	0	
batch_normalizati...			
(Activation)	192)		

activation_160 batch_normalizat...	(None, 12, 12,	0	
(Activation)	192)		
conv2d_191 (Conv2D)	(None, 12, 12,	258,048	
activation_155[0...	192)		
conv2d_196 (Conv2D)	(None, 12, 12,	258,048	
activation_160[0...	192)		
batch_normalizatio...	(None, 12, 12,	576	conv2d_191[0]
[0]	(BatchNormalizatio...	192)	
batch_normalizatio...	(None, 12, 12,	576	conv2d_196[0]
[0]	(BatchNormalizatio...	192)	
activation_156 batch_normalizat...	(None, 12, 12,	0	
(Activation)	192)		
activation_161 batch_normalizat...	(None, 12, 12,	0	
(Activation)	192)		
average_pooling2d_...	(None, 12, 12,	0	mixed6[0][0]
(AveragePooling2D)	768)		

conv2d_189 (Conv2D)	(None, 12, 12, 192)	147,456	mixed6[0][0]
conv2d_192 (Conv2D)	(None, 12, 12, 192)	258,048	
conv2d_197 (Conv2D)	(None, 12, 12, 192)	258,048	
conv2d_198 (Conv2D)	(None, 12, 12, 192)	147,456	
batch_normalization_189 [0]	(None, 12, 12, 192)	576	conv2d_189[0]
batch_normalization_192 [0]	(None, 12, 12, 192)	576	conv2d_192[0]
batch_normalization_197 [0]	(None, 12, 12, 192)	576	conv2d_197[0]
batch_normalization_198 [0]	(None, 12, 12, 192)	576	conv2d_198[0]
activation_154	(None, 12, 12, 0)	0	

batch_normalizat...	(Activation)	192)		
activation_157	(None, 12, 12,	0		
batch_normalizat...	(Activation)	192)		
activation_162	(None, 12, 12,	0		
batch_normalizat...	(Activation)	192)		
activation_163	(None, 12, 12,	0		
batch_normalizat...	(Activation)	192)		
mixed7	(None, 12, 12,	0		
activation_154[0...	(Concatenate)	768)		
activation_157[0...				
activation_162[0...				
activation_163[0...				
conv2d_201 (Conv2D)	(None, 12, 12,	147,456	mixed7[0][0]	
	192)			
batch_normalizatio...	(None, 12, 12,	576	conv2d_201[0]	
[0]	(BatchNormalizatio...	192)		
activation_166	(None, 12, 12,	0		
batch_normalizat...	(Activation)	192)		

conv2d_202 (Conv2D)	(None, 12, 12,	258,048	
activation_166[0...	192)		
batch_normalizatio...	(None, 12, 12,	576	conv2d_202[0]
[0]			
(BatchNormalizatio...	192)		
activation_167	(None, 12, 12,	0	
batch_normalizat...			
(Activation)	192)		
conv2d_199 (Conv2D)	(None, 12, 12,	147,456	mixed7[0][0]
	192)		
conv2d_203 (Conv2D)	(None, 12, 12,	258,048	
activation_167[0...	192)		
batch_normalizatio...	(None, 12, 12,	576	conv2d_199[0]
[0]			
(BatchNormalizatio...	192)		
batch_normalizatio...	(None, 12, 12,	576	conv2d_203[0]
[0]			
(BatchNormalizatio...	192)		
activation_164	(None, 12, 12,	0	
batch_normalizat...			
(Activation)	192)		

activation_168 batch_normalizat...	(None, 12, 12, 192)	0	
conv2d_200 (Conv2D) activation_164[0...	(None, 5, 5, 320)	552,960	
conv2d_204 (Conv2D) activation_168[0...	(None, 5, 5, 192)	331,776	
batch_normalizatio... [0]	(None, 5, 5, 320)	960	conv2d_200[0]
(BatchNormalizatio...			
batch_normalizatio... [0]	(None, 5, 5, 192)	576	conv2d_204[0]
(BatchNormalizatio...			
activation_165 batch_normalizat...	(None, 5, 5, 320)	0	
(Activation)			
activation_169 batch_normalizat...	(None, 5, 5, 192)	0	
(Activation)			
max_pooling2d_22 (MaxPooling2D)	(None, 5, 5, 768)	0	mixed7[0][0]
mixed8 activation_165[0...	(None, 5, 5, 1280)	0	
(Concatenate)			
activation_169[0...			

max_pooling2d_22...			
conv2d_209 (Conv2D)	(None, 5, 5, 448)	573,440	mixed8[0][0]
batch_normalizatio... [0]	(None, 5, 5, 448)	1,344	conv2d_209[0]
(BatchNormalizatio...			
activation_174 batch_normalizat...	(None, 5, 5, 448)	0	
(Activation)			
conv2d_206 (Conv2D)	(None, 5, 5, 384)	491,520	mixed8[0][0]
conv2d_210 (Conv2D)	(None, 5, 5, 384)	1,548,288	
activation_174[0...			
batch_normalizatio... [0]	(None, 5, 5, 384)	1,152	conv2d_206[0]
(BatchNormalizatio...			
batch_normalizatio... [0]	(None, 5, 5, 384)	1,152	conv2d_210[0]
(BatchNormalizatio...			
activation_171 batch_normalizat...	(None, 5, 5, 384)	0	
(Activation)			
activation_175 batch_normalizat...	(None, 5, 5, 384)	0	
(Activation)			

conv2d_207 (Conv2D)	(None, 5, 5, 384)	442,368	
activation_171[0...			
conv2d_208 (Conv2D)	(None, 5, 5, 384)	442,368	
activation_171[0...			
conv2d_211 (Conv2D)	(None, 5, 5, 384)	442,368	
activation_175[0...			
conv2d_212 (Conv2D)	(None, 5, 5, 384)	442,368	
activation_175[0...			
average_pooling2d_...	(None, 5, 5,	0	mixed8[0][0]
(AveragePooling2D)	1280)		
conv2d_205 (Conv2D)	(None, 5, 5, 320)	409,600	mixed8[0][0]
batch_normalizatio...	(None, 5, 5, 384)	1,152	conv2d_207[0]
[0]			
(BatchNormalizatio...			
batch_normalizatio...	(None, 5, 5, 384)	1,152	conv2d_208[0]
[0]			
(BatchNormalizatio...			
batch_normalizatio...	(None, 5, 5, 384)	1,152	conv2d_211[0]
[0]			
(BatchNormalizatio...			
batch_normalizatio...	(None, 5, 5, 384)	1,152	conv2d_212[0]
[0]			
(BatchNormalizatio...			

conv2d_213 (Conv2D)	(None, 5, 5, 192)	245,760	
average_pooling2...			
batch_normalizatio...	(None, 5, 5, 320)	960	conv2d_205[0]
(BatchNormalizatio...			
activation_172	(None, 5, 5, 384)	0	
batch_normalizat...			
(Activation)			
activation_173	(None, 5, 5, 384)	0	
batch_normalizat...			
(Activation)			
activation_176	(None, 5, 5, 384)	0	
batch_normalizat...			
(Activation)			
activation_177	(None, 5, 5, 384)	0	
batch_normalizat...			
(Activation)			
batch_normalizatio...	(None, 5, 5, 192)	576	conv2d_213[0]
(BatchNormalizatio...			
activation_170	(None, 5, 5, 320)	0	
batch_normalizat...			
(Activation)			

mixed9_0	(None, 5, 5, 768)	0	
activation_172[0...]	(Concatenate)		
activation_173[0...]			
concatenate_5	(None, 5, 5, 768)	0	
activation_176[0...]	(Concatenate)		
activation_177[0...]			
activation_178	(None, 5, 5, 192)	0	
batch_normalizat...	(Activation)		
mixed9	(None, 5, 5,	0	
activation_170[0...]	(Concatenate)	2048)	mixed9_0[0]
[0],			
concatenate_5[0]...			
activation_178[0...]			
conv2d_218 (Conv2D)	(None, 5, 5, 448)	917,504	mixed9[0][0]
batch_normalizatio...	(None, 5, 5, 448)	1,344	conv2d_218[0]
[0]	(BatchNormalizatio...		
activation_183	(None, 5, 5, 448)	0	
batch_normalizat...	(Activation)		
conv2d_215 (Conv2D)	(None, 5, 5, 384)	786,432	mixed9[0][0]
conv2d_219 (Conv2D)	(None, 5, 5, 384)	1,548,288	

activation_183[0...			
batch_normalization_183[0]	(None, 5, 5, 384)	1,152	conv2d_215[0]
(BatchNormalization)			
batch_normalization_184[0]	(None, 5, 5, 384)	1,152	conv2d_219[0]
(BatchNormalization)			
activation_180	(None, 5, 5, 384)	0	
batch_normalization_180	(Activation)		
activation_184	(None, 5, 5, 384)	0	
batch_normalization_184	(Activation)		
conv2d_216 (Conv2D)	(None, 5, 5, 384)	442,368	
activation_180[0...			
conv2d_217 (Conv2D)	(None, 5, 5, 384)	442,368	
activation_180[0...			
conv2d_220 (Conv2D)	(None, 5, 5, 384)	442,368	
activation_184[0...			
conv2d_221 (Conv2D)	(None, 5, 5, 384)	442,368	
activation_184[0...			
average_pooling2d_9	(None, 5, 5,	0	mixed9[0][0]
(AveragePooling2D)	2048)		

conv2d_214 (Conv2D)	(None, 5, 5, 320)	655,360	mixed9[0][0]
batch_normalization_180 [0]	(None, 5, 5, 384)	1,152	conv2d_216[0]
(BatchNormalization)			
batch_normalization_181 [0]	(None, 5, 5, 384)	1,152	conv2d_217[0]
(BatchNormalization)			
batch_normalization_182 [0]	(None, 5, 5, 384)	1,152	conv2d_220[0]
(BatchNormalization)			
batch_normalization_183 [0]	(None, 5, 5, 384)	1,152	conv2d_221[0]
(BatchNormalization)			
conv2d_222 (Conv2D)	(None, 5, 5, 192)	393,216	
average_pooling2d_1 [0]			
batch_normalization_184 [0]	(None, 5, 5, 320)	960	conv2d_214[0]
(BatchNormalization)			
activation_181	(None, 5, 5, 384)	0	
batch_normalization_185 (Activation)			
activation_182	(None, 5, 5, 384)	0	
batch_normalization_186 (Activation)			

activation_185	(None, 5, 5, 384)	0	
batch_normalizat...			
(Activation)			
activation_186	(None, 5, 5, 384)	0	
batch_normalizat...			
(Activation)			
batch_normalizatio...	(None, 5, 5, 192)	576	conv2d_222[0]
[0]			
(BatchNormalizatio...			
activation_179	(None, 5, 5, 320)	0	
batch_normalizat...			
(Activation)			
mixed9_1	(None, 5, 5, 768)	0	
activation_181[0...			
(Concatenate)			
activation_182[0...			
concatenate_6	(None, 5, 5, 768)	0	
activation_185[0...			
(Concatenate)			
activation_186[0...			
activation_187	(None, 5, 5, 192)	0	
batch_normalizat...			
(Activation)			
mixed10	(None, 5, 5,	0	
activation_179[0...			
(Concatenate)	2048)		mixed9_1[0]
[0],			
concatenate_6[0]...			

activation_187[0...			
global_average_poo...	(None, 2048)	0	mixed10[0][0]
(GlobalAveragePool...			
dense_22 (Dense)	(None, 1024)	2,098,176	
global_average_p...			
dense_23 (Dense)	(None, 196)	200,900	dense_22[0]
[0]			

Total params: 24,101,860 (91.94 MB)

Trainable params: 2,299,076 (8.77 MB)

Non-trainable params: 21,802,784 (83.17 MB)

Epoch 1/10

1/1 _____ 10s 10s/step - accuracy: 0.0000e+00 - loss: 46.1529 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 2/10

1/1 _____ 1s 729ms/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 3/10

1/1 _____ 1s 675ms/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 4/10

1/1 _____ 1s 682ms/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 5/10

1/1 _____ 1s 714ms/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 6/10

1/1 _____ 1s 703ms/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 7/10

1/1 _____ 1s 713ms/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 8/10

1/1 _____ 1s 752ms/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 9/10


```
1/1 _____ 1s 687ms/step - accuracy: 1.0000 - loss:
0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 10/10
1/1 _____ 1s 668ms/step - accuracy: 1.0000 - loss:
0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

<keras.src.callbacks.history.History at 0x1abf1d67230>
```

6C. AlexNet

```
# Define paths
image_dir = 'Car_Images/Car Images/Test Images' # Adjust based on
your directory structure

# Prepare data
images = []
labels = []

for index, row in test_annotations_df.iterrows():
    image_name = row['Image Name']
    #image_path = os.path.join(image_dir, image_name)
    #image_path = find_image_path(image_name,
os.path.join('Car_Images', 'Car Images', 'Test Images')) # Search in
subfolders

    # Load and preprocess the image
    image = cv2.imread(image_path)
    image = cv2.resize(image, (227, 227)) # Resize to 227x227 pixels
(AlexNet input size)
    images.append(image)

    # Assuming 'Image class' contains the class label
    labels.append(row['Image class'])

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

# Encode labels
unique_classes = np.unique(labels)

def create_alexnet_model(input_shape, num_classes):
    model = Sequential()

    # First Convolutional Layer
    model.add(Conv2D(96, (11, 11), strides=(4, 4), activation='relu',
input_shape=input_shape))
    model.add(MaxPooling2D(pool_size=(3, 3), strides=(2, 2)))
    model.add(BatchNormalization())
```

```

# Second Convolutional Layer
model.add(Conv2D(256, (5, 5), padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=(3, 3), strides=(2, 2)))
model.add(BatchNormalization())

# Third Convolutional Layer
model.add(Conv2D(384, (3, 3), padding='same', activation='relu'))

# Fourth Convolutional Layer
model.add(Conv2D(384, (3, 3), padding='same', activation='relu'))

# Fifth Convolutional Layer
model.add(Conv2D(256, (3, 3), padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=(3, 3), strides=(2, 2)))
model.add(BatchNormalization())

# Flatten the output
model.add(Flatten())

# Fully Connected Layers
model.add(Dense(4096, activation='relu'))
model.add(Dropout(0.5))

model.add(Dense(4096, activation='relu'))
model.add(Dropout(0.5))

model.add(Dense(num_classes, activation='softmax'))

return model

# Create the model
input_shape = (224, 224, 3) # Image dimensions for AlexNet
num_classes = len(unique_classes)
model = create_alexnet_model(input_shape, num_classes)

model.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])

# Data augmentation
datagen = ImageDataGenerator(rotation_range=20, width_shift_range=0.2,
                             height_shift_range=0.2, shear_range=0.2,
                             zoom_range=0.2, horizontal_flip=True,
                             fill_mode='nearest')

model.summary()

# Train the model
model.fit(
    train_images, # Preprocessed training images
    train_labels, # One-hot encoded training labels

```

```

    epochs=10,
    batch_size=32,
    validation_data=(test_images, test_labels)
)

```

Model: "sequential_3"

Layer (type) Param #	Output Shape	
conv2d_109 (Conv2D) 34,944	(None, 54, 54, 96)	
max_pooling2d_13 (MaxPooling2D) 0	(None, 26, 26, 96)	
batch_normalization_103 384 (BatchNormalization)	(None, 26, 26, 96)	
conv2d_110 (Conv2D) 614,656	(None, 26, 26, 256)	
max_pooling2d_14 (MaxPooling2D) 0	(None, 12, 12, 256)	
batch_normalization_104 1,024 (BatchNormalization)	(None, 12, 12, 256)	
conv2d_111 (Conv2D) 885,120	(None, 12, 12, 384)	
conv2d_112 (Conv2D) 1,327,488	(None, 12, 12, 384)	
conv2d_113 (Conv2D)	(None, 12, 12, 256)	

884,992				
		max_pooling2d_15 (MaxPooling2D)	(None, 5, 5, 256)	
0				
		batch_normalization_105	(None, 5, 5, 256)	
1,024		(BatchNormalization)		
		flatten_4 (Flatten)	(None, 6400)	
0				
		dense_13 (Dense)	(None, 4096)	
26,218,496				
		dropout_7 (Dropout)	(None, 4096)	
0				
		dense_14 (Dense)	(None, 4096)	
16,781,312				
		dropout_8 (Dropout)	(None, 4096)	
0				
		dense_15 (Dense)	(None, 196)	
803,012				

Total params: 47,552,452 (181.40 MB)

Trainable params: 47,551,236 (181.39 MB)

Non-trainable params: 1,216 (4.75 KB)

Epoch 1/10

1/1 ————— 3s 3s/step - accuracy: 0.0000e+00 - loss: 6.6543 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

Epoch 2/10

1/1 ————— 1s 604ms/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

```

Epoch 3/10
1/1 _____ 1s 505ms/step - accuracy: 1.0000 - loss:
0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 4/10
1/1 _____ 1s 511ms/step - accuracy: 1.0000 - loss:
0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 5/10
1/1 _____ 1s 508ms/step - accuracy: 1.0000 - loss:
0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 6/10
1/1 _____ 1s 533ms/step - accuracy: 1.0000 - loss:
0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 7/10
1/1 _____ 1s 542ms/step - accuracy: 1.0000 - loss:
0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 8/10
1/1 _____ 0s 499ms/step - accuracy: 1.0000 - loss:
0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 9/10
1/1 _____ 0s 493ms/step - accuracy: 1.0000 - loss:
0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 10/10
1/1 _____ 1s 540ms/step - accuracy: 1.0000 - loss:
0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00

<keras.src.callbacks.history.History at 0x1abf06110a0>

```

6D.U-Net

```

train_images = np.random.rand(100, 128, 128, 3)
train_masks = np.random.rand(100, 128, 128, 1)

def unet_model(input_size=(128, 128, 3)):
    inputs = keras.Input(shape=input_size)

    # Encoder
    conv1 = layers.Conv2D(64, (3, 3), activation='relu',
padding='same')(inputs)
    conv1 = layers.Conv2D(64, (3, 3), activation='relu',
padding='same')(conv1)
    pool1 = layers.MaxPooling2D(pool_size=(2, 2))(conv1)

    conv2 = layers.Conv2D(128, (3, 3), activation='relu',
padding='same')(pool1)
    conv2 = layers.Conv2D(128, (3, 3), activation='relu',
padding='same')(conv2)
    pool2 = layers.MaxPooling2D(pool_size=(2, 2))(conv2)

    conv3 = layers.Conv2D(256, (3, 3), activation='relu',
padding='same')(pool2)

```

```

conv3 = layers.Conv2D(256, (3, 3), activation='relu',
padding='same')(conv3)
pool3 = layers.MaxPooling2D(pool_size=(2, 2))(conv3)

# Bottleneck
conv4 = layers.Conv2D(512, (3, 3), activation='relu',
padding='same')(pool3)
conv4 = layers.Conv2D(512, (3, 3), activation='relu',
padding='same')(conv4)

# Decoder
up5 = layers.UpSampling2D(size=(2, 2))(conv4)
concat5 = layers.Concatenate()([up5, conv3])
conv5 = layers.Conv2D(256, (3, 3), activation='relu',
padding='same')(concat5)
conv5 = layers.Conv2D(256, (3, 3), activation='relu',
padding='same')(conv5)

up6 = layers.UpSampling2D(size=(2, 2))(conv5)
concat6 = layers.Concatenate()([up6, conv2])
conv6 = layers.Conv2D(128, (3, 3), activation='relu',
padding='same')(concat6)
conv6 = layers.Conv2D(128, (3, 3), activation='relu',
padding='same')(conv6)

up7 = layers.UpSampling2D(size=(2, 2))(conv6)
concat7 = layers.Concatenate()([up7, conv1])
conv7 = layers.Conv2D(64, (3, 3), activation='relu',
padding='same')(concat7)
conv7 = layers.Conv2D(64, (3, 3), activation='relu',
padding='same')(conv7)

outputs = layers.Conv2D(1, (1, 1), activation='sigmoid')(conv7)

model = keras.Model(inputs, outputs)
return model

# Compile model
model = unet_model()
model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])

# Summary
model.summary()

# Train the model
model.fit(train_images, train_masks, epochs=10, batch_size=16,
validation_split=0.1)

Model: "functional_70"

```

Layer (type)	Output Shape	Param #	Connected to
input_layer_6 (InputLayer)	(None, 128, 128, 3)	0	-
conv2d_114 (Conv2D) input_layer_6[0]...	(None, 128, 128, 64)	1,792	
conv2d_115 (Conv2D) [0]	(None, 128, 128, 64)	36,928	conv2d_114[0]
max_pooling2d_16 [0] (MaxPooling2D)	(None, 64, 64, 64)	0	conv2d_115[0]
conv2d_116 (Conv2D) max_pooling2d_16...	(None, 64, 64, 128)	73,856	
conv2d_117 (Conv2D) [0]	(None, 64, 64, 128)	147,584	conv2d_116[0]
max_pooling2d_17 [0] (MaxPooling2D)	(None, 32, 32, 128)	0	conv2d_117[0]
conv2d_118 (Conv2D) max_pooling2d_17...	(None, 32, 32, 128)	295,168	

	256)		
conv2d_119 (Conv2D)	(None, 32, 32,	590,080	conv2d_118[0]
	256)		
max_pooling2d_18 (MaxPooling2D)	(None, 16, 16,	0	conv2d_119[0]
	256)		
conv2d_120 (Conv2D)	(None, 16, 16,	1,180,160	
max_pooling2d_18...	512)		
conv2d_121 (Conv2D)	(None, 16, 16,	2,359,808	conv2d_120[0]
	512)		
up_sampling2d (UpSampling2D)	(None, 32, 32,	0	conv2d_121[0]
	512)		
concatenate_2 (Concatenate)	(None, 32, 32,	0	
up_sampling2d[0]...	768)		conv2d_119[0]
conv2d_122 (Conv2D)	(None, 32, 32,	1,769,728	
concatenate_2[0]...	256)		
conv2d_123 (Conv2D)	(None, 32, 32,	590,080	conv2d_122[0]
	256)		

up_sampling2d_1 [0]	(None, 64, 64, (UpSampling2D)	256)	0	conv2d_123[0]
concatenate_3 up_sampling2d_1[... [0]	(Concatenate)	384)	0	conv2d_117[0]
conv2d_124 (Conv2D) concatenate_3[0]...	(None, 64, 64, 128)	442,496		
conv2d_125 (Conv2D) [0]	(None, 64, 64, 128)	147,584	conv2d_124[0]	
up_sampling2d_2 [0]	(None, 128, 128, (UpSampling2D)	128)	0	conv2d_125[0]
concatenate_4 up_sampling2d_2[... [0]	(Concatenate)	192)	0	conv2d_115[0]
conv2d_126 (Conv2D) concatenate_4[0]...	(None, 128, 128, 64)	110,656		
conv2d_127 (Conv2D) [0]	(None, 128, 128, 64)	36,928	conv2d_126[0]	

conv2d_128 (Conv2D)	(None, 128, 128,	65	conv2d_127[0]
[0]	1)		

Total params: 7,782,913 (29.69 MB)

Trainable params: 7,782,913 (29.69 MB)

Non-trainable params: 0 (0.00 B)

Epoch 1/10

6/6 ————— 19s 2s/step - accuracy: 0.0000e+00 - loss: 0.6935 - val_accuracy: 0.0000e+00 - val_loss: 0.6932

Epoch 2/10

6/6 ————— 31s 6s/step - accuracy: 0.0000e+00 - loss: 0.6932 - val_accuracy: 0.0000e+00 - val_loss: 0.6932

Epoch 3/10

6/6 ————— 25s 2s/step - accuracy: 0.0000e+00 - loss: 0.6932 - val_accuracy: 0.0000e+00 - val_loss: 0.6931

Epoch 4/10

6/6 ————— 15s 2s/step - accuracy: 0.0000e+00 - loss: 0.6931 - val_accuracy: 0.0000e+00 - val_loss: 0.6931

Epoch 5/10

6/6 ————— 15s 2s/step - accuracy: 0.0000e+00 - loss: 0.6931 - val_accuracy: 0.0000e+00 - val_loss: 0.6931

Epoch 6/10

6/6 ————— 15s 2s/step - accuracy: 0.0000e+00 - loss: 0.6931 - val_accuracy: 0.0000e+00 - val_loss: 0.6931

Epoch 7/10

6/6 ————— 15s 2s/step - accuracy: 0.0000e+00 - loss: 0.6931 - val_accuracy: 0.0000e+00 - val_loss: 0.6931

Epoch 8/10

6/6 ————— 14s 2s/step - accuracy: 0.0000e+00 - loss: 0.6931 - val_accuracy: 0.0000e+00 - val_loss: 0.6931

Epoch 9/10

6/6 ————— 14s 2s/step - accuracy: 0.0000e+00 - loss: 0.6931 - val_accuracy: 0.0000e+00 - val_loss: 0.6931

Epoch 10/10

6/6 ————— 15s 2s/step - accuracy: 0.0000e+00 - loss: 0.6931 - val_accuracy: 0.0000e+00 - val_loss: 0.6932

<keras.src.callbacks.history.History at 0x1abefa12870>

1. Summary