COMPARISON_CNN

June 21, 2025

[1]:
```
import tensorflow as tf
from tensorflow.keras.utils import to_categorical
import os
from PIL import Image, UnidentifiedImageError
import shutil

# Configuration
IMG_SIZE = (28, 28)
BATCH_SIZE = 32
VALIDATION_SPLIT = 0.4
SEED = 42
ROOT_PATH = ''
DATASET_PATH = os.path.join(ROOT_PATH,"raw_data")
CORRUPT_PATH = os.path.join(ROOT_PATH,"corrupt_images")
os.makedirs(CORRUPT_PATH, exist_ok=True)

for root, dirs, files in os.walk(DATASET_PATH):
    for file in files:
        ext = os.path.splitext(file)[1].lower()
        if ext in [".jpg", ".jpeg", ".png", ".bmp", ".gif"]:
            path = os.path.join(root, file)
            try:
                with Image.open(path) as img:
                    img.verify()  # Check integrity
            except (UnidentifiedImageError, OSError, IOError) as e:
                # Move the corrupt image
                print(f"Corrupt image found: {path} - moving to {CORRUPT_PATH}")
                dest_path = os.path.join(CORRUPT_PATH, os.path.relpath(path,␣
↪DATASET_PATH))
                os.makedirs(os.path.dirname(dest_path), exist_ok=True)
                shutil.move(path, dest_path)

LANDMARK_DIR = os.path.join(ROOT_PATH,"data")
RAW_IMAGE_DIR = os.path.join(ROOT_PATH,"raw_data")
FILTERED_IMAGE_DIR = os.path.join(ROOT_PATH,"filtered_raw_data")
DATASET_PATH = FILTERED_IMAGE_DIR
# Supported image extensions
```

```
IMAGE_EXTENSIONS = ['.jpg', '.jpeg', '.png', '.bmp']

# Create filtered output structure
os.makedirs(FILTERED_IMAGE_DIR, exist_ok=True)

for class_name in os.listdir(LANDMARK_DIR):
    if class_name == 'debug':
        continue
    landmark_class_dir = os.path.join(LANDMARK_DIR, class_name)
    raw_class_dir = os.path.join(RAW_IMAGE_DIR, class_name)
    filtered_class_dir = os.path.join(FILTERED_IMAGE_DIR, class_name)
    os.makedirs(filtered_class_dir, exist_ok=True)

    for file in os.listdir(landmark_class_dir):
        if not file.endswith("_landmarks.json"):
            continue

        # Get base filename without "_landmarks.json"
        base_name = file.replace("_landmarks.json", "")

        # Look for corresponding image in raw directory
        for ext in IMAGE_EXTENSIONS:
            image_file = os.path.join(raw_class_dir, base_name + ext)
            if os.path.exists(image_file):
                # Copy to filtered folder
                shutil.copy(image_file, os.path.join(filtered_class_dir, os.
↪path.basename(image_file)))
                break

# Load training dataset with validation split
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    DATASET_PATH,
    validation_split=VALIDATION_SPLIT,
    subset="training",
    seed=SEED,
    color_mode="grayscale",
    image_size=IMG_SIZE,
    batch_size=BATCH_SIZE
)
num_classes = len(train_ds.class_names)
label_map = train_ds.class_names

val_ds = tf.keras.preprocessing.image_dataset_from_directory(
    DATASET_PATH,
    validation_split=VALIDATION_SPLIT,
    subset="validation",
    seed=SEED,
```

```
    color_mode="grayscale",
    image_size=IMG_SIZE,
    batch_size=BATCH_SIZE
)

test_ds = val_ds.shard(2,0)
val_ds = val_ds.shard(2,1)
# Normalize pixel values to [0, 1]
normalization_layer = tf.keras.layers.Rescaling(1./255)
train_ds = train_ds.map(lambda x, y: (normalization_layer(x), y))
val_ds = val_ds.map(lambda x, y: (normalization_layer(x), y))
test_ds = test_ds.map(lambda x, y: (normalization_layer(x), y))
# Cache and prefetch for performance
AUTOTUNE = tf.data.AUTOTUNE
train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
val_ds = val_ds.cache().prefetch(buffer_size=AUTOTUNE)
test_ds = test_ds.cache().prefetch(buffer_size=AUTOTUNE)
```

```
Found 1722 files belonging to 25 classes.
Using 1034 files for training.
Found 1722 files belonging to 25 classes.
Using 688 files for validation.
```

[2]:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dropout,␣
 ↪BatchNormalization,Input
from tensorflow.keras.layers import Flatten, Dense, GlobalAveragePooling2D
from tensorflow.keras.optimizers import Adam
model = Sequential([
    Input((28, 28, 1)),
    Conv2D(16, (3, 3), activation='relu'),
    BatchNormalization(),
    MaxPooling2D(pool_size=(2, 2)),
    Dropout(0.1),

    Conv2D(32, (3, 3), activation='relu'),
    BatchNormalization(),
    MaxPooling2D(pool_size=(2, 2)),
    Dropout(0.2),

    GlobalAveragePooling2D(),
    Flatten(),

    Dense(128, activation='relu'),
    Dropout(0.2),

    Dense(num_classes, activation='softmax')
```

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])

model.compile(optimizer=Adam(1e-3),
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

[3]:
```
history = model.fit(train_ds, validation_data=val_ds, epochs=50)
```

```
Epoch 1/50
33/33                 4s 31ms/step -
accuracy: 0.0330 - loss: 3.2906 - val_accuracy: 0.0536 - val_loss: 3.2048
Epoch 2/50
33/33                 0s 8ms/step -
accuracy: 0.1316 - loss: 2.9325 - val_accuracy: 0.0744 - val_loss: 3.1997
Epoch 3/50
33/33                 0s 7ms/step -
accuracy: 0.1729 - loss: 2.8238 - val_accuracy: 0.0387 - val_loss: 3.1962
Epoch 4/50
33/33                 0s 7ms/step -
accuracy: 0.1702 - loss: 2.7346 - val_accuracy: 0.0387 - val_loss: 3.2049
Epoch 5/50
33/33                 0s 7ms/step -
accuracy: 0.2110 - loss: 2.6178 - val_accuracy: 0.0387 - val_loss: 3.2202
Epoch 6/50
33/33                 0s 7ms/step -
accuracy: 0.2411 - loss: 2.5069 - val_accuracy: 0.0387 - val_loss: 3.2863
Epoch 7/50
33/33                 0s 7ms/step -
accuracy: 0.2843 - loss: 2.4128 - val_accuracy: 0.0387 - val_loss: 3.3748
Epoch 8/50
33/33                 0s 7ms/step -
accuracy: 0.3216 - loss: 2.2604 - val_accuracy: 0.0387 - val_loss: 3.4201
Epoch 9/50
33/33                 0s 7ms/step -
accuracy: 0.3249 - loss: 2.1878 - val_accuracy: 0.0387 - val_loss: 3.4895
Epoch 10/50
33/33                 0s 7ms/step -
accuracy: 0.3586 - loss: 2.1285 - val_accuracy: 0.0387 - val_loss: 3.5828
Epoch 11/50
33/33                 0s 7ms/step -
accuracy: 0.4626 - loss: 1.9134 - val_accuracy: 0.0446 - val_loss: 3.4289
Epoch 12/50
33/33                 0s 7ms/step -
accuracy: 0.4390 - loss: 1.8934 - val_accuracy: 0.0446 - val_loss: 3.4718
Epoch 13/50
33/33                 0s 7ms/step -
accuracy: 0.4551 - loss: 1.8142 - val_accuracy: 0.0655 - val_loss: 3.5000
Epoch 14/50
```

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33/33            0s 7ms/step -
accuracy: 0.4899 - loss: 1.7235 - val_accuracy: 0.0625 - val_loss: 3.4196
Epoch 15/50
33/33            0s 7ms/step -
accuracy: 0.5198 - loss: 1.5872 - val_accuracy: 0.1042 - val_loss: 3.2784
Epoch 16/50
33/33            0s 7ms/step -
accuracy: 0.5113 - loss: 1.5855 - val_accuracy: 0.1071 - val_loss: 3.3172
Epoch 17/50
33/33            0s 8ms/step -
accuracy: 0.5756 - loss: 1.4017 - val_accuracy: 0.1280 - val_loss: 2.8988
Epoch 18/50
33/33            0s 8ms/step -
accuracy: 0.5982 - loss: 1.3808 - val_accuracy: 0.1548 - val_loss: 2.8156
Epoch 19/50
33/33            0s 8ms/step -
accuracy: 0.6177 - loss: 1.3102 - val_accuracy: 0.2500 - val_loss: 2.3193
Epoch 20/50
33/33            0s 7ms/step -
accuracy: 0.6163 - loss: 1.2898 - val_accuracy: 0.2857 - val_loss: 2.3503
Epoch 21/50
33/33            0s 7ms/step -
accuracy: 0.6569 - loss: 1.1560 - val_accuracy: 0.5030 - val_loss: 1.8065
Epoch 22/50
33/33            0s 8ms/step -
accuracy: 0.6720 - loss: 1.0999 - val_accuracy: 0.3333 - val_loss: 2.0837
Epoch 23/50
33/33            0s 8ms/step -
accuracy: 0.6643 - loss: 1.1010 - val_accuracy: 0.4732 - val_loss: 1.6617
Epoch 24/50
33/33            0s 8ms/step -
accuracy: 0.7202 - loss: 0.9765 - val_accuracy: 0.3631 - val_loss: 2.1200
Epoch 25/50
33/33            0s 8ms/step -
accuracy: 0.7117 - loss: 0.9863 - val_accuracy: 0.3929 - val_loss: 1.8804
Epoch 26/50
33/33            0s 8ms/step -
accuracy: 0.7427 - loss: 0.8931 - val_accuracy: 0.3661 - val_loss: 1.9151
Epoch 27/50
33/33            0s 7ms/step -
accuracy: 0.7171 - loss: 0.9346 - val_accuracy: 0.5238 - val_loss: 1.5425
Epoch 28/50
33/33            0s 8ms/step -
accuracy: 0.7127 - loss: 0.9039 - val_accuracy: 0.4494 - val_loss: 1.8013
Epoch 29/50
33/33            0s 7ms/step -
accuracy: 0.7170 - loss: 0.8738 - val_accuracy: 0.6280 - val_loss: 1.3445
Epoch 30/50
```

```
33/33              0s 8ms/step -
accuracy: 0.7233 - loss: 0.8256 - val_accuracy: 0.6488 - val_loss: 1.2111
Epoch 31/50
33/33              0s 8ms/step -
accuracy: 0.7410 - loss: 0.8019 - val_accuracy: 0.5863 - val_loss: 1.3743
Epoch 32/50
33/33              0s 8ms/step -
accuracy: 0.8014 - loss: 0.6540 - val_accuracy: 0.6042 - val_loss: 1.2813
Epoch 33/50
33/33              0s 9ms/step -
accuracy: 0.7509 - loss: 0.7777 - val_accuracy: 0.6458 - val_loss: 1.1719
Epoch 34/50
33/33              0s 7ms/step -
accuracy: 0.7982 - loss: 0.6895 - val_accuracy: 0.6607 - val_loss: 1.0779
Epoch 35/50
33/33              0s 8ms/step -
accuracy: 0.7980 - loss: 0.6757 - val_accuracy: 0.5833 - val_loss: 1.3448
Epoch 36/50
33/33              0s 8ms/step -
accuracy: 0.8026 - loss: 0.6616 - val_accuracy: 0.5982 - val_loss: 1.3248
Epoch 37/50
33/33              0s 7ms/step -
accuracy: 0.8144 - loss: 0.6013 - val_accuracy: 0.6607 - val_loss: 1.0365
Epoch 38/50
33/33              0s 8ms/step -
accuracy: 0.8182 - loss: 0.5962 - val_accuracy: 0.6964 - val_loss: 0.9699
Epoch 39/50
33/33              0s 8ms/step -
accuracy: 0.7942 - loss: 0.6368 - val_accuracy: 0.6815 - val_loss: 0.9876
Epoch 40/50
33/33              0s 8ms/step -
accuracy: 0.8179 - loss: 0.5917 - val_accuracy: 0.5774 - val_loss: 1.3849
Epoch 41/50
33/33              0s 8ms/step -
accuracy: 0.7977 - loss: 0.6398 - val_accuracy: 0.6429 - val_loss: 1.2568
Epoch 42/50
33/33              0s 8ms/step -
accuracy: 0.8297 - loss: 0.5400 - val_accuracy: 0.7143 - val_loss: 0.9835
Epoch 43/50
33/33              0s 8ms/step -
accuracy: 0.8315 - loss: 0.5463 - val_accuracy: 0.6458 - val_loss: 1.1713
Epoch 44/50
33/33              0s 8ms/step -
accuracy: 0.8401 - loss: 0.5246 - val_accuracy: 0.7440 - val_loss: 0.8725
Epoch 45/50
33/33              0s 8ms/step -
accuracy: 0.8518 - loss: 0.4858 - val_accuracy: 0.5655 - val_loss: 1.4858
Epoch 46/50
```

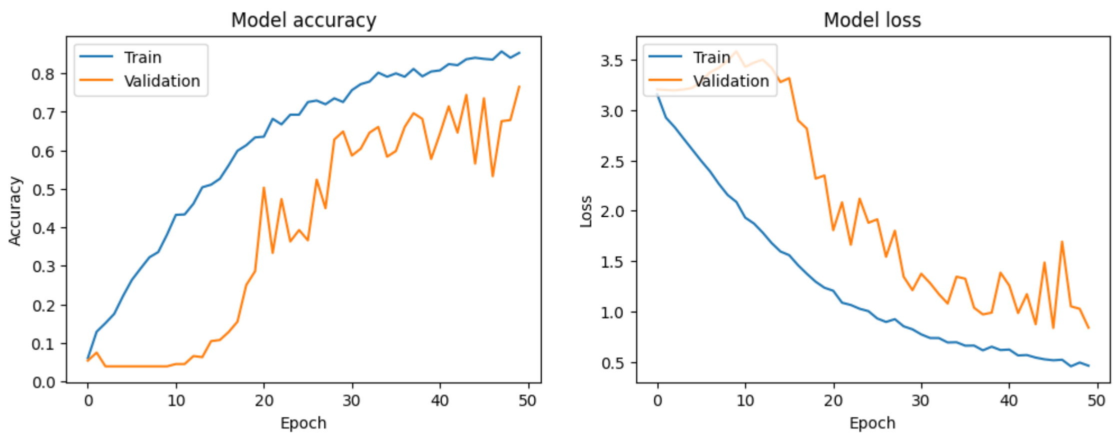
```
33/33                0s 9ms/step -
accuracy: 0.8310 - loss: 0.5130 - val_accuracy: 0.7351 - val_loss: 0.8360
Epoch 47/50
33/33                0s 8ms/step -
accuracy: 0.8480 - loss: 0.5035 - val_accuracy: 0.5327 - val_loss: 1.6933
Epoch 48/50
33/33                0s 8ms/step -
accuracy: 0.8549 - loss: 0.4719 - val_accuracy: 0.6756 - val_loss: 1.0504
Epoch 49/50
33/33                0s 7ms/step -
accuracy: 0.8405 - loss: 0.5182 - val_accuracy: 0.6786 - val_loss: 1.0258
Epoch 50/50
33/33                0s 8ms/step -
accuracy: 0.8666 - loss: 0.4545 - val_accuracy: 0.7649 - val_loss: 0.8380
```

[4]:
```
test_loss, test_accuracy = model.evaluate(test_ds)
print(f"Test Accuracy: {test_accuracy:.4f}")
print(f"Test Loss: {test_loss:.4f}")
```

```
11/11                0s 13ms/step -
accuracy: 0.7739 - loss: 0.7912
Test Accuracy: 0.7784
Test Loss: 0.7928
```

[5]:
```
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns
import numpy as np
```

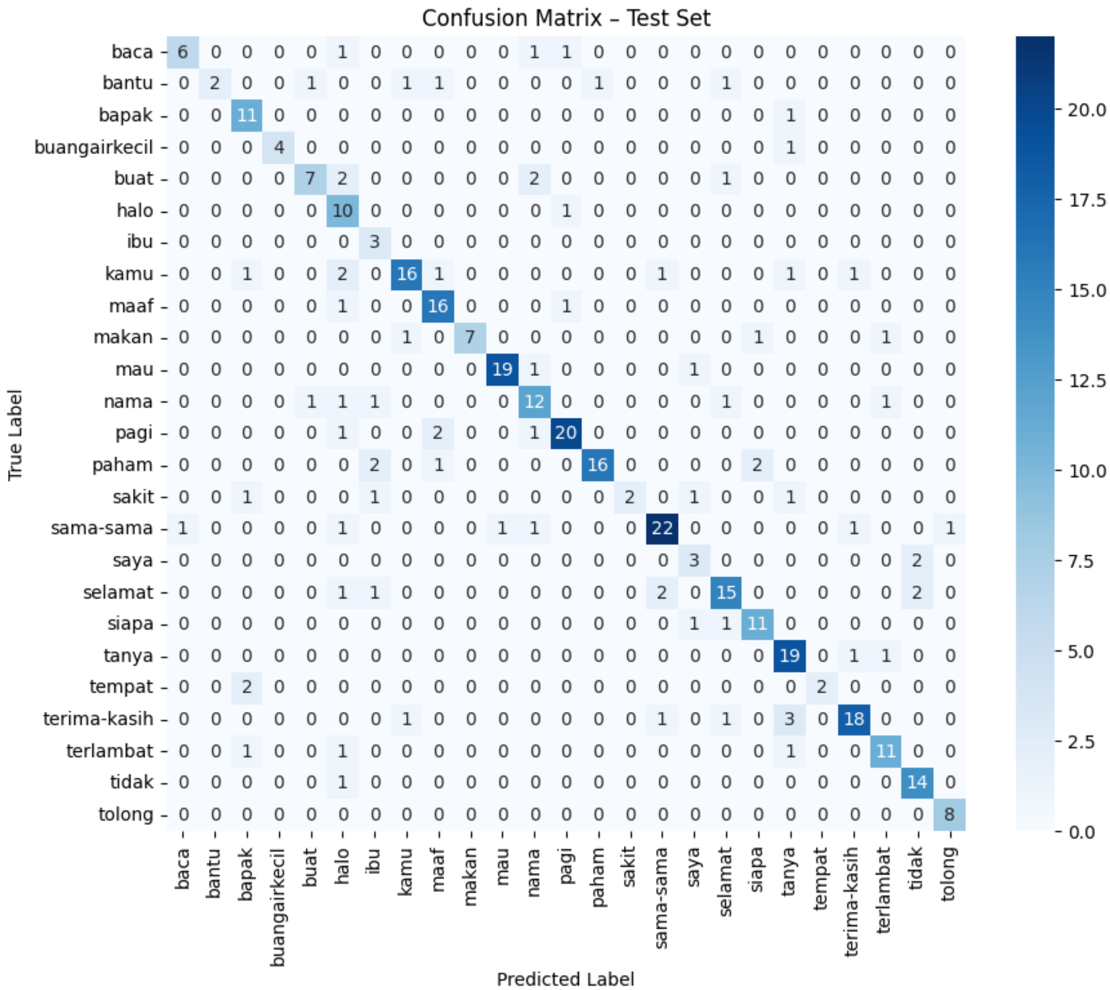
[6]:
```
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')
# Plot training & validation loss values
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()
```



[7]:
```python
y_true, y_pred = [], []
target_names = [label_map[i] for i in range(len(label_map))]
for X_batch, y_batch in test_ds:
    y_true.append(y_batch.numpy())

    batch_pred = model.predict(X_batch, verbose=0)
    y_pred.append(np.argmax(batch_pred, axis=1))

y_true = np.concatenate(y_true)
y_pred = np.concatenate(y_pred)

print(classification_report(
    y_true, y_pred,
    digits=3,
    target_names=target_names
))

cm = confusion_matrix(y_true, y_pred, labels=range(len(label_map)))
labels = [label_map[i] for i in range(len(label_map))]

plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
            xticklabels=labels, yticklabels=labels)
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix - Test Set")
plt.show()
```

```
              precision    recall  f1-score   support

        baca      0.857     0.667     0.750         9
       bantu      1.000     0.286     0.444         7
```

bapak	0.688	0.917	0.786	12
buangairkecil	1.000	0.800	0.889	5
buat	0.778	0.583	0.667	12
halo	0.455	0.909	0.606	11
ibu	0.375	1.000	0.545	3
kamu	0.842	0.696	0.762	23
maaf	0.762	0.889	0.821	18
makan	1.000	0.700	0.824	10
mau	0.950	0.905	0.927	21
nama	0.667	0.706	0.686	17
pagi	0.870	0.833	0.851	24
paham	0.941	0.762	0.842	21
sakit	1.000	0.333	0.500	6
sama-sama	0.846	0.786	0.815	28
saya	0.500	0.600	0.545	5
selamat	0.750	0.714	0.732	21
siapa	0.786	0.846	0.815	13
tanya	0.704	0.905	0.792	21
tempat	1.000	0.500	0.667	4
terima-kasih	0.857	0.750	0.800	24
terlambat	0.786	0.786	0.786	14
tidak	0.778	0.933	0.848	15
tolong	0.889	1.000	0.941	8
accuracy			0.778	352
macro avg	0.803	0.752	0.746	352
weighted avg	0.812	0.778	0.779	352


Confusion Matrix – Test Set
True Label
Predicted Label