2347138_Lab_4

October 18, 2024

[12]:
```
import numpy as np
import tensorflow as tf
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
import seaborn as sns

# Step 1: Load the Kuzushiji dataset
# Ensure that you have extracted the dataset and update the paths accordingly
train_images = np.load('/content/k49-train-imgs.npz')['arr_0']
train_labels = np.load('/content/k49-train-labels.npz')['arr_0']
test_images = np.load('/content/k49-test-imgs.npz')['arr_0']
test_labels = np.load('/content/k49-test-labels.npz')['arr_0']

# Normalize the images to values between 0 and 1
train_images = train_images.astype('float32') / 255.0
test_images = test_images.astype('float32') / 255.0

# Reshape the images to 28x28 pixels with 1 channel for grayscale
train_images = train_images.reshape(-1, 28, 28, 1)
test_images = test_images.reshape(-1, 28, 28, 1)

# Check the number of unique labels to ensure correct number of classes
num_classes = len(np.unique(train_labels))  # Should be 10 for Kuzushiji-MNIST,␣
 ↪or 49 for Kuzushiji-49
print(f"Number of classes: {num_classes}")

# Convert labels to one-hot encoding for training and test sets
train_labels = to_categorical(train_labels, num_classes)
test_labels = to_categorical(test_labels, num_classes)

# Split the training data into training and validation sets (80% training, 20%␣
 ↪validation)
```

```python
X_train, X_val, y_train, y_val = train_test_split(train_images, train_labels,␣
↪test_size=0.2, random_state=42)

# Print data shapes to verify
print(f"X_train shape: {X_train.shape}")
print(f"y_train shape: {y_train.shape}")
print(f"X_val shape: {X_val.shape}")
print(f"y_val shape: {y_val.shape}")
print(f"test_images shape: {test_images.shape}")
print(f"test_labels shape: {test_labels.shape}")

# Step 2: Build the CNN Model

model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
    MaxPooling2D(pool_size=(2, 2)),

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

    Flatten(),
    Dense(128, activation='relu'),
    Dense(num_classes, activation='softmax')  # Output layer should match the␣
↪number of classes
])

# Step 3: Compile the Model

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

# Print the model summary
model.summary()

# Step 4: Train the Model

history = model.fit(X_train, y_train, validation_data=(X_val, y_val),␣
↪epochs=10, batch_size=32)

# Step 5: Evaluate the Model on the Test Set

test_loss, test_acc = model.evaluate(test_images, test_labels)
print(f"Test accuracy: {test_acc}")

# Step 6: Plot Training and Validation Accuracy

plt.plot(history.history['accuracy'], label='train accuracy')
```

```python
plt.plot(history.history['val_accuracy'], label='val accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Step 7: Confusion Matrix

y_pred = model.predict(test_images)
y_pred_classes = np.argmax(y_pred, axis=1)
y_true = np.argmax(test_labels, axis=1)

conf_matrix = confusion_matrix(y_true, y_pred_classes)

# Plot confusion matrix
plt.figure(figsize=(10, 8))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=np.
 ↪arange(num_classes), yticklabels=np.arange(num_classes))
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```

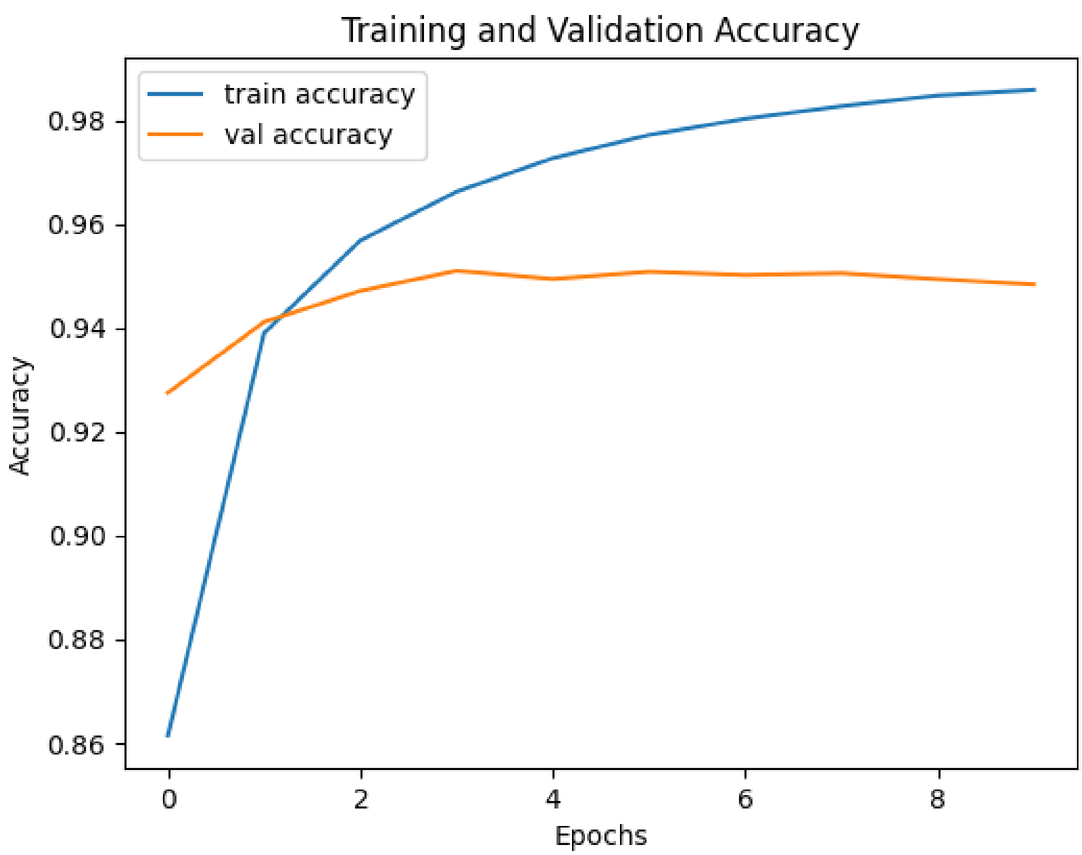
```
Number of classes: 49
X_train shape: (185892, 28, 28, 1)
y_train shape: (185892, 49)
X_val shape: (46473, 28, 28, 1)
y_val shape: (46473, 49)
test_images shape: (38547, 28, 28, 1)
test_labels shape: (38547, 49)
```

```
/usr/local/lib/python3.10/dist-
packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

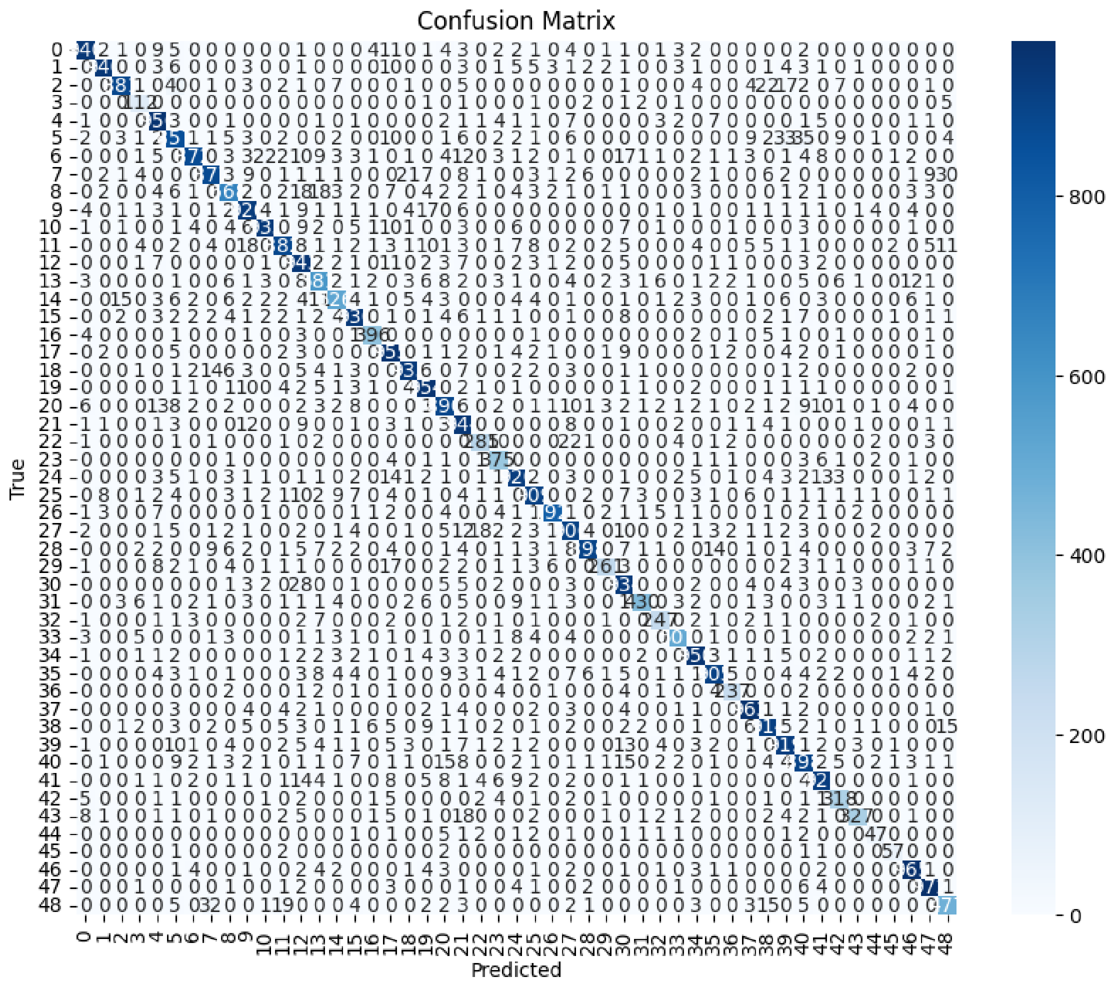
```
Model: "sequential_3"


 Layer (type)                         Output Shape                          ␣
↪Param #

 conv2d_6 (Conv2D)                    (None, 26, 26, 32)                      ␣
↪320
```

```
max_pooling2d_6 (MaxPooling2D)         (None, 13, 13, 32)                  ␣
↪  0

conv2d_7 (Conv2D)                      (None, 11, 11, 64)               ␣
↪18,496

max_pooling2d_7 (MaxPooling2D)         (None, 5, 5, 64)                    ␣
↪  0

flatten_3 (Flatten)                    (None, 1600)                        ␣
↪  0

dense_6 (Dense)                        (None, 128)                     ␣
↪204,928

dense_7 (Dense)                        (None, 49)                        ␣
↪6,321


Total params: 230,065 (898.69 KB)

Trainable params: 230,065 (898.69 KB)

Non-trainable params: 0 (0.00 B)

Epoch 1/10
5810/5810            204s 35ms/step
- accuracy: 0.7669 - loss: 0.9036 - val_accuracy: 0.9275 - val_loss: 0.2661
Epoch 2/10
5810/5810            194s 33ms/step
- accuracy: 0.9376 - loss: 0.2234 - val_accuracy: 0.9411 - val_loss: 0.2114
Epoch 3/10
5810/5810            201s 33ms/step
- accuracy: 0.9586 - loss: 0.1474 - val_accuracy: 0.9471 - val_loss: 0.1920
Epoch 4/10
5810/5810            196s 34ms/step
- accuracy: 0.9684 - loss: 0.1101 - val_accuracy: 0.9509 - val_loss: 0.1857
Epoch 5/10
5810/5810            198s 33ms/step
- accuracy: 0.9744 - loss: 0.0857 - val_accuracy: 0.9494 - val_loss: 0.1997
Epoch 6/10
5810/5810            203s 33ms/step
- accuracy: 0.9790 - loss: 0.0687 - val_accuracy: 0.9507 - val_loss: 0.2048
Epoch 7/10
5810/5810            204s 34ms/step
```

```
- accuracy: 0.9824 - loss: 0.0555 - val_accuracy: 0.9501 - val_loss: 0.2163
Epoch 8/10
5810/5810            199s 33ms/step
- accuracy: 0.9846 - loss: 0.0477 - val_accuracy: 0.9505 - val_loss: 0.2327
Epoch 9/10
5810/5810            212s 35ms/step
- accuracy: 0.9863 - loss: 0.0422 - val_accuracy: 0.9493 - val_loss: 0.2591
Epoch 10/10
5810/5810            193s 33ms/step
- accuracy: 0.9872 - loss: 0.0384 - val_accuracy: 0.9483 - val_loss: 0.2700
1205/1205            12s 10ms/step -
accuracy: 0.9139 - loss: 0.5365
Test accuracy: 0.9141048789024353
```




```
1205/1205            11s 9ms/step
```



0.1 Graph Interpretation

0.1.1 Training Accuracy (Blue Line):

The training accuracy increases rapidly during the first few epochs and continues to improve steadily as the model learns from the training data.

By the 10th epoch, the training accuracy approaches nearly 99%, indicating that the model is learning the training data well.

0.1.2 Validation Accuracy (Orange Line):

The validation accuracy improves significantly during the first few epochs and reaches around 94%-95% by the 3rd or 4th epoch.

However, after this point, the validation accuracy plateaus, and even slightly declines towards the last epochs.

0.1.3 Strengths of RBF Networks for This Dataset:

1. Simple Training Process: Easier to train compared to deep networks.
2. Good for Small/Medium Datasets: Works well with fewer data points.
3. Efficient for Linearly Separable Data: Can handle data that can be separated well after transformation.
4. Localized Responses: Focuses on specific regions of the data, useful for clustered data points. ### Limitations of RBF Networks for This Dataset:
5. Not Ideal for Large Datasets: Struggles with large datasets like Kuzushiji-49 with many classes.
6. Requires Careful Tuning: Needs careful adjustment of parameters to perform well.
7. No Hierarchical Feature Learning: Unlike CNNs, RBF networks can't learn complex features in layers.
8. Scalability Issues: The more RBF units, the slower and more complex the model becomes. ### Effect of Number of RBF Units on Performance:
9. Too Few Units: Leads to underfitting and poor performance.
10. Optimal Units: Enough units allow the model to perform well.
11. Too Many Units: Leads to overfitting, slower training, and poor generalization.

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