

# Multiclass Image Classification Project

## Analisis Sederhana terhadap Data

Link dataset: <https://www.kaggle.com/datasets/varpit94/disaster-images-dataset/code>

Dataset yang digunakan terdiri atas 6 kategori utama, yaitu:

1. Damaged\_Infrastructure (Earthquake, Infrastructure): gambar kerusakan infrastruktur / dampak gempa.
2. Fire\_Disaster (Urban\_Fire, Wild\_Fire): gambar kebakaran di urban fire dan wild fire.
3. Human\_Damage: gambar dampak bencana terhadap manusia
4. Land\_Disaster (Drought, Land\_Slide): gambar bencana tanah seperti drought dan land slide.
5. Non\_Damage (Non\_Damage\_Buildings\_Street, Non\_Damage\_Wildfire\_Forest, human, sea): gambar tanpa kerusakan, seperti bangunan dan hutan utuh, manusia, dan perairan.
6. Water\_Disaster: gambar bencana yang disebabkan oleh air.

Untuk project multiclass image classification ini, terdapat 4 class yang akan digunakan, yaitu Earthquake, Urban\_Fire, Land\_Slide, dan Water\_Disaster. Dari analisis pada tahap data preparation, dapat diketahui bahwa terdapat class imbalance pada Earthquake (jumlah gambarnya jauh lebih sedikit dibandingkan class lainnya), sehingga diperlukan beberapa pendekatan agar proses training tetap optimal.

## Environment Setup

Import modules and libraries

```
import zipfile
import random
import os
import shutil
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from PIL import Image, ImageFile
from collections import defaultdict, Counter
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix,
ConfusionMatrixDisplay
from sklearn.utils.class_weight import compute_class_weight
from sklearn.model_selection import train_test_split
```

```

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten,
Dense, Dropout, Input, BatchNormalization, GlobalAveragePooling2D,
LeakyReLU
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping,
ReduceLROnPlateau, CSVLogger
from tensorflow.keras.preprocessing import
image ,image_dataset_from_directory
from tensorflow.keras.preprocessing.image import ImageDataGenerator,
load_img, img_to_array
from tensorflow.keras.models import Model, load_model, Sequential
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.optimizers import Adam

```

Set up seed = 42

```

SEED_VALUE = 42
np.random.seed(SEED_VALUE)
random.seed(SEED_VALUE)
tf.random.set_seed(SEED_VALUE)

```

## Data Preparation

```

with zipfile.ZipFile('CDD.zip', 'r') as zip_ref:
    zip_ref.extractall('data')

dataset_root = os.path.join('data', 'Comprehensive Disaster
Dataset(CDD)')
dataset_path = 'data'
source_map = {
    'Fire_Disaster/Urban_Fire': 'Urban Fire',
    'Water_Disaster': 'Water Disaster',
    'Land_Disaster/Land_Slide': 'Land Slide',
    'Damaged_Infrastructure/Earthquake': 'Earthquake'
}

```

## EDA

### 1. Distribusi jumlah gambar per class

```

image_count = defaultdict(int)
for rel_path, class_name in source_map.items():
    full_path = os.path.join(dataset_root, rel_path)
    if os.path.isdir(full_path):
        count = len([
            fname for fname in os.listdir(full_path)

```

```

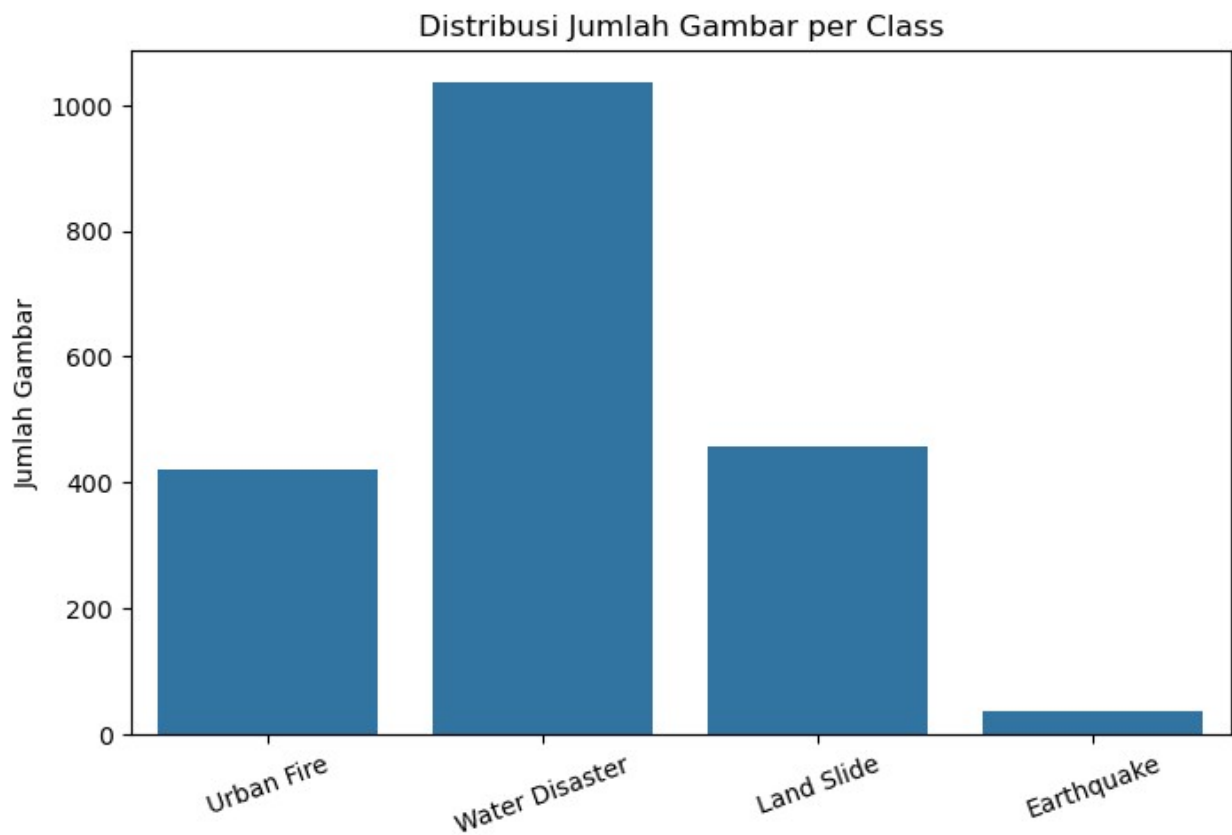
    ])
    image_count[class_name] += count

print("Jumlah gambar per class sebelum splitting:")
for cls, count in image_count.items():
    print(f"{cls}: {count}")

Jumlah gambar per class sebelum splitting:
Urban Fire: 419
Water Disaster: 1035
Land Slide: 456
Earthquake: 36

plt.figure(figsize=(8,5))
sns.barplot(x=list(image_count.keys()), y=list(image_count.values()))
plt.title("Distribusi Jumlah Gambar per Class")
plt.ylabel("Jumlah Gambar")
plt.xticks(rotation=20)
plt.show()

```



Dataset memiliki distribusi jumlah gambar yang tidak seimbang antar class. Terlihat bahwa Water Disaster (1035 gambar) mendominasi dataset, sementara Earthquake (36 gambar) sangat sedikit sehingga berpotensi menyebabkan **class imbalance** pada model.

## 2. Contoh gambar dari setiap class

```
plt.figure(figsize=(12, 8))
for i, (rel_path, class_name) in enumerate(source_map.items()):
    full_path = os.path.join(dataset_root, rel_path)
    sample_img = random.choice(os.listdir(full_path))
    img = Image.open(os.path.join(full_path, sample_img))
    plt.subplot(2, 2, i+1)
    plt.imshow(img)
    plt.title(class_name)
    plt.axis("off")
plt.suptitle("Contoh Gambar dari Setiap Class", fontsize=16)
plt.show()
```

### Contoh Gambar dari Setiap Class

Urban Fire



Water Disaster



Land Slide



Earthquake



Berdasarkan contoh gambar dari masing-masing class di atas, dapat diketahui bahwa ciri khasnya adalah:

- Urban Fire: api di area perkotaan
- Water Disaster: banjir atau bencana air
- Land Slide: longsor di area pemukiman atau jalan
- Earthquake: reruntuhan akibat gempa bumi

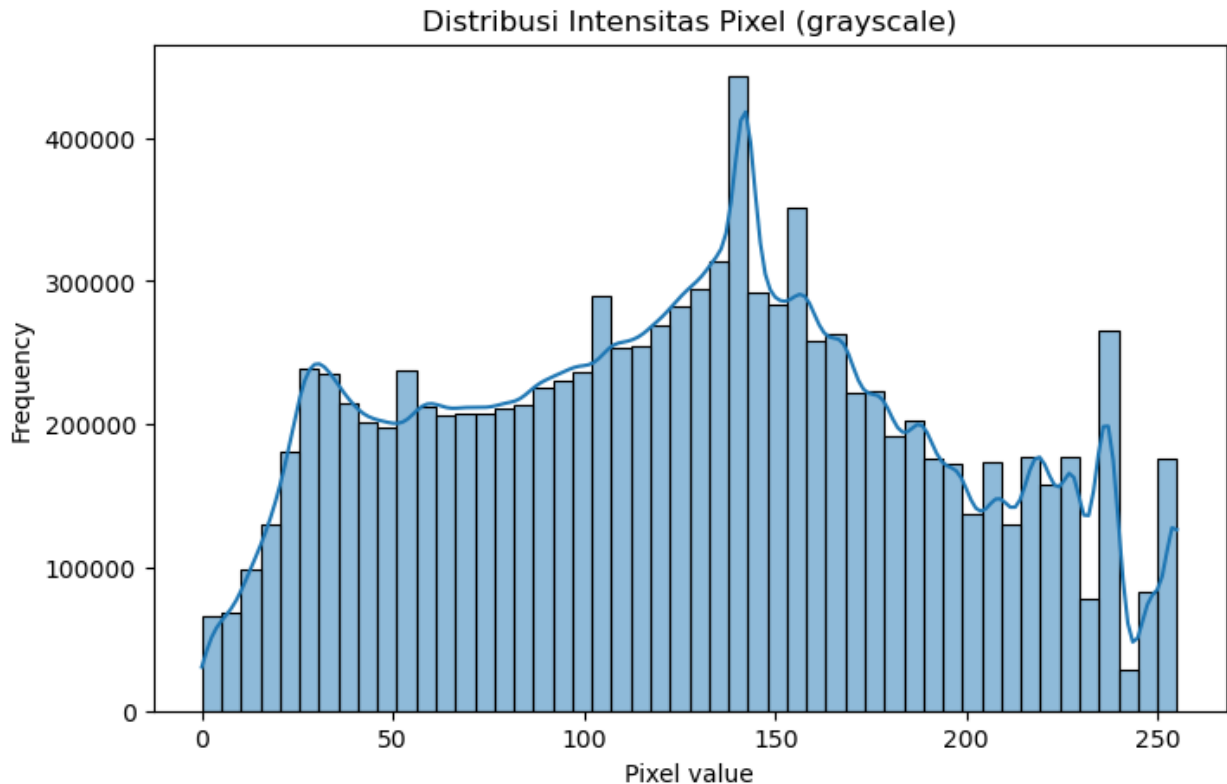
Visualisasi ini membantu memastikan bahwa label data sudah sesuai dengan isi gambar.

### 3. Distribusi intensitas pixel (10 sample per class)

```
sample_paths = []
for rel_path, _ in source_map.items():
    full_path = os.path.join(dataset_root, rel_path)
    sample_paths.extend([os.path.join(full_path, f) for f in
os.listdir(full_path)[:10]])

pixels = []
for sp in sample_paths:
    img = Image.open(sp).convert("L")
    pixels.extend(np.array(img).flatten())
    img.close()

plt.figure(figsize=(8,5))
sns.histplot(pixels, bins=50, kde=True)
plt.title("Distribusi Intensitas Pixel (grayscale)")
plt.xlabel("Pixel value")
plt.ylabel("Frequency")
plt.show()
```



Analisis ini dilakukan dengan mengambil 10 sampel gambar dari tiap class (total 40 gambar), lalu mengonversinya ke grayscale dan menghitung distribusi nilai piksel (0 = hitam, 255 = putih).

- Nilai piksel tersebar dari 0 hingga 255, menandakan adanya variasi pencahayaan yang luas.
- Terlihat puncak distribusi di sekitar 150, menandakan banyak gambar memiliki area terang.
- Frekuensi piksel gelap (< 50) juga cukup tinggi, menandakan keberadaan objek kontras seperti api, reruntuhan, atau bayangan.

Dapat disimpulkan bahwa dataset memiliki kontras tinggi antara area gelap dan terang, sehingga preprocessing seperti normalisasi pixel akan sangat dibutuhkan agar model lebih stabil saat training.

## Splitting Data

```
for split in ['train', 'test']:
    split_dir = os.path.join(dataset_path, split)
    if os.path.exists(split_dir):
        shutil.rmtree(split_dir)

split_ratio = 0.8

for rel_path, label in source_map.items():
```

```

src_folder = os.path.join(dataset_root, rel_path)
all_files = [f for f in os.listdir(src_folder)]
random.shuffle(all_files)

split_idx = int(len(all_files) * split_ratio)
train_files = all_files[:split_idx]
test_files = all_files[split_idx:]

for fname in train_files:
    dst = os.path.join(dataset_path, 'train', label)
    os.makedirs(dst, exist_ok=True)
    shutil.copy(os.path.join(src_folder, fname), os.path.join(dst,
fname))

for fname in test_files:
    dst = os.path.join(dataset_path, 'test', label)
    os.makedirs(dst, exist_ok=True)
    shutil.copy(os.path.join(src_folder, fname), os.path.join(dst,
fname))

print(f"{label} - train: {len(train_files)}, test:
{len(test_files)}")

```

```

Urban Fire - train: 335, test: 84
Water Disaster - train: 828, test: 207
Land Slide - train: 364, test: 92
Earthquake - train: 28, test: 8

```

```

def detect_tf_decode_errors(directory):
    problematic_files = []
    for root, _, files in os.walk(directory):
        for file in files:
            if file.lower().endswith(('.jpg', '.jpeg', '.png', '.bmp',
'.gif')):
                file_path = os.path.join(root, file)
                try:
                    image_data = tf.io.read_file(file_path)
                    _ = tf.image.decode_image(image_data, channels=3)
                except tf.errors.InvalidArgumentError:
                    print("TensorFlow decode error:", file_path)
                    problematic_files.append(file_path)
    return problematic_files

```

```

train_dir = "data/train"
test_dir = "data/test"

```

```

errors_train = detect_tf_decode_errors(train_dir)
errors_test = detect_tf_decode_errors(test_dir)

```

```

TensorFlow decode error: data/train\Land Slide\04_01_0007.png
TensorFlow decode error: data/train\Land Slide\04_01_0335.png

```

TensorFlow decode error: data/train\Urban Fire\01\_01\_0060.png  
TensorFlow decode error: data/test\Land Slide\04\_01\_0373.png

```
files_to_remove = [  
    "data/train/Land Slide/04_01_0007.png",  
    "data/train/Land Slide/04_01_0335.png",  
    "data/train/Urban Fire/01_01_0060.png",  
    "data/test/Land Slide/04_01_0373.png"  
]  
  
for file_path in files_to_remove:  
    if os.path.exists(file_path):  
        os.remove(file_path)  
        print(f"file removed: {file_path}")  
    else:  
        print(f"file not found: {file_path}")  
  
file removed: data/train/Land Slide/04_01_0007.png  
file removed: data/train/Land Slide/04_01_0335.png  
file removed: data/train/Urban Fire/01_01_0060.png  
file removed: data/test/Land Slide/04_01_0373.png  
  
image_size = (224, 224)  
batch_size = 32  
AUTOTUNE = tf.data.AUTOTUNE  
  
train_ds = tf.keras.preprocessing.image_dataset_from_directory(  
    os.path.join(dataset_path, 'train'),  
    validation_split=0.2,  
    subset="training",  
    seed=SEED_VALUE,  
    label_mode='categorical',  
    image_size=image_size,  
    batch_size=batch_size,  
    shuffle=True  
)  
  
val_ds = tf.keras.preprocessing.image_dataset_from_directory(  
    os.path.join(dataset_path, 'train'),  
    validation_split=0.2,  
    subset="validation",  
    seed=SEED_VALUE,  
    label_mode='categorical',  
    image_size=image_size,  
    batch_size=batch_size,  
    shuffle=True  
)  
  
test_ds = tf.keras.preprocessing.image_dataset_from_directory(  
    os.path.join(dataset_path, 'test'),
```



```

        label_mode='categorical',
        image_size=image_size,
        batch_size=batch_size,
        shuffle=False
    )

    Found 1552 files belonging to 4 classes.
    Using 1242 files for training.
    Found 1552 files belonging to 4 classes.
    Using 310 files for validation.
    Found 390 files belonging to 4 classes.

    label_names = train_ds.class_names

```

## Normalization

```

normalization_layer = tf.keras.layers.Rescaling(1./255)
train_ds = train_ds.map(lambda x, y: (normalization_layer(x), y),
    num_parallel_calls=AUTOTUNE)
val_ds = val_ds.map(lambda x, y: (normalization_layer(x), y),
    num_parallel_calls=AUTOTUNE)
test_ds = test_ds.map(lambda x, y: (normalization_layer(x), y),
    num_parallel_calls=AUTOTUNE)

```

Data normalization ini berfungsi untuk meningkatkan akurasi dengan mengubah pixel dari 0-255 (RGB) jadi nilai 0-1.

## Augmentation

```

data_augmentation = tf.keras.Sequential([
    tf.keras.layers.RandomFlip("horizontal"),
    tf.keras.layers.RandomRotation(0.05),
    tf.keras.layers.RandomZoom(0.1),
    tf.keras.layers.RandomContrast(0.1)
])

train_ds = train_ds.map(lambda x, y: (data_augmentation(x,
    training=True), y), num_parallel_calls=AUTOTUNE)

```

Data augmentation berfungsi untuk menghindari overfitting dengan menambah variasi data training secara acak.

## Prefetch

```

train_ds = train_ds.prefetch(buffer_size=AUTOTUNE)
val_ds = val_ds.prefetch(buffer_size=AUTOTUNE)
test_ds = test_ds.prefetch(buffer_size=AUTOTUNE)

```

Prefetch untuk meningkatkan optimasi performance.

# Modelling and Experimentation

```
early_stop = EarlyStopping(monitor='val_loss', patience=5,
restore_best_weights=True)

all_labels = []
for images, labels in train_ds.unbatch():
    label_val = labels.numpy()
    if label_val.ndim > 0 and label_val.size > 1:
        label_scalar = np.argmax(label_val)
    else:
        label_scalar = label_val.item()
    all_labels.append(label_scalar)

all_labels = np.array(all_labels)

class_weights = compute_class_weight(
    class_weight='balanced',
    classes=np.unique(all_labels),
    y=all_labels
)

class_weight_dict = dict(enumerate(class_weights))
print("class weights:", class_weight_dict)

class weights: {0: 14.785714285714286, 1: 1.0315614617940199, 2:
1.154275092936803, 3: 0.4769585253456221}
```

Dari distribusi data di atas, terlihat bahwa jumlah sampel pada kelas Earthquake jauh lebih sedikit dibandingkan kelas lain (hanya 36 gambar). Jika dilakukan training pada dataset yang imbalanced, model cenderung bias terhadap kelas mayoritas dan menyebabkan performa prediksi pada kelas minoritas (seperti Earthquake) akan buruk.

Untuk mengurangi masalah tersebut, digunakan metode class weighting, yaitu memberikan bobot lebih besar pada kelas yang jumlah datanya sedikit, dan bobot lebih kecil pada kelas dengan jumlah data yang banyak.

```
label_names
['Earthquake', 'Land Slide', 'Urban Fire', 'Water Disaster']
```

LABEL:

0 - Earthquake ; 1 - Land slide ; 2 - Urban Fire ; 3 - Water Disaster

## Model 1 (from scratch)

```
def design_model1(input_shape=(224, 224, 3), num_classes=4):
    model = Sequential([
        Input(shape=input_shape),
```

```

Conv2D(32, (3, 3), activation='relu'),
MaxPooling2D(pool_size=(2, 2)),
BatchNormalization(),

Conv2D(64, (3, 3), activation='relu'),
MaxPooling2D(pool_size=(2, 2)),
BatchNormalization(),

Conv2D(128, (3, 3), activation='relu'),
MaxPooling2D(pool_size=(2, 2)),
BatchNormalization(),

Flatten(),
Dense(128, activation='relu'),
Dropout(0.5),
Dense(num_classes, activation='softmax')
])
return model

```

- Terdiri atas 4 hidden layers dengan aktivasi relu.
- Output layer menggunakan fungsi aktivasi softmax karena digunakan untuk klasifikasi multi-class.

```

model1 = design_model1()
model1.compile(optimizer=Adam(learning_rate=0.001), loss='categorical_crossentropy', metrics=['accuracy'])

```

```
model1.summary()
```

Model: "sequential\_1"

Layer (type) Param #	Output Shape
conv2d (Conv2D) 896	(None, 222, 222, 32)
max_pooling2d (MaxPooling2D) 0	(None, 111, 111, 32)
batch_normalization 128 (BatchNormalization)	(None, 111, 111, 32)

conv2d_1 (Conv2D)	(None, 109, 109, 64)
18,496	
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 64)
0	
batch_normalization_1	(None, 54, 54, 64)
256	
(BatchNormalization)	
conv2d_2 (Conv2D)	(None, 52, 52, 128)
73,856	
max_pooling2d_2 (MaxPooling2D)	(None, 26, 26, 128)
0	
batch_normalization_2	(None, 26, 26, 128)
512	
(BatchNormalization)	
flatten (Flatten)	(None, 86528)
0	
dense (Dense)	(None, 128)
11,075,712	
dropout (Dropout)	(None, 128)
0	
dense_1 (Dense)	(None, 4)
516	

Total params: 11,170,372 (42.61 MB)

Trainable params: 11,169,924 (42.61 MB)

Non-trainable params: 448 (1.75 KB)

```
history_model1 = model1.fit(train_ds,
                             validation_data=val_ds,
                             epochs=50,
                             callbacks=[early_stop],
                             class_weight=class_weight_dict)
```

Epoch 1/50

39/39 \_\_\_\_\_ 87s 2s/step - accuracy: 0.3901 - loss: 13.6744 - val\_accuracy: 0.2065 - val\_loss: 5.9115

Epoch 2/50

39/39 \_\_\_\_\_ 78s 2s/step - accuracy: 0.4790 - loss: 12.7139 - val\_accuracy: 0.0484 - val\_loss: 10.7566

Epoch 3/50

39/39 \_\_\_\_\_ 76s 2s/step - accuracy: 0.4607 - loss: 8.5047 - val\_accuracy: 0.2032 - val\_loss: 16.0583

Epoch 4/50

39/39 \_\_\_\_\_ 71s 2s/step - accuracy: 0.5029 - loss: 7.4182 - val\_accuracy: 0.4613 - val\_loss: 4.6407

Epoch 5/50

39/39 \_\_\_\_\_ 69s 2s/step - accuracy: 0.5269 - loss: 3.8800 - val\_accuracy: 0.5806 - val\_loss: 2.5381

Epoch 6/50

39/39 \_\_\_\_\_ 70s 2s/step - accuracy: 0.4924 - loss: 3.0708 - val\_accuracy: 0.4290 - val\_loss: 2.7457

Epoch 7/50

39/39 \_\_\_\_\_ 74s 2s/step - accuracy: 0.4681 - loss: 3.8117 - val\_accuracy: 0.5355 - val\_loss: 6.3857

Epoch 8/50

39/39 \_\_\_\_\_ 75s 2s/step - accuracy: 0.4989 - loss: 4.4235 - val\_accuracy: 0.3935 - val\_loss: 6.3608

Epoch 9/50

39/39 \_\_\_\_\_ 75s 2s/step - accuracy: 0.4102 - loss: 2.3355 - val\_accuracy: 0.3065 - val\_loss: 5.7916

Epoch 10/50

39/39 \_\_\_\_\_ 74s 2s/step - accuracy: 0.4531 - loss: 2.0704 - val\_accuracy: 0.4516 - val\_loss: 7.8406

## Model 2 (params < 10M)

```
def design_model2(input_shape=(224, 224, 3), num_classes=4):
    base_model = MobileNetV2(include_top=False, weights='imagenet',
                              input_shape=input_shape)
    base_model.trainable = True

    for layer in base_model.layers[:-50]:
        layer.trainable = False

    x = base_model.output
```

```

x = GlobalAveragePooling2D()(x)
x = Dropout(0.3)(x)
x = Dense(128, activation='relu')(x)
x = Dropout(0.3)(x)
predictions = Dense(num_classes, activation='softmax')(x)

model = Model(inputs=base_model.input, outputs=predictions)
return model

```

- Output layer menggunakan fungsi aktivasi softmax karena digunakan untuk klasifikasi multi-class.

```

model2 = design_model2()
model2.compile(optimizer=Adam(learning_rate=0.0001),
               loss='categorical_crossentropy',
               metrics=['accuracy'])

```

```
model2.summary()
```

```
Model: "functional_2"
```

Layer (type)	Output Shape
Param #	Connected to
input_layer_2 (InputLayer)	(None, 224, 224, 3)
0   -	
Conv1 (Conv2D)	(None, 112, 112, 32)
864   input_layer_2[0][0]	
bn_Conv1 (BatchNormalization)	(None, 112, 112, 32)
128   Conv1[0][0]	
Conv1_relu (ReLU)	(None, 112, 112, 32)
0   bn_Conv1[0][0]	
expanded_conv_depthwise	(None, 112, 112, 32)
288   Conv1_relu[0][0]	
(DepthwiseConv2D)	
expanded_conv_depthwise_BN	(None, 112, 112, 32)

128	expanded_conv_depthwise[0...		
	(BatchNormalization)		
	expanded_conv_depthwise_relu	(None, 112, 112, 32)	
0	expanded_conv_depthwise_B...		
	(ReLU)		
	expanded_conv_project	(None, 112, 112, 16)	
512	expanded_conv_depthwise_r...		
	(Conv2D)		
	expanded_conv_project_BN	(None, 112, 112, 16)	
64	expanded_conv_project[0][...		
	(BatchNormalization)		
	block_1_expand (Conv2D)	(None, 112, 112, 96)	
1,536	expanded_conv_project_BN[...		
	block_1_expand_BN	(None, 112, 112, 96)	
384	block_1_expand[0][0]		
	(BatchNormalization)		
	block_1_expand_relu (ReLU)	(None, 112, 112, 96)	
0	block_1_expand_BN[0][0]		
	block_1_pad (ZeroPadding2D)	(None, 113, 113, 96)	
0	block_1_expand_relu[0][0]		
	block_1_depthwise	(None, 56, 56, 96)	
864	block_1_pad[0][0]		
	(DepthwiseConv2D)		
	block_1_depthwise_BN	(None, 56, 56, 96)	
384	block_1_depthwise[0][0]		

	(BatchNormalization)		
	block_1_depthwise_relu (ReLU)	(None, 56, 56, 96)	
0	block_1_depthwise_BN[0][0]		
	block_1_project (Conv2D)	(None, 56, 56, 24)	
2,304	block_1_depthwise_relu[0]...		
	block_1_project_BN	(None, 56, 56, 24)	
96	block_1_project[0][0]		
	(BatchNormalization)		
	block_2_expand (Conv2D)	(None, 56, 56, 144)	
3,456	block_1_project_BN[0][0]		
	block_2_expand_BN	(None, 56, 56, 144)	
576	block_2_expand[0][0]		
	(BatchNormalization)		
	block_2_expand_relu (ReLU)	(None, 56, 56, 144)	
0	block_2_expand_BN[0][0]		
	block_2_depthwise	(None, 56, 56, 144)	
1,296	block_2_expand_relu[0][0]		
	(DepthwiseConv2D)		
	block_2_depthwise_BN	(None, 56, 56, 144)	
576	block_2_depthwise[0][0]		
	(BatchNormalization)		
	block_2_depthwise_relu (ReLU)	(None, 56, 56, 144)	
0	block_2_depthwise_BN[0][0]		
	block_2_project (Conv2D)	(None, 56, 56, 24)	



3,456		block_2_depthwise_relu[0]...		
		block_2_project_BN		(None, 56, 56, 24)
96		block_2_project[0][0]		
		(BatchNormalization)		
		block_2_add (Add)		(None, 56, 56, 24)
0		block_1_project_BN[0][0],		
		block_2_project_BN[0][0]		
		block_3_expand (Conv2D)		(None, 56, 56, 144)
3,456		block_2_add[0][0]		
		block_3_expand_BN		(None, 56, 56, 144)
576		block_3_expand[0][0]		
		(BatchNormalization)		
		block_3_expand_relu (ReLU)		(None, 56, 56, 144)
0		block_3_expand_BN[0][0]		
		block_3_pad (ZeroPadding2D)		(None, 57, 57, 144)
0		block_3_expand_relu[0][0]		
		block_3_depthwise		(None, 28, 28, 144)
1,296		block_3_pad[0][0]		
		(DepthwiseConv2D)		
		block_3_depthwise_BN		(None, 28, 28, 144)
576		block_3_depthwise[0][0]		
		(BatchNormalization)		
		block_3_depthwise_relu (ReLU)		(None, 28, 28, 144)
0		block_3_depthwise_BN[0][0]		

4,608	block_3_project (Conv2D)	(None, 28, 28, 32)	
	block_3_depthwise_relu[0]...		
128	block_3_project_BN	(None, 28, 28, 32)	
	block_3_project[0][0]		
	(BatchNormalization)		
6,144	block_4_expand (Conv2D)	(None, 28, 28, 192)	
	block_3_project_BN[0][0]		
768	block_4_expand_BN	(None, 28, 28, 192)	
	block_4_expand[0][0]		
	(BatchNormalization)		
0	block_4_expand_relu (ReLU)	(None, 28, 28, 192)	
	block_4_expand_BN[0][0]		
1,728	block_4_depthwise	(None, 28, 28, 192)	
	block_4_expand_relu[0][0]		
	(DepthwiseConv2D)		
768	block_4_depthwise_BN	(None, 28, 28, 192)	
	block_4_depthwise[0][0]		
	(BatchNormalization)		
0	block_4_depthwise_relu (ReLU)	(None, 28, 28, 192)	
	block_4_depthwise_BN[0][0]		
6,144	block_4_project (Conv2D)	(None, 28, 28, 32)	
	block_4_depthwise_relu[0]...		
128	block_4_project_BN	(None, 28, 28, 32)	
	block_4_project[0][0]		
	(BatchNormalization)		

	block_4_add (Add)	(None, 28, 28, 32)	
0	block_3_project_BN[0][0],		
	block_4_project_BN[0][0]		
	block_5_expand (Conv2D)	(None, 28, 28, 192)	
6,144	block_4_add[0][0]		
	block_5_expand_BN	(None, 28, 28, 192)	
768	block_5_expand[0][0]		
	(BatchNormalization)		
	block_5_expand_relu (ReLU)	(None, 28, 28, 192)	
0	block_5_expand_BN[0][0]		
	block_5_depthwise	(None, 28, 28, 192)	
1,728	block_5_expand_relu[0][0]		
	(DepthwiseConv2D)		
	block_5_depthwise_BN	(None, 28, 28, 192)	
768	block_5_depthwise[0][0]		
	(BatchNormalization)		
	block_5_depthwise_relu (ReLU)	(None, 28, 28, 192)	
0	block_5_depthwise_BN[0][0]		
	block_5_project (Conv2D)	(None, 28, 28, 32)	
6,144	block_5_depthwise_relu[0]...		
	block_5_project_BN	(None, 28, 28, 32)	
128	block_5_project[0][0]		
	(BatchNormalization)		
	block_5_add (Add)	(None, 28, 28, 32)	
0	block_4_add[0][0],		

block_5_project_BN[0][0]		
block_6_expand (Conv2D) 6,144   block_5_add[0][0]	(None, 28, 28, 192)	
block_6_expand_BN 768   block_6_expand[0][0] (BatchNormalization)	(None, 28, 28, 192)	
block_6_expand_relu (ReLU) 0   block_6_expand_BN[0][0]	(None, 28, 28, 192)	
block_6_pad (ZeroPadding2D) 0   block_6_expand_relu[0][0]	(None, 29, 29, 192)	
block_6_depthwise 1,728   block_6_pad[0][0] (DepthwiseConv2D)	(None, 14, 14, 192)	
block_6_depthwise_BN 768   block_6_depthwise[0][0] (BatchNormalization)	(None, 14, 14, 192)	
block_6_depthwise_relu (ReLU) 0   block_6_depthwise_BN[0][0]	(None, 14, 14, 192)	
block_6_project (Conv2D) 12,288   block_6_depthwise_relu[0]...	(None, 14, 14, 64)	
block_6_project_BN 256   block_6_project[0][0] (BatchNormalization)	(None, 14, 14, 64)	
block_7_expand (Conv2D)	(None, 14, 14, 384)	

24,576		block_6_project_BN[0][0]			
		block_7_expand_BN		(None, 14, 14, 384)	
1,536		block_7_expand[0][0]			
		(BatchNormalization)			
		block_7_expand_relu (ReLU)		(None, 14, 14, 384)	
0		block_7_expand_BN[0][0]			
		block_7_depthwise		(None, 14, 14, 384)	
3,456		block_7_expand_relu[0][0]			
		(DepthwiseConv2D)			
		block_7_depthwise_BN		(None, 14, 14, 384)	
1,536		block_7_depthwise[0][0]			
		(BatchNormalization)			
		block_7_depthwise_relu (ReLU)		(None, 14, 14, 384)	
0		block_7_depthwise_BN[0][0]			
		block_7_project (Conv2D)		(None, 14, 14, 64)	
24,576		block_7_depthwise_relu[0]...			
		block_7_project_BN		(None, 14, 14, 64)	
256		block_7_project[0][0]			
		(BatchNormalization)			
		block_7_add (Add)		(None, 14, 14, 64)	
0		block_6_project_BN[0][0],			
		block_7_project_BN[0][0]			
		block_8_expand (Conv2D)		(None, 14, 14, 384)	
24,576		block_7_add[0][0]			

1,536	block_8_expand_BN block_8_expand[0][0] (BatchNormalization)	(None, 14, 14, 384)	
0	block_8_expand_relu (ReLU) block_8_expand_BN[0][0]	(None, 14, 14, 384)	
3,456	block_8_depthwise block_8_expand_relu[0][0] (DepthwiseConv2D)	(None, 14, 14, 384)	
1,536	block_8_depthwise_BN block_8_depthwise[0][0] (BatchNormalization)	(None, 14, 14, 384)	
0	block_8_depthwise_relu (ReLU) block_8_depthwise_BN[0][0]	(None, 14, 14, 384)	
24,576	block_8_project (Conv2D) block_8_depthwise_relu[0]...	(None, 14, 14, 64)	
256	block_8_project_BN block_8_project[0][0] (BatchNormalization)	(None, 14, 14, 64)	
0	block_8_add (Add) block_7_add[0][0], block_8_project_BN[0][0]	(None, 14, 14, 64)	
24,576	block_9_expand (Conv2D) block_8_add[0][0]	(None, 14, 14, 384)	
1,536	block_9_expand_BN block_9_expand[0][0] (BatchNormalization)	(None, 14, 14, 384)	

	block_9_expand_relu (ReLU)	(None, 14, 14, 384)	
0	block_9_expand_BN[0][0]		
	block_9_depthwise	(None, 14, 14, 384)	
3,456	block_9_expand_relu[0][0]		
	(DepthwiseConv2D)		
	block_9_depthwise_BN	(None, 14, 14, 384)	
1,536	block_9_depthwise[0][0]		
	(BatchNormalization)		
	block_9_depthwise_relu (ReLU)	(None, 14, 14, 384)	
0	block_9_depthwise_BN[0][0]		
	block_9_project (Conv2D)	(None, 14, 14, 64)	
24,576	block_9_depthwise_relu[0]...		
	block_9_project_BN	(None, 14, 14, 64)	
256	block_9_project[0][0]		
	(BatchNormalization)		
	block_9_add (Add)	(None, 14, 14, 64)	
0	block_8_add[0][0],		
	block_9_project_BN[0][0]		
	block_10_expand (Conv2D)	(None, 14, 14, 384)	
24,576	block_9_add[0][0]		
	block_10_expand_BN	(None, 14, 14, 384)	
1,536	block_10_expand[0][0]		
	(BatchNormalization)		

	block_10_expand_relu (ReLU)	(None, 14, 14, 384)	
0	block_10_expand_BN[0][0]		
	block_10_depthwise	(None, 14, 14, 384)	
3,456	block_10_expand_relu[0][0]		
	(DepthwiseConv2D)		
	block_10_depthwise_BN	(None, 14, 14, 384)	
1,536	block_10_depthwise[0][0]		
	(BatchNormalization)		
	block_10_depthwise_relu	(None, 14, 14, 384)	
0	block_10_depthwise_BN[0][...]		
	(ReLU)		
	block_10_project (Conv2D)	(None, 14, 14, 96)	
36,864	block_10_depthwise_relu[0]...		
	block_10_project_BN	(None, 14, 14, 96)	
384	block_10_project[0][0]		
	(BatchNormalization)		
	block_11_expand (Conv2D)	(None, 14, 14, 576)	
55,296	block_10_project_BN[0][0]		
	block_11_expand_BN	(None, 14, 14, 576)	
2,304	block_11_expand[0][0]		
	(BatchNormalization)		
	block_11_expand_relu (ReLU)	(None, 14, 14, 576)	
0	block_11_expand_BN[0][0]		
	block_11_depthwise	(None, 14, 14, 576)	
5,184	block_11_expand_relu[0][0]		
	(DepthwiseConv2D)		



	block_11_depthwise_BN	(None, 14, 14, 576)	
2,304	block_11_depthwise[0][0]		
	(BatchNormalization)		
	block_11_depthwise_relu	(None, 14, 14, 576)	
0	block_11_depthwise_BN[0][...]		
	(ReLU)		
	block_11_project (Conv2D)	(None, 14, 14, 96)	
55,296	block_11_depthwise_relu[0...		
	block_11_project_BN	(None, 14, 14, 96)	
384	block_11_project[0][0]		
	(BatchNormalization)		
	block_11_add (Add)	(None, 14, 14, 96)	
0	block_10_project_BN[0][0],		
	block_11_project_BN[0][0]		
	block_12_expand (Conv2D)	(None, 14, 14, 576)	
55,296	block_11_add[0][0]		
	block_12_expand_BN	(None, 14, 14, 576)	
2,304	block_12_expand[0][0]		
	(BatchNormalization)		
	block_12_expand_relu (ReLU)	(None, 14, 14, 576)	
0	block_12_expand_BN[0][0]		
	block_12_depthwise	(None, 14, 14, 576)	
5,184	block_12_expand_relu[0][0]		
	(DepthwiseConv2D)		

2,304	block_12_depthwise_BN   block_12_depthwise[0][0] (BatchNormalization)	(None, 14, 14, 576)	
0	block_12_depthwise_relu   block_12_depthwise_BN[0][...] (ReLU)	(None, 14, 14, 576)	
55,296	block_12_project (Conv2D)   block_12_depthwise_relu[0...]	(None, 14, 14, 96)	
384	block_12_project_BN   block_12_project[0][0] (BatchNormalization)	(None, 14, 14, 96)	
0	block_12_add (Add)   block_11_add[0][0],   block_12_project_BN[0][0]	(None, 14, 14, 96)	
55,296	block_13_expand (Conv2D)   block_12_add[0][0]	(None, 14, 14, 576)	
2,304	block_13_expand_BN   block_13_expand[0][0] (BatchNormalization)	(None, 14, 14, 576)	
0	block_13_expand_relu (ReLU)   block_13_expand_BN[0][0]	(None, 14, 14, 576)	
0	block_13_pad (ZeroPadding2D)   block_13_expand_relu[0][0]	(None, 15, 15, 576)	
5,184	block_13_depthwise   block_13_pad[0][0]	(None, 7, 7, 576)	

	(DepthwiseConv2D)		
2,304	block_13_depthwise_BN block_13_depthwise[0][0] (BatchNormalization)	(None, 7, 7, 576)	
0	block_13_depthwise_relu block_13_depthwise_BN[0][...] (ReLU)	(None, 7, 7, 576)	
92,160	block_13_project (Conv2D) block_13_depthwise_relu[0]...	(None, 7, 7, 160)	
640	block_13_project_BN block_13_project[0][0] (BatchNormalization)	(None, 7, 7, 160)	
153,600	block_14_expand (Conv2D) block_13_project_BN[0][0]	(None, 7, 7, 960)	
3,840	block_14_expand_BN block_14_expand[0][0] (BatchNormalization)	(None, 7, 7, 960)	
0	block_14_expand_relu (ReLU) block_14_expand_BN[0][0]	(None, 7, 7, 960)	
8,640	block_14_depthwise block_14_expand_relu[0][0] (DepthwiseConv2D)	(None, 7, 7, 960)	
3,840	block_14_depthwise_BN block_14_depthwise[0][0] (BatchNormalization)	(None, 7, 7, 960)	

	block_14_depthwise_relu	(None, 7, 7, 960)	
0	block_14_depthwise_BN[0][...]		
	(ReLU)		
	block_14_project (Conv2D)	(None, 7, 7, 160)	
153,600	block_14_depthwise_relu[0...]		
	block_14_project_BN	(None, 7, 7, 160)	
640	block_14_project[0][0]		
	(BatchNormalization)		
	block_14_add (Add)	(None, 7, 7, 160)	
0	block_13_project_BN[0][0],		
	block_14_project_BN[0][0]		
	block_15_expand (Conv2D)	(None, 7, 7, 960)	
153,600	block_14_add[0][0]		
	block_15_expand_BN	(None, 7, 7, 960)	
3,840	block_15_expand[0][0]		
	(BatchNormalization)		
	block_15_expand_relu (ReLU)	(None, 7, 7, 960)	
0	block_15_expand_BN[0][0]		
	block_15_depthwise	(None, 7, 7, 960)	
8,640	block_15_expand_relu[0][0]		
	(DepthwiseConv2D)		
	block_15_depthwise_BN	(None, 7, 7, 960)	
3,840	block_15_depthwise[0][0]		
	(BatchNormalization)		

	block_15_depthwise_relu	(None, 7, 7, 960)	
0	block_15_depthwise_BN[0][...]		
	(ReLU)		
	block_15_project (Conv2D)	(None, 7, 7, 160)	
153,600	block_15_depthwise_relu[0...]		
	block_15_project_BN	(None, 7, 7, 160)	
640	block_15_project[0][0]		
	(BatchNormalization)		
	block_15_add (Add)	(None, 7, 7, 160)	
0	block_14_add[0][0],		
	block_15_project_BN[0][0]		
	block_16_expand (Conv2D)	(None, 7, 7, 960)	
153,600	block_15_add[0][0]		
	block_16_expand_BN	(None, 7, 7, 960)	
3,840	block_16_expand[0][0]		
	(BatchNormalization)		
	block_16_expand_relu (ReLU)	(None, 7, 7, 960)	
0	block_16_expand_BN[0][0]		
	block_16_depthwise	(None, 7, 7, 960)	
8,640	block_16_expand_relu[0][0]		
	(DepthwiseConv2D)		
	block_16_depthwise_BN	(None, 7, 7, 960)	
3,840	block_16_depthwise[0][0]		
	(BatchNormalization)		

0	block_16_depthwise_relu block_16_depthwise_BN[0][...] (ReLU)	(None, 7, 7, 960)	
307,200	block_16_project (Conv2D) block_16_depthwise_relu[0...]	(None, 7, 7, 320)	
1,280	block_16_project_BN block_16_project[0][0] (BatchNormalization)	(None, 7, 7, 320)	
409,600	Conv_1 (Conv2D) block_16_project_BN[0][0]	(None, 7, 7, 1280)	
5,120	Conv_1_bn Conv_1[0][0] (BatchNormalization)	(None, 7, 7, 1280)	
0	out_relu (ReLU) Conv_1_bn[0][0]	(None, 7, 7, 1280)	
0	global_average_pooling2d out_relu[0][0] (GlobalAveragePooling2D)	(None, 1280)	
0	dropout_1 (Dropout) global_average_pooling2d[...]	(None, 1280)	
163,968	dense_2 (Dense) dropout_1[0][0]	(None, 128)	
0	dropout_2 (Dropout) dense_2[0][0]	(None, 128)	
	dense_3 (Dense)	(None, 4)	

516 | dropout\_2[0][0]

Total params: 2,422,468 (9.24 MB)

Trainable params: 2,019,588 (7.70 MB)

Non-trainable params: 402,880 (1.54 MB)

Model 2 memiliki parameter kurang dari 10M, yaitu sebanyak 2,422,468 parameters, dengan trainable parameters sebanyak 2,019,588 parameters.

```
history_model2 = model2.fit(train_ds,  
                             validation_data=val_ds,  
                             epochs=50,  
                             callbacks=[early_stop],  
                             class_weight=class_weight_dict)
```

Epoch 1/50

39/39 ————— 101s 2s/step - accuracy: 0.4319 - loss: 1.3842 - val\_accuracy: 0.7355 - val\_loss: 0.6650

Epoch 2/50

39/39 ————— 56s 1s/step - accuracy: 0.6588 - loss: 0.7380 - val\_accuracy: 0.7645 - val\_loss: 0.5461

Epoch 3/50

39/39 ————— 56s 1s/step - accuracy: 0.7628 - loss: 0.5676 - val\_accuracy: 0.7806 - val\_loss: 0.5580

Epoch 4/50

39/39 ————— 57s 1s/step - accuracy: 0.7866 - loss: 0.5068 - val\_accuracy: 0.8097 - val\_loss: 0.5090

Epoch 5/50

39/39 ————— 56s 1s/step - accuracy: 0.8196 - loss: 0.4267 - val\_accuracy: 0.8097 - val\_loss: 0.5443

Epoch 6/50

39/39 ————— 55s 1s/step - accuracy: 0.8166 - loss: 0.3878 - val\_accuracy: 0.7871 - val\_loss: 0.6200

Epoch 7/50

39/39 ————— 56s 1s/step - accuracy: 0.8677 - loss: 0.3076 - val\_accuracy: 0.7968 - val\_loss: 0.6183

Epoch 8/50

39/39 ————— 55s 1s/step - accuracy: 0.8911 - loss: 0.3105 - val\_accuracy: 0.7871 - val\_loss: 0.6096

Epoch 9/50

39/39 ————— 56s 1s/step - accuracy: 0.8829 - loss: 0.2541 - val\_accuracy: 0.7742 - val\_loss: 0.7455

Berdasarkan hasil evaluation, dapat diketahui bahwa model 2 adalah model yang lebih optimal dibandingkan model 1.

Oleh karena itu, dilakukan hyperparameter tuning untuk mengetahui best learning rate pada model ini.

```
def design_tuning_model2(input_shape=(224, 224, 3), num_classes=4):
    base_model = MobileNetV2(include_top=False, weights='imagenet',
input_shape=input_shape)
    base_model.trainable = True

    for layer in base_model.layers[:-50]:
        layer.trainable = False

    x = base_model.output
    x = GlobalAveragePooling2D()(x)
    x = Dropout(0.3)(x)
    x = Dense(128, activation='relu')(x)
    x = Dropout(0.3)(x)
    predictions = Dense(num_classes, activation='softmax')(x)

    model = Model(inputs=base_model.input, outputs=predictions)
    return model

highest_accuracy= 0
best_learningrate = None
for lr in [0.001, 0.0001, 0.00001]:
    print(f"Learning rate = {lr}")

    tuning_model2 = design_tuning_model2()
    tuning_model2.compile(
        optimizer=keras.optimizers.Adam(learning_rate = lr),
        loss='categorical_crossentropy',
        metrics=['accuracy'])

    history_tuning_model2 = tuning_model2.fit(train_ds,
                                                validation_data =
val_ds,
                                                epochs = 50,
                                                callbacks=[early_stop],

class_weight=class_weight_dict)

    val_accuracy = max(history_tuning_model2.history['val_accuracy'])
    if val_accuracy > highest_accuracy:
        highest_accuracy = val_accuracy
        best_learningrate = lr
        best_model = tuning_model2

print(f"Learning rate with the highest accuracy is:
{best_learningrate}")

Learning rate = 0.001
Epoch 1/50
```



```
39/39 _____ 99s 2s/step - accuracy: 0.6042 - loss:
1.0110 - val_accuracy: 0.7258 - val_loss: 1.1253
Epoch 2/50
39/39 _____ 56s 1s/step - accuracy: 0.7799 - loss:
0.5544 - val_accuracy: 0.6677 - val_loss: 1.3379
Epoch 3/50
39/39 _____ 55s 1s/step - accuracy: 0.8469 - loss:
0.4668 - val_accuracy: 0.5097 - val_loss: 2.5695
Epoch 4/50
39/39 _____ 57s 1s/step - accuracy: 0.7880 - loss:
0.6623 - val_accuracy: 0.4065 - val_loss: 3.8080
Epoch 5/50
39/39 _____ 54s 1s/step - accuracy: 0.8187 - loss:
0.4592 - val_accuracy: 0.5516 - val_loss: 3.1095
Epoch 6/50
39/39 _____ 56s 1s/step - accuracy: 0.8496 - loss:
0.3810 - val_accuracy: 0.4484 - val_loss: 5.1572
Learning rate = 0.0001
Epoch 1/50
39/39 _____ 95s 1s/step - accuracy: 0.4328 - loss:
1.3370 - val_accuracy: 0.7323 - val_loss: 0.7277
Epoch 2/50
39/39 _____ 56s 1s/step - accuracy: 0.6899 - loss:
0.7077 - val_accuracy: 0.7484 - val_loss: 0.6960
Epoch 3/50
39/39 _____ 54s 1s/step - accuracy: 0.7247 - loss:
0.5997 - val_accuracy: 0.7516 - val_loss: 0.7766
Epoch 4/50
39/39 _____ 56s 1s/step - accuracy: 0.7921 - loss:
0.4929 - val_accuracy: 0.7613 - val_loss: 0.8251
Epoch 5/50
39/39 _____ 56s 1s/step - accuracy: 0.8198 - loss:
0.4144 - val_accuracy: 0.7742 - val_loss: 0.7438
Epoch 6/50
39/39 _____ 56s 1s/step - accuracy: 0.8307 - loss:
0.3967 - val_accuracy: 0.7742 - val_loss: 0.6996
Epoch 7/50
39/39 _____ 56s 1s/step - accuracy: 0.8334 - loss:
0.3785 - val_accuracy: 0.7968 - val_loss: 0.6358
Epoch 8/50
39/39 _____ 55s 1s/step - accuracy: 0.8845 - loss:
0.2888 - val_accuracy: 0.7871 - val_loss: 0.6454
Epoch 9/50
39/39 _____ 56s 1s/step - accuracy: 0.8752 - loss:
0.2667 - val_accuracy: 0.7839 - val_loss: 0.7424
Epoch 10/50
39/39 _____ 56s 1s/step - accuracy: 0.9003 - loss:
0.2312 - val_accuracy: 0.8065 - val_loss: 0.5996
Epoch 11/50
```

```
39/39 _____ 55s 1s/step - accuracy: 0.9041 - loss:
0.2265 - val_accuracy: 0.7968 - val_loss: 0.7261
Epoch 12/50
39/39 _____ 56s 1s/step - accuracy: 0.9229 - loss:
0.1901 - val_accuracy: 0.7935 - val_loss: 0.6586
Epoch 13/50
39/39 _____ 57s 1s/step - accuracy: 0.9373 - loss:
0.1777 - val_accuracy: 0.8129 - val_loss: 0.6230
Epoch 14/50
39/39 _____ 57s 1s/step - accuracy: 0.9470 - loss:
0.1416 - val_accuracy: 0.7774 - val_loss: 0.7706
Epoch 15/50
39/39 _____ 56s 1s/step - accuracy: 0.9437 - loss:
0.1796 - val_accuracy: 0.7806 - val_loss: 0.8516
Learning rate = 1e-05
Epoch 1/50
39/39 _____ 95s 1s/step - accuracy: 0.1757 - loss:
1.6689 - val_accuracy: 0.1645 - val_loss: 1.6534
Epoch 2/50
39/39 _____ 55s 1s/step - accuracy: 0.2547 - loss:
1.6122 - val_accuracy: 0.2968 - val_loss: 1.4447
Epoch 3/50
39/39 _____ 53s 1s/step - accuracy: 0.3031 - loss:
1.2940 - val_accuracy: 0.4258 - val_loss: 1.2893
Epoch 4/50
39/39 _____ 56s 1s/step - accuracy: 0.3753 - loss:
1.2088 - val_accuracy: 0.5290 - val_loss: 1.1773
Epoch 5/50
39/39 _____ 56s 1s/step - accuracy: 0.3885 - loss:
1.1988 - val_accuracy: 0.5613 - val_loss: 1.0898
Epoch 6/50
39/39 _____ 56s 1s/step - accuracy: 0.4621 - loss:
1.0809 - val_accuracy: 0.6032 - val_loss: 1.0075
Epoch 7/50
39/39 _____ 56s 1s/step - accuracy: 0.4718 - loss:
1.0705 - val_accuracy: 0.6484 - val_loss: 0.9360
Epoch 8/50
39/39 _____ 56s 1s/step - accuracy: 0.5108 - loss:
1.0121 - val_accuracy: 0.6774 - val_loss: 0.8877
Epoch 9/50
39/39 _____ 56s 1s/step - accuracy: 0.5448 - loss:
0.8696 - val_accuracy: 0.7065 - val_loss: 0.8386
Epoch 10/50
39/39 _____ 56s 1s/step - accuracy: 0.5476 - loss:
0.8698 - val_accuracy: 0.7194 - val_loss: 0.7963
Epoch 11/50
39/39 _____ 55s 1s/step - accuracy: 0.6170 - loss:
0.7850 - val_accuracy: 0.7484 - val_loss: 0.7567
Epoch 12/50
```

39/39 \_\_\_\_\_ 57s 1s/step - accuracy: 0.5885 - loss:  
0.8119 - val\_accuracy: 0.7452 - val\_loss: 0.7301  
Epoch 13/50  
39/39 \_\_\_\_\_ 56s 1s/step - accuracy: 0.5878 - loss:  
0.7990 - val\_accuracy: 0.7581 - val\_loss: 0.7016  
Epoch 14/50  
39/39 \_\_\_\_\_ 56s 1s/step - accuracy: 0.6245 - loss:  
0.7513 - val\_accuracy: 0.7645 - val\_loss: 0.6786  
Epoch 15/50  
39/39 \_\_\_\_\_ 56s 1s/step - accuracy: 0.6375 - loss:  
0.7583 - val\_accuracy: 0.7742 - val\_loss: 0.6607  
Epoch 16/50  
39/39 \_\_\_\_\_ 54s 1s/step - accuracy: 0.6847 - loss:  
0.7342 - val\_accuracy: 0.7806 - val\_loss: 0.6363  
Epoch 17/50  
39/39 \_\_\_\_\_ 55s 1s/step - accuracy: 0.6878 - loss:  
0.6600 - val\_accuracy: 0.7774 - val\_loss: 0.6188  
Epoch 18/50  
39/39 \_\_\_\_\_ 53s 1s/step - accuracy: 0.7022 - loss:  
0.6880 - val\_accuracy: 0.7774 - val\_loss: 0.6090  
Epoch 19/50  
39/39 \_\_\_\_\_ 37s 917ms/step - accuracy: 0.7266 - loss:  
0.6227 - val\_accuracy: 0.7774 - val\_loss: 0.5970  
Epoch 20/50  
39/39 \_\_\_\_\_ 36s 894ms/step - accuracy: 0.7316 - loss:  
0.6160 - val\_accuracy: 0.7806 - val\_loss: 0.5814  
Epoch 21/50  
39/39 \_\_\_\_\_ 37s 911ms/step - accuracy: 0.7387 - loss:  
0.6012 - val\_accuracy: 0.7839 - val\_loss: 0.5703  
Epoch 22/50  
39/39 \_\_\_\_\_ 37s 914ms/step - accuracy: 0.7319 - loss:  
0.5608 - val\_accuracy: 0.7871 - val\_loss: 0.5693  
Epoch 23/50  
39/39 \_\_\_\_\_ 35s 876ms/step - accuracy: 0.7458 - loss:  
0.5933 - val\_accuracy: 0.7839 - val\_loss: 0.5650  
Epoch 24/50  
39/39 \_\_\_\_\_ 41s 1s/step - accuracy: 0.7709 - loss:  
0.5677 - val\_accuracy: 0.7903 - val\_loss: 0.5515  
Epoch 25/50  
39/39 \_\_\_\_\_ 36s 861ms/step - accuracy: 0.7718 - loss:  
0.4890 - val\_accuracy: 0.7968 - val\_loss: 0.5335  
Epoch 26/50  
39/39 \_\_\_\_\_ 35s 846ms/step - accuracy: 0.7459 - loss:  
0.5611 - val\_accuracy: 0.8065 - val\_loss: 0.5220  
Epoch 27/50  
39/39 \_\_\_\_\_ 40s 980ms/step - accuracy: 0.7962 - loss:  
0.4936 - val\_accuracy: 0.8065 - val\_loss: 0.5211  
Epoch 28/50  
39/39 \_\_\_\_\_ 36s 875ms/step - accuracy: 0.7701 - loss:

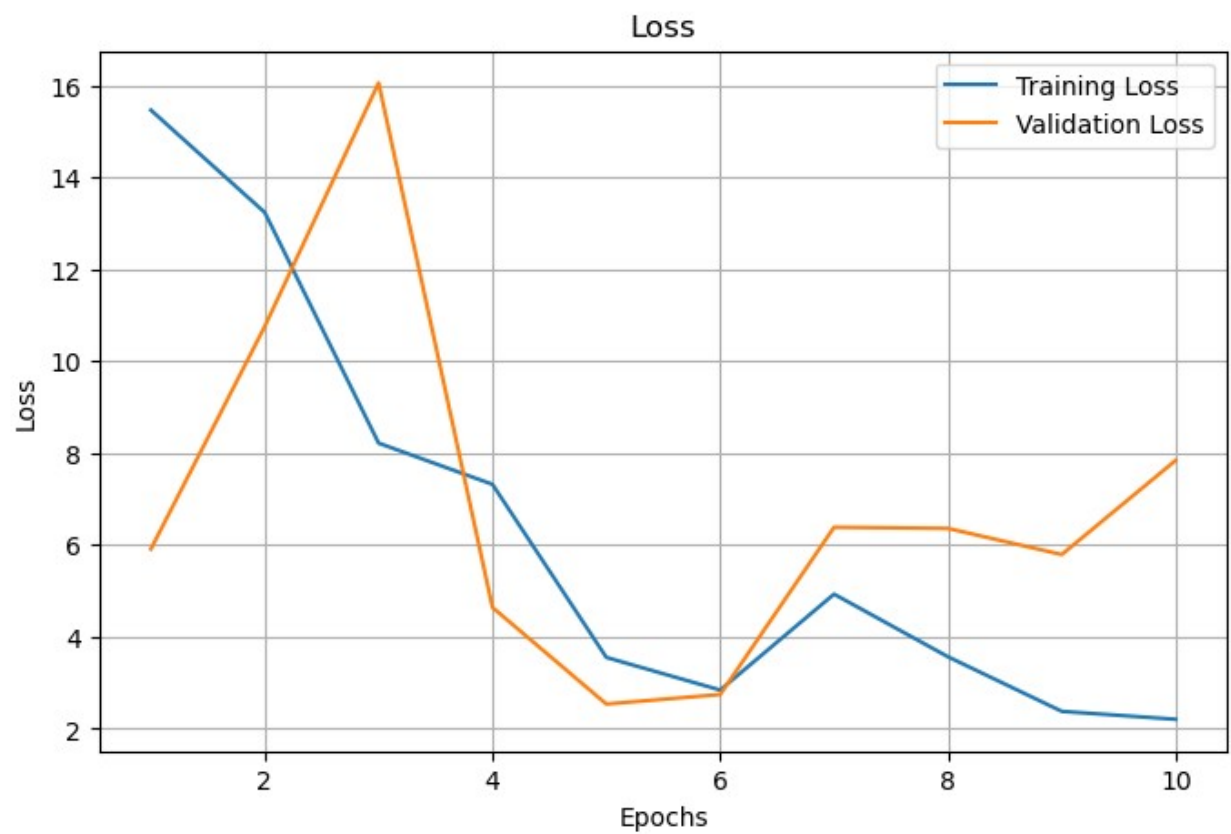
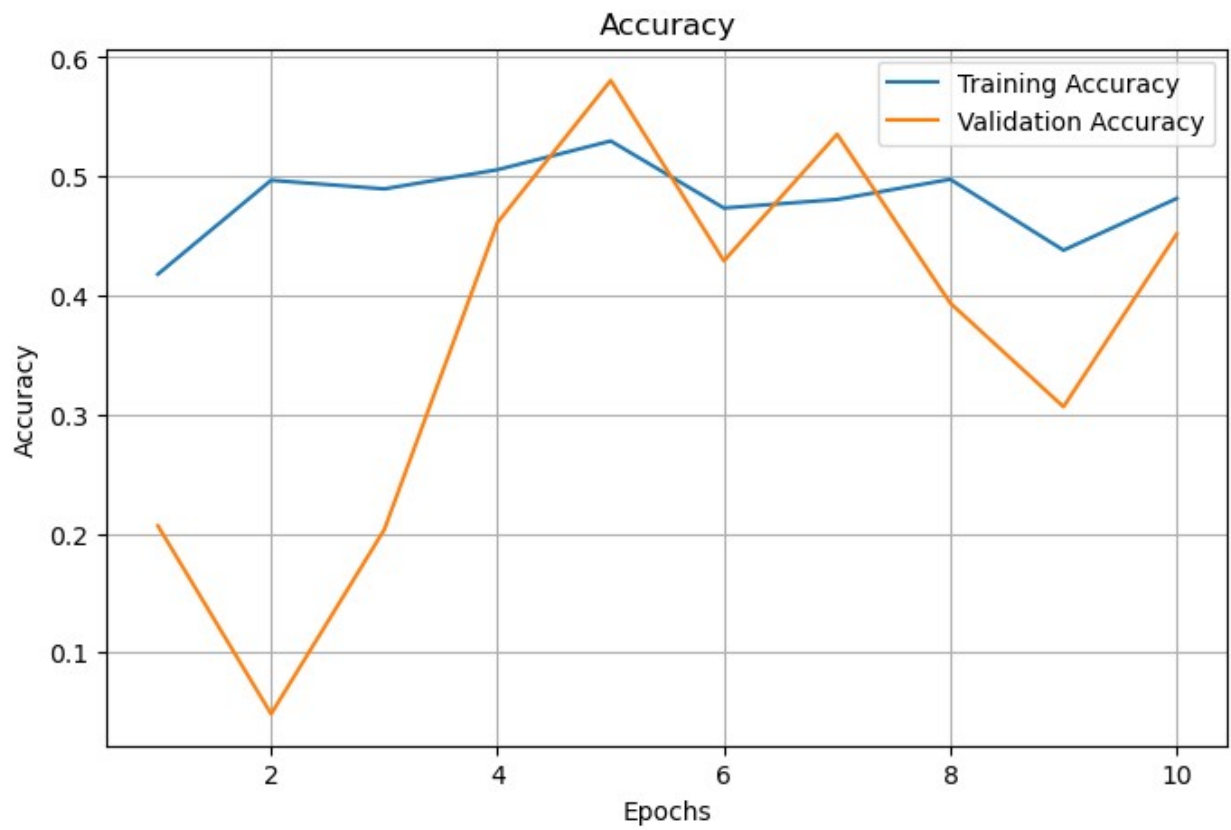
0.4907 - val\_accuracy: 0.8032 - val\_loss: 0.5156  
Epoch 29/50  
39/39 \_\_\_\_\_ 37s 918ms/step - accuracy: 0.7716 - loss: 0.5143 - val\_accuracy: 0.8032 - val\_loss: 0.5137  
Epoch 30/50  
39/39 \_\_\_\_\_ 37s 921ms/step - accuracy: 0.7745 - loss: 0.4818 - val\_accuracy: 0.8065 - val\_loss: 0.5122  
Epoch 31/50  
39/39 \_\_\_\_\_ 37s 917ms/step - accuracy: 0.7755 - loss: 0.4757 - val\_accuracy: 0.8097 - val\_loss: 0.5005  
Epoch 32/50  
39/39 \_\_\_\_\_ 37s 921ms/step - accuracy: 0.8128 - loss: 0.4234 - val\_accuracy: 0.8097 - val\_loss: 0.4883  
Epoch 33/50  
39/39 \_\_\_\_\_ 41s 915ms/step - accuracy: 0.8163 - loss: 0.4140 - val\_accuracy: 0.8161 - val\_loss: 0.4844  
Epoch 34/50  
39/39 \_\_\_\_\_ 37s 920ms/step - accuracy: 0.8038 - loss: 0.4305 - val\_accuracy: 0.8194 - val\_loss: 0.4821  
Epoch 35/50  
39/39 \_\_\_\_\_ 37s 915ms/step - accuracy: 0.8187 - loss: 0.4351 - val\_accuracy: 0.8161 - val\_loss: 0.4802  
Epoch 36/50  
39/39 \_\_\_\_\_ 37s 909ms/step - accuracy: 0.8311 - loss: 0.3659 - val\_accuracy: 0.8161 - val\_loss: 0.4752  
Epoch 37/50  
39/39 \_\_\_\_\_ 41s 904ms/step - accuracy: 0.8249 - loss: 0.4330 - val\_accuracy: 0.8129 - val\_loss: 0.4770  
Epoch 38/50  
39/39 \_\_\_\_\_ 37s 907ms/step - accuracy: 0.8352 - loss: 0.3823 - val\_accuracy: 0.8129 - val\_loss: 0.4760  
Epoch 39/50  
39/39 \_\_\_\_\_ 37s 913ms/step - accuracy: 0.8065 - loss: 0.4121 - val\_accuracy: 0.8194 - val\_loss: 0.4691  
Epoch 40/50  
39/39 \_\_\_\_\_ 38s 919ms/step - accuracy: 0.8181 - loss: 0.4090 - val\_accuracy: 0.8194 - val\_loss: 0.4614  
Epoch 41/50  
39/39 \_\_\_\_\_ 38s 930ms/step - accuracy: 0.8098 - loss: 0.4078 - val\_accuracy: 0.8226 - val\_loss: 0.4665  
Epoch 42/50  
39/39 \_\_\_\_\_ 38s 922ms/step - accuracy: 0.8324 - loss: 0.3604 - val\_accuracy: 0.8258 - val\_loss: 0.4665  
Epoch 43/50  
39/39 \_\_\_\_\_ 36s 886ms/step - accuracy: 0.8327 - loss: 0.4014 - val\_accuracy: 0.8226 - val\_loss: 0.4675  
Epoch 44/50  
39/39 \_\_\_\_\_ 36s 892ms/step - accuracy: 0.8319 - loss: 0.3758 - val\_accuracy: 0.8226 - val\_loss: 0.4679

Epoch 45/50  
39/39 ————— 42s 916ms/step - accuracy: 0.8488 - loss:  
0.3723 - val\_accuracy: 0.8258 - val\_loss: 0.4675  
Learning rate with the highest accuracy is: 1e-05

## Evaluation

Berdasarkan hasil plot accuracy dan loss

```
def plot_history(history, model_name):  
    acc = history.history['accuracy']  
    val_acc = history.history.get('val_accuracy')  
    loss = history.history['loss']  
    val_loss = history.history.get('val_loss')  
    epochs = range(1, len(acc) + 1)  
  
    plt.figure(figsize=(8, 5))  
    plt.plot(epochs, acc, label='Training Accuracy')  
    if val_acc:  
        plt.plot(epochs, val_acc, label='Validation Accuracy')  
    plt.title(f'Accuracy')  
    plt.xlabel('Epochs')  
    plt.ylabel('Accuracy')  
    plt.legend()  
    plt.grid(True)  
    plt.show()  
  
    plt.figure(figsize=(8, 5))  
    plt.plot(epochs, loss, label='Training Loss')  
    if val_loss:  
        plt.plot(epochs, val_loss, label='Validation Loss')  
    plt.title(f'Loss')  
    plt.xlabel('Epochs')  
    plt.ylabel('Loss')  
    plt.legend()  
    plt.grid(True)  
    plt.show()  
  
plot_history(history_model1, model1)
```

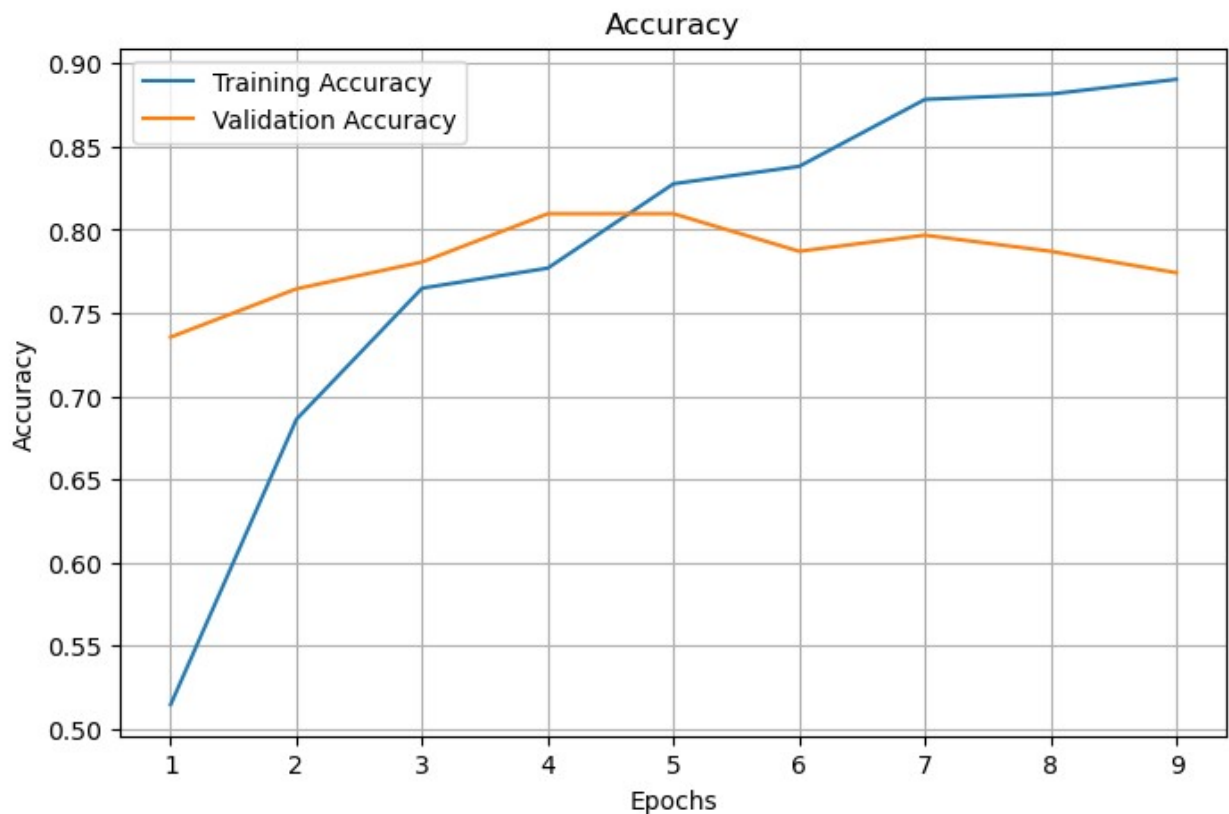


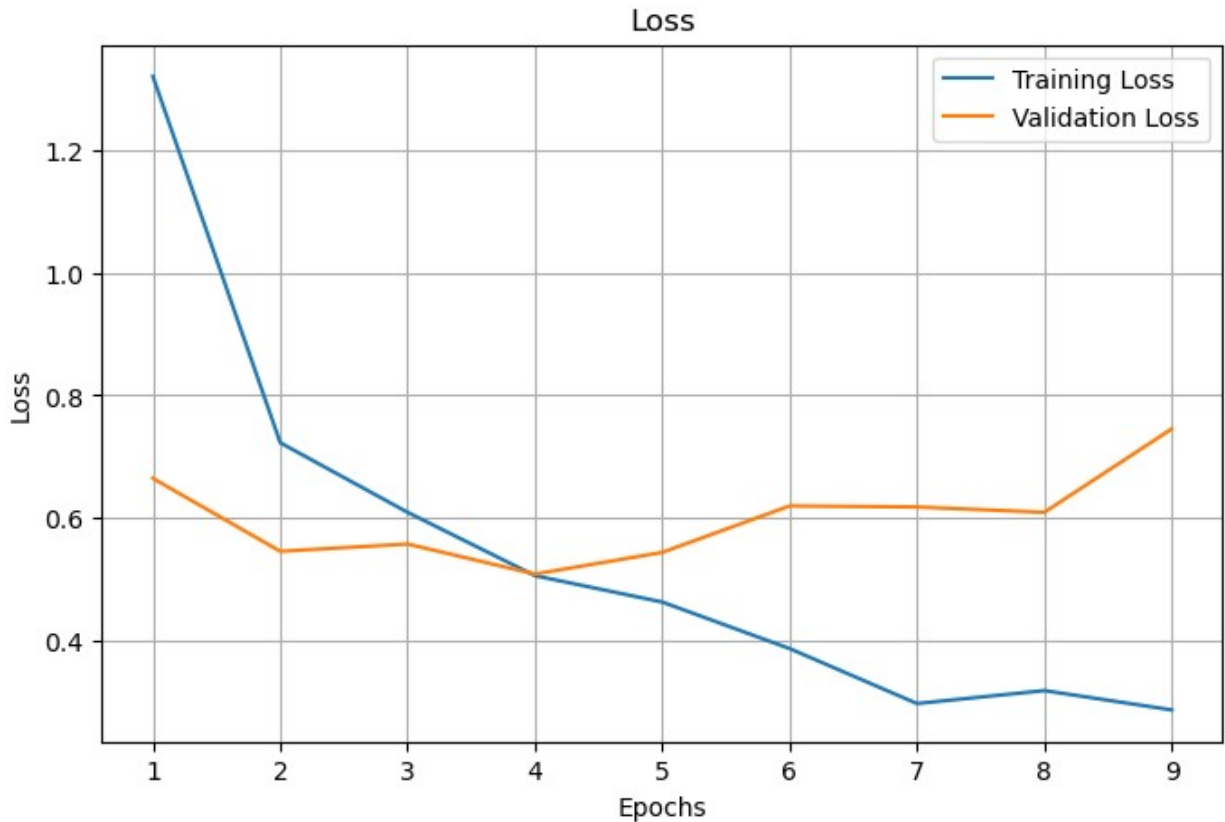
Berdasarkan grafik hasil training model 1, dapat dilihat bahwa:

- Training accuracy meningkat secara bertahap dari awal hingga mencapai sekitar 53% pada epoch ke-5, kemudian fluktuatif di kisaran 45–50% hingga akhir.
- Validation accuracy sempat mengalami peningkatan signifikan pada epoch ke-3 hingga ke-5, namun setelah itu cenderung menurun cukup drastis hingga sekitar 30% di epoch ke-9, lalu sedikit meningkat kembali pada epoch ke-10 (sekitar 45%).
- Training loss menurun konsisten dari awal hingga menjadi sekeitar 2.2 pada akhir epoch.
- Validation loss sangat fluktuatif: naik tajam di awal hingga ~16 (epoch ke-3), kemudian turun drastis hingga sekitar 2.5 pada epoch ke-5–6, tetapi kembali meningkat hingga 8 pada akhir epoch.

Secara keseluruhan, grafik ini menunjukkan bahwa model masih dalam proses belajar yang cukup baik, namun performanya masih tergolong moderate karena belum menunjukkan generalisasi yang sangat kuat.

```
plot_history(history_model2, model2)
```





Berdasarkan grafik hasil training model 2 (parameter < 10M), dapat dilihat bahwa:

- Training accuracy meningkat secara stabil dan konsisten, dari sekitar 51% pada epoch pertama hingga 89% pada epoch ke-9.
- Validation accuracy mengalami peningkatan hingga epoch ke-5, kemudian cenderung stagnan bahkan sedikit menurun setelah epoch ke-6. Hal ini mengindikasikan bahwa meskipun model semakin baik pada data training, kemampuannya untuk menggeneralisasi ke data validasi mulai menurun.
- Training loss mengalami penurunan yang signifikan dan stabil, yang menandakan bahwa model terus memperbaiki prediksinya terhadap data yang sudah dikenal.
- Validation loss mengalami penurunan yang cenderung stagnan, bahkan sedikit meningkat setelah epoch ke-6, kemungkinan besar overfitting.

Melalui kedua grafik tersebut, dapat diketahui bahwa model ke-2 yang memanfaatkan arsitektur MobileNetV2 ini menunjukkan hasil yang lebih efisien dibandingkan model 1. Hal tersebut dikarenakan hasil accuracy training dan validation yang lebih tinggi dan stabil.

## Berdasarkan hasil classification report dan correlation matrix

```
def evaluate(model, test_ds, label_names):
    y_true = []
    y_pred = []
```



```

for x, y in test_ds:
    pred = model.predict(x)
    y_pred.extend(np.argmax(pred, axis=1))
    y_true.extend(np.argmax(y.numpy(), axis=1))

print(classification_report(y_true, y_pred,
target_names=label_names))
cm = confusion_matrix(y_true, y_pred)
ConfusionMatrixDisplay(cm, display_labels=label_names).plot()

evaluate(model1, test_ds, label_names)

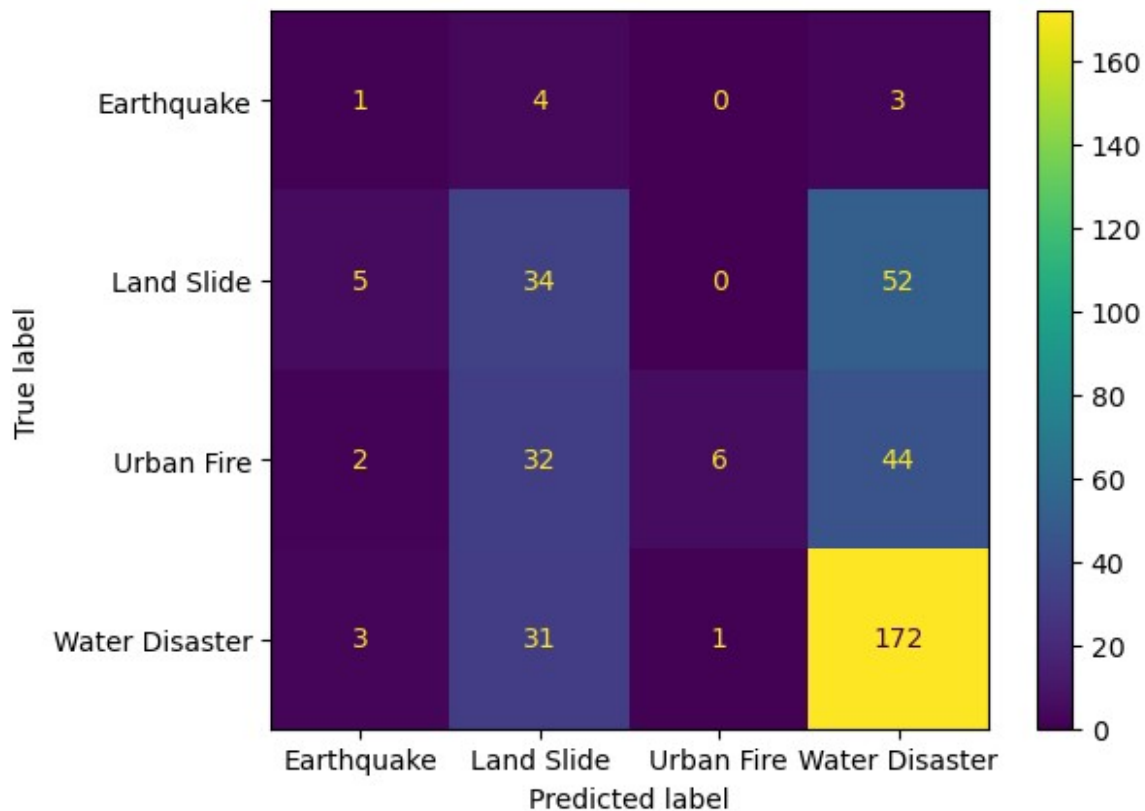
```

```

1/1 ─────────── 1s 999ms/step
1/1 ─────────── 0s 370ms/step
1/1 ─────────── 0s 358ms/step
1/1 ─────────── 0s 370ms/step
1/1 ─────────── 0s 393ms/step
1/1 ─────────── 0s 395ms/step
1/1 ─────────── 0s 392ms/step
1/1 ─────────── 0s 422ms/step
1/1 ─────────── 0s 429ms/step
1/1 ─────────── 0s 372ms/step
1/1 ─────────── 0s 376ms/step
1/1 ─────────── 0s 373ms/step
1/1 ─────────── 0s 434ms/step

```

	precision	recall	f1-score	support
Earthquake	0.09	0.12	0.11	8
Land Slide	0.34	0.37	0.35	91
Urban Fire	0.86	0.07	0.13	84
Water Disaster	0.63	0.83	0.72	207
accuracy			0.55	390
macro avg	0.48	0.35	0.33	390
weighted avg	0.60	0.55	0.50	390



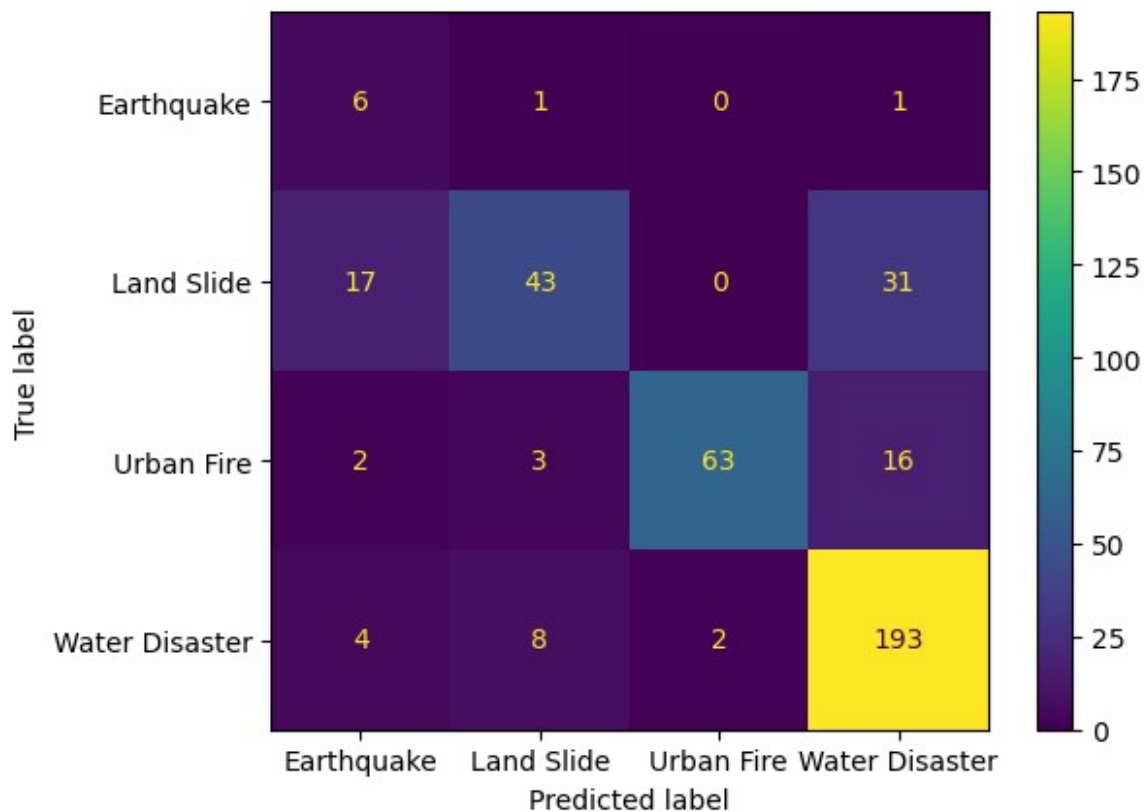
Berdasarkan hasil correlation matrix model 1, dapat diketahui bahwa model 1 paling baik mengenali Water Disaster dengan prediksi benar terbanyak, sementara kelas Earthquake dan Urban Fire sulit dikenali karena banyak salah klasifikasi. Selain itu, terdapat kekeliruan yang cukup besar antara kelas Land Slide dan Water Disaster.

```
evaluate(model2, test_ds, label_names)
```

```
1/1 _____ 3s 3s/step
1/1 _____ 1s 580ms/step
1/1 _____ 1s 571ms/step
1/1 _____ 1s 540ms/step
1/1 _____ 1s 579ms/step
1/1 _____ 1s 557ms/step
1/1 _____ 1s 557ms/step
1/1 _____ 1s 578ms/step
1/1 _____ 1s 548ms/step
1/1 _____ 1s 533ms/step
1/1 _____ 1s 558ms/step
1/1 _____ 1s 552ms/step
1/1 _____ 2s 2s/step
```

	precision	recall	f1-score	support
Earthquake	0.21	0.75	0.32	8
Land Slide	0.78	0.47	0.59	91
Urban Fire	0.97	0.75	0.85	84

Water Disaster	0.80	0.93	0.86	207
accuracy			0.78	390
macro avg	0.69	0.73	0.66	390
weighted avg	0.82	0.78	0.78	390



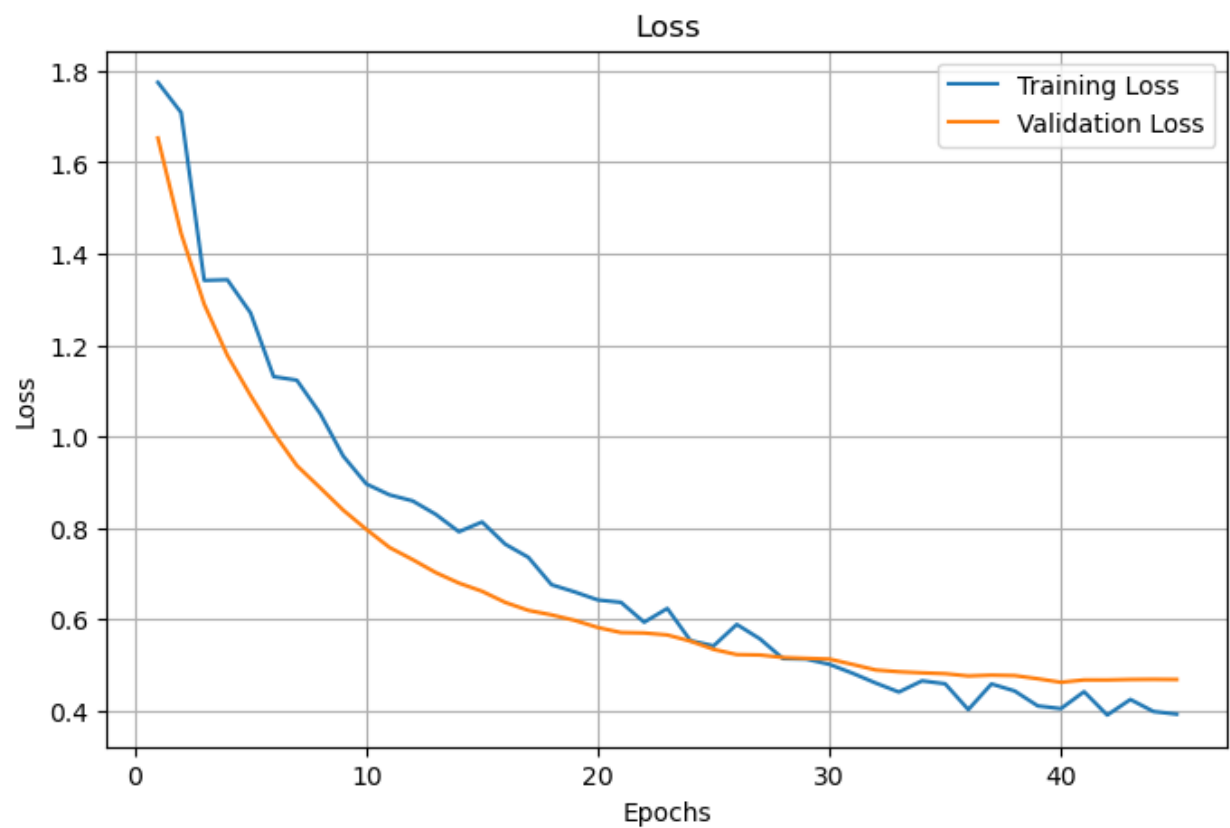
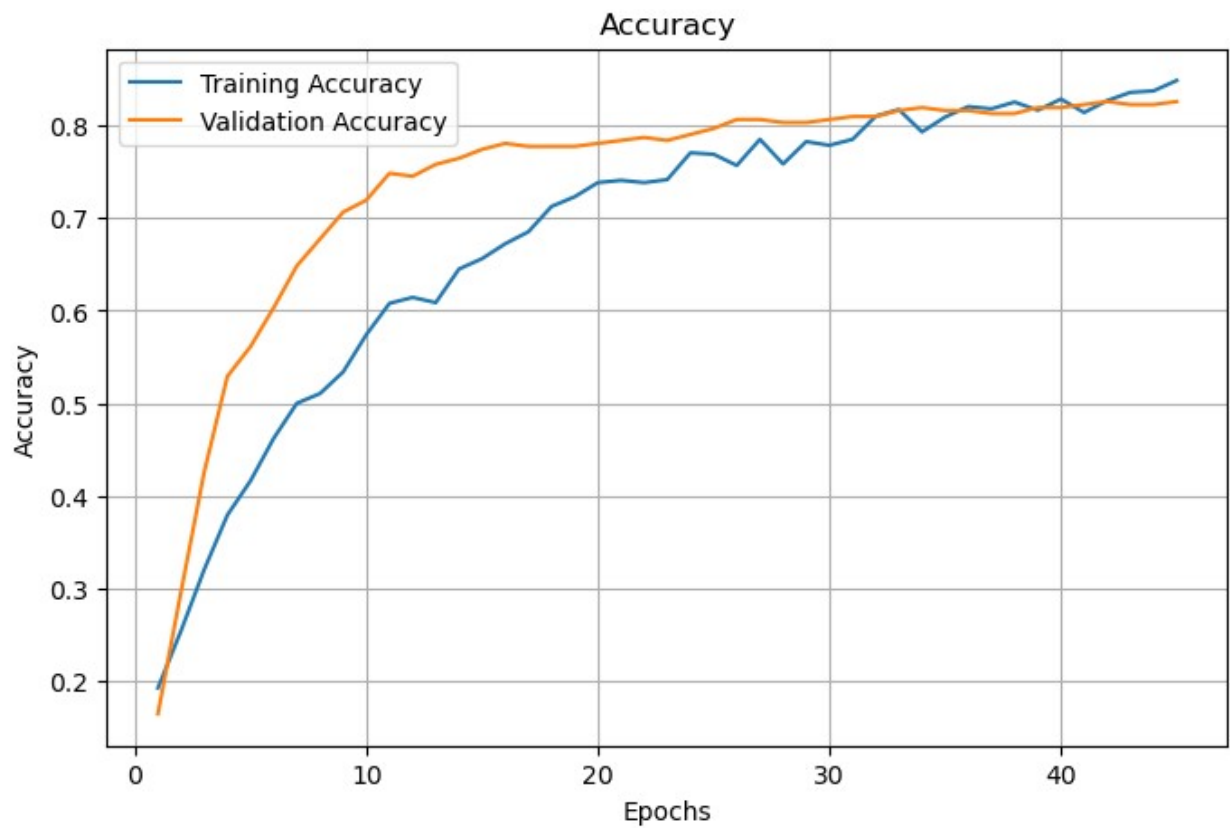
Jika dilihat berdasarkan classification report dan correlation matrix kedua model tersebut, dapat disimpulkan bahwa secara keseluruhan, model ke-2 adalah model yang lebih optimal dibandingkan model ke-1 untuk dataset ini. Model 2 lebih unggul dalam semua metric dan kemampuannya dalam mengklasifikasikan class minoritas seperti Earthquake dengan f1-score yang meningkat signifikan dibanding model pertama.

## Best Model

BEST MODEL = MODEL 2

Evaluasi untuk best model yang telah di hyperparameter tuning

```
plot_history(history_tuning_model2, best_model)
```



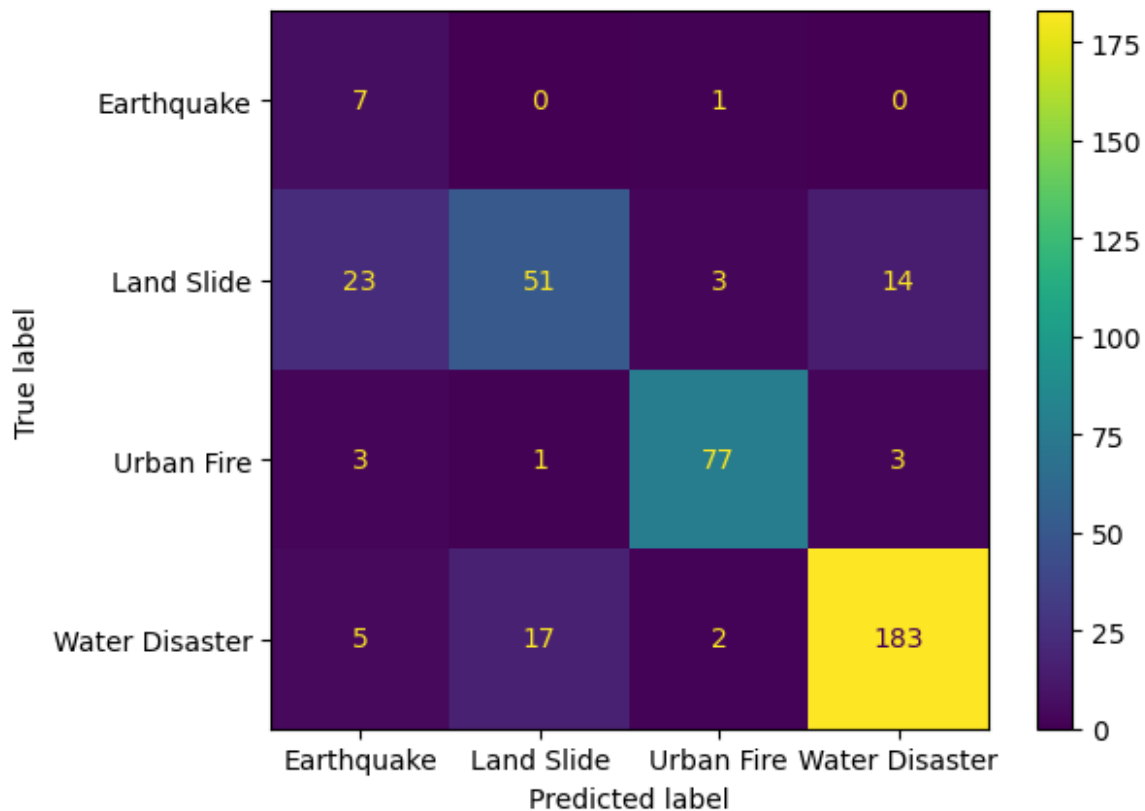
Berdasarkan grafik hasil training dari best model (model 2 dengan learning rate 0.00001), dapat dilihat bahwa:

- Training accuracy meningkat secara konsisten dari 20% hingga mencapai angka yang cukup tinggi sekitar 85% di akhir epoch.
- Validation accuracy naik cukup tajam pada awal training, kemudian cenderung stabil di kisaran 80%, yang berarti model mampu menjaga performanya pada data validasi.
- Training loss menurun signifikan dari awal dan terus berkurang hingga berada di bawah 0.4, menunjukkan bahwa model terus memperbaiki prediksinya terhadap data training.
- Validation loss juga menunjukkan pola penurunan yang konsisten dan stabil hingga akhir epoch.

Grafik ini memperlihatkan bahwa model belajar secara efektif dan mampu melakukan generalisasi dengan baik terhadap data validasi. Performa stabil tanpa gejala overfitting serius, sehingga model ini lebih efisien dan lebih baik dibanding model 1.

```
evaluate(best_model, test_ds, label_names)
```

1/1	_____	3s	3s/step		
1/1	_____	1s	544ms/step		
1/1	_____	1s	559ms/step		
1/1	_____	1s	548ms/step		
1/1	_____	1s	538ms/step		
1/1	_____	1s	547ms/step		
1/1	_____	1s	556ms/step		
1/1	_____	1s	534ms/step		
1/1	_____	1s	571ms/step		
1/1	_____	1s	527ms/step		
1/1	_____	1s	533ms/step		
1/1	_____	1s	586ms/step		
1/1	_____	3s	3s/step		
		precision	recall	f1-score	support
Earthquake		0.18	0.88	0.30	8
Land Slide		0.74	0.56	0.64	91
Urban Fire		0.93	0.92	0.92	84
Water Disaster		0.92	0.88	0.90	207
accuracy				0.82	390
macro avg		0.69	0.81	0.69	390
weighted avg		0.86	0.82	0.83	390



Best model (hasil hypertuning model 2) menunjukkan performa model yang sudah sangat baik dengan akurasi keseluruhan sebesar 82%. Model mampu mengenali kelas Urban Fire dan Water Disaster dengan sangat baik (f1-score di atas 0.9), sementara kelas Land Slide juga cukup solid dengan F1-score 0.64. Bahkan untuk kelas Earthquake, meski datanya lebih sedikit, recall mencapai 0.88 yang berarti model cukup handal dalam mendeteksi kejadian tersebut. Secara keseluruhan, hasil ini membuktikan bahwa hypertuning berhasil meningkatkan kualitas model.

## Documentation

```
def predictions_of_the_best_model(model, dataset, num_images,
label_names):
    for images, labels in dataset.take(1):
        preds = model.predict(images)
        pred_labels = tf.argmax(preds, axis=1).numpy()
        true_labels = tf.argmax(labels, axis=1).numpy()

        num_to_show = min(num_images, images.shape[0])

        plt.figure(figsize=(18, num_to_show // 5 * 3))
        for i in range(num_to_show):
            ax = plt.subplot((num_to_show + 4) // 5, 5, i + 1)
            img = (images[i].numpy() * 255).astype("uint8")
            plt.imshow(img)
```

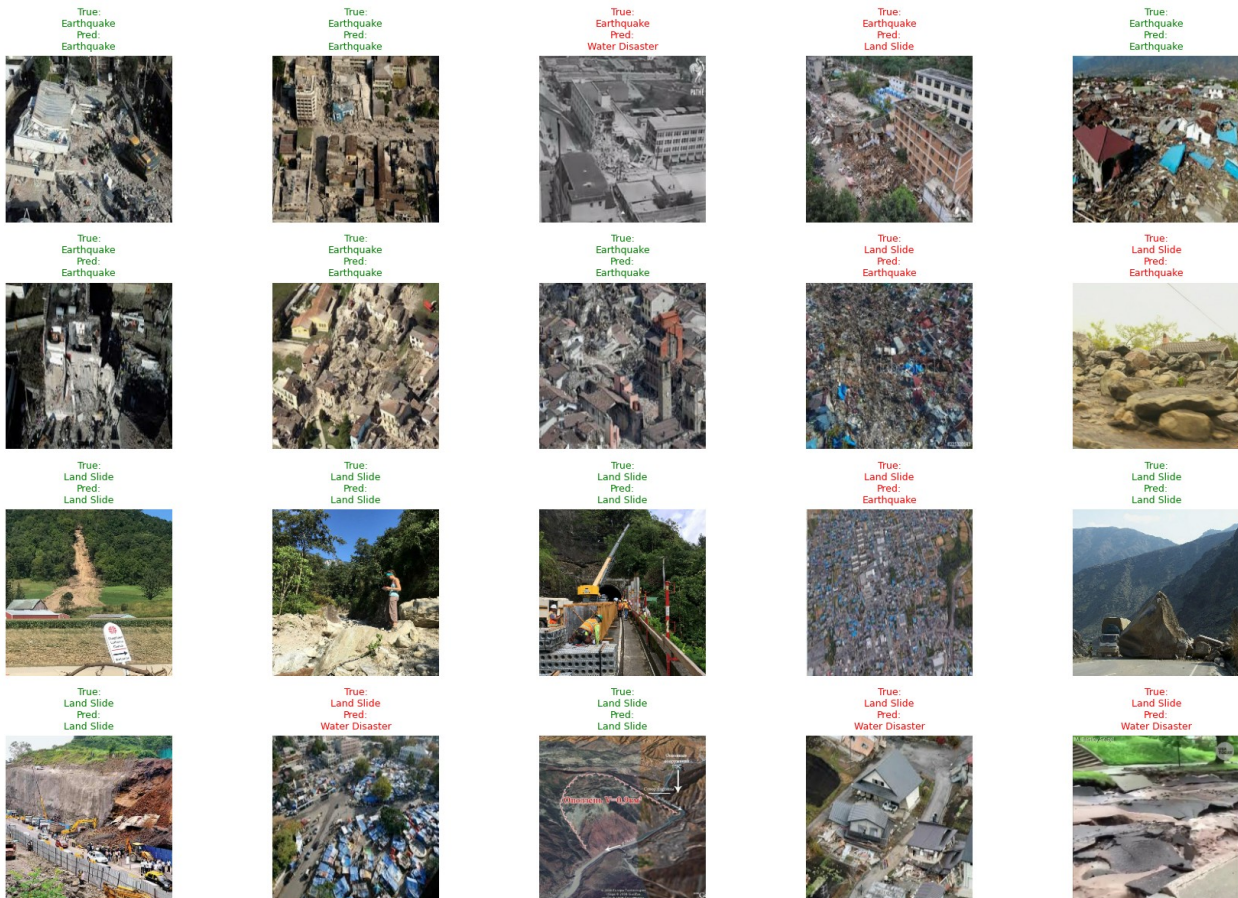
```

plt.title("Hasil prediksi dari best model")
true_text = label_names[true_labels[i]]
pred_text = label_names[pred_labels[i]]
color = "green" if true_text == pred_text else "red"
plt.title(f"True:\n{true_text}\nPred:\n{pred_text}",
fontsize=9, color=color)
plt.axis("off")
plt.tight_layout()
plt.show()

num_images = 20
predictions_of_the_best_model(model2, test_ds, num_images,
label_names)

```

1/1 ————— 1s 563ms/step



Distribusi data yang digunakan:

- Urban Fire: 419
- Water Disaster: 1035
- Land Slide: 456

- Earthquake: 36 -> unbalanced sehingga menggunakan class\_weight dengan perbandingan:

Earthquake: 14.785714285714286, Urban Fire: 1.0315614617940199, Land Slide: 1.154275092936803, Water Disaster: 0.4769585253456221

Dimensi setiap gambar di resize menjadi 224 x 224

```
model1.evaluate(val_ds)
model1.evaluate(test_ds)

10/10 ————— 3s 246ms/step - accuracy: 0.5533 - loss: 2.6707
13/13 ————— 3s 233ms/step - accuracy: 0.4056 - loss: 3.2489

[2.556565046310425, 0.5461538434028625]

best_model.evaluate(val_ds)
best_model.evaluate(test_ds)

10/10 ————— 5s 485ms/step - accuracy: 0.8106 - loss: 0.4907
13/13 ————— 6s 452ms/step - accuracy: 0.7407 - loss: 0.7133

[0.5448195338249207, 0.8153846263885498]
```

Model 2 yang menggunakan arsitektur MobileNetV2 (dengan learning rate 0.0001) terbukti lebih unggul dibandingkan model 1. Hal tersebut dikarenakan model 2 memanfaatkan arsitektur MobileNetV2 yang memang dirancang untuk efisiensi komputasi, sehingga sangat cocok digunakan dalam proyek klasifikasi gambar seperti ini yang membutuhkan performa tinggi namun tetap ringan dari sisi resource. Dengan memanfaatkan transfer learning dari MobileNetV2, proses training menjadi lebih cepat dan hasilnya juga lebih akurat.

Selain itu, dari hasil training, model 2 menunjukkan akurasi validasi yang lebih tinggi dan lebih stabil dibandingkan model 1, yang menunjukkan bahwa model tidak hanya belajar dengan baik dari data training, tetapi juga mampu melakukan generalisasi dengan lebih baik terhadap data yang belum pernah dilihat sebelumnya. Sedangkan model 1 merupakan arsitektur CNN yang dibangun from scratch, dengan struktur yang relatif sederhana, sehingga model ini kurang mampu menangkap pola fitur yang kompleks dan cenderung menghasilkan model yang bias terhadap data training (contohnya biased pada Water\_Disaster).