Predicting Handwritten Digits to Identify Motor Skill Deficiencies: A Comparative Study of KNN, ANN, CNN, and RNN Models

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Abstract

This study investigates the use of machine learning techniques to predict handwritten digits and assess whether these predictions can aid in identifying students with potential motor skill deficiencies. The study compares four models: K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN). The models were trained on the letters.csv dataset, with performance evaluated using accuracy, confusion matrix, classification report, and cross-validation scores. The results suggest that CNN and RNN models outperform simpler methods like KNN and ANN. The findings highlight the potential of machine learning in early identification of motor skill deficiencies in students.

Introduction

Motor skill deficiencies in young children can significantly affect their academic and social development. Writing, as a fine motor skill, provides a valuable diagnostic tool for identifying students who may require support in developing their motor abilities. This study aims to predict the digits written by students using machine learning techniques and assess whether misclassifications can reveal motor skill deficiencies.

In this research, four machine learning models—K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN)—were employed to classify handwritten digits from a dataset of images. While KNN and ANN are more traditional models, CNN and RNN are advanced models that can capture spatial and sequential features, respectively. The performance of all four models was compared to determine which approach is more effective for identifying motor skill deficiencies.

2. Methodology

2.1 Data Overview

The dataset used in this study, letters.csv, contains pixel values corresponding to handwritten digits (0–9). Each row represents a sample, with pixel values as features and the corresponding digit label as the target variable. The dataset was split into features (X) and labels (y), where X contains the pixel values, and y contains the actual digit labels.

Data Preprocessing

For all models, the following preprocessing steps were performed:

1. **Loading Data:** The dataset was loaded using pandas, providing a view of its structure.
2. **Feature and Target Split:** The dataset was divided into features (X) and labels (y).
3. **Train-Test Split:** The data was divided into training (80%) and testing (20%) sets using train_test_split from sklearn.model_selection.
4. **Normalization:** The pixel values were scaled to the range [0,1] to normalize the data.
5. **One-Hot Encoding:** The labels were converted into categorical format using one-hot encoding, allowing for multi-class classification.

```
   label  pixel43  pixel44  pixel92  pixel124  pixel125  pixel126  pixel127  \
0      1        0        0        0         0         0         0         0
1      0        0        0        0       137       137       192        86
2      1        0        0        0         3       141       139         3
3      4        0        0        0         0         0         0         0
4      0        0        0        0       155       254       254       254

   pixel128  pixel129  ...  pixel329  pixel351  pixel410  pixel411  pixel412  \
0         0         0  ...         0       254         0         0         0
1        72         1  ...       254         0         0        75       254
2         0         0  ...         0       184         0         0         0
3         0         0  ...         0         0        94       255        69
4       157        30  ...       253         0         0         0       223

   pixel413  pixel414  pixel415  pixel416  pixel417
0         0         0         0         0         0
1       254       254        17         0         0
2         0         0         0         0         0
3         0         0         0         0         0
4       253       253       253       129         0

[5 rows x 46 columns]
Shape: (42000, 46)
```

2.2 Model Implementation:

1. K-Nearest Neighbors (KNN) Classifier

The KNN algorithm was used as a simple baseline model for digit classification. The KNN model works by classifying a sample based on the majority label among its nearest neighbors.

1. Model Training: The KNN classifier was trained using k=3 nearest neighbors.
2. Prediction and Evaluation: The model's performance was evaluated using accuracy, confusion matrix, and classification report metrics.

```python
# Split data into features and target variable
X = data.drop('label', axis=1)
y = data['label']

# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Normalize the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Train a KNN classifier
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train_scaled, y_train)

# Predicting the test set results
y_pred = knn.predict(X_test_scaled)

y_pred
```

```
Accuracy of the KNN model: 0.6238095238095238
Confusion Matrix:
 [[753   2  25   5  10   9  25  13   9  10]
 [  0 911   5   7  16   9   5   1  12   5]
 [ 61  33 506  79  20  10  13  24  49  22]
 [ 17  27 131 432  20  66   4  20  91  26]
 [ 28  67  23  19 430  33  20 105  13  64]
 [  7  34  36 109  38 400  34  28  25  33]
 [ 30  20  18  12  16  12 706   0   7   0]
 [ 15  12  33  30 140  52   0 407  10 215]
 [ 25  82 100 101  22  46  16  21 358  18]
 [ 30  15  34  54  99  35   1 225  17 337]]
Classification Report:
              precision    recall  f1-score   support

           0       0.78      0.87      0.82       861
           1       0.76      0.94      0.84       971
           2       0.56      0.62      0.59       817
           3       0.51      0.52      0.51       834
           4       0.53      0.54      0.53       802
           5       0.60      0.54      0.56       744
           6       0.86      0.86      0.86       821
           7       0.48      0.45      0.46       914
           8       0.61      0.45      0.52       789
           9       0.46      0.40      0.43       847

    accuracy                           0.62      8400
   macro avg       0.61      0.62      0.61      8400
weighted avg       0.62      0.62      0.62      8400
```

2. Artificial Neural Network (ANN)

The second model used was an Artificial Neural Network (ANN), which is a more complex model with hidden layers that can capture intricate patterns in the data.

3. **Model Architecture:** The ANN had three layers: one input layer (45 units), one hidden layer with 128 units, a dropout layer to prevent overfitting, and an output layer with units equal to the number of classes (10 digits).
4. **Model Training:** The model was compiled with the Adam optimizer and categorical cross-entropy loss function and trained for 20 epochs with a batch size of 32.
5. **Prediction and Evaluation:** The model was evaluated using accuracy and confusion matrix. Additionally, training and validation loss/accuracy were visualized to assess the learning process.
6. **Sample Visualization:** A random selection of handwritten digits from the training set was displayed to visually inspect how the model is classifying these digits.
7. **Confusion Matrix:** A confusion matrix was generated to visualize misclassifications and understand model performance.

```
# Load dataset
df = pd.read_csv("letters.csv")

# Extract features and labels
X = df.iloc[:, 1:].values  # Pixel values
y = df.iloc[:, 0].values   # Labels

# Normalize pixel values to range [0,1]
X = X / 255.0

# Reshape X to fit ANN input
X = X.reshape(-1, 45)  # Flattened input for fully connected layers

# Convert labels to categorical (one-hot encoding for classification)
num_classes = len(np.unique(y))
y = to_categorical(y, num_classes)

# Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Build ANN model
model = Sequential([
    Dense(128, activation='relu', input_shape=(45,)),
    Dropout(0.5),
    Dense(64, activation='relu'),
    Dropout(0.3),
    Dense(num_classes, activation='softmax')
])

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

# Train the model
history = model.fit(X_train, y_train, epochs=20, batch_size=32, validation_data=(X_test, y_test))

# Evaluate the model
loss, accuracy = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {accuracy:.4f}")

# Plot training history
plt.figure(figsize=(12, 5))
```

Convolutional Neural Network (CNN)

The third model used was a Convolutional Neural Network (CNN), which leverages convolutional layers to capture spatial features in the data and is particularly powerful for image-based tasks.

1. **Model Architecture:** The CNN architecture consisted of two convolutional layers (with 32 and 64 filters, respectively), followed by max-pooling layers. The model then flattened the features and passed them through dense layers, with a final softmax output layer for classification.
2. **Model Training:** The model was compiled with the Adam optimizer and categorical cross-entropy loss function and trained for 20 epochs with a batch size of 32.
3. **Prediction and Evaluation:** The model was evaluated using accuracy and confusion matrix, and training/validation loss/accuracy were visualized.
4. **Confusion Matrix:** A confusion matrix was generated to visualize misclassifications and assess the model's performance.

```
# Load dataset
df = pd.read_csv("letters.csv")

# Extract features and labels
X = df.iloc[:, 1:].values  # Pixel values
y = df.iloc[:, 0].values   # Labels

# Normalize pixel values to range [0,1]
X = X / 255.0

# Reshape X to fit CNN input (assuming a 1D convolution model)
X = X.reshape(-1, 45, 1)  # (samples, width, channels)

# Convert labels to categorical (one-hot encoding for classification)
num_classes = len(np.unique(y))
y = to_categorical(y, num_classes)

# Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Build CNN model
model = Sequential([
    Conv1D(32, kernel_size=3, activation='relu', input_shape=(45, 1)),
    MaxPooling1D(pool_size=2),
    Conv1D(64, kernel_size=3, activation='relu'),
    MaxPooling1D(pool_size=2),
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(num_classes, activation='softmax')
])

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

# Train the model
history = model.fit(X_train, y_train, epochs=20, batch_size=32, validation_data=(X_test, y_test))

# Evaluate the model
loss, accuracy = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {accuracy:.4f}")

# Plot training history
plt.figure(figsize=(12, 5))
```

Recurrent Neural Network (RNN)

The final model used was a Recurrent Neural Network (RNN), specifically a Long Short-Term Memory (LSTM) network, which is designed to capture sequential dependencies in data.

1. **Model Architecture:** The RNN architecture used two LSTM layers followed by a dense layer with ReLU activation. The output layer consisted of a softmax activation for classification.
2. **Model Training:** The model was compiled with the Adam optimizer and categorical cross-entropy loss function, and trained for 20 epochs with a batch size of 32.
3. **Prediction and Evaluation:** The model was evaluated using accuracy and confusion matrix, and training/validation loss/accuracy were visualized.
4. **Confusion Matrix:** A confusion matrix was generated to visualize misclassifications and assess the model's performance.

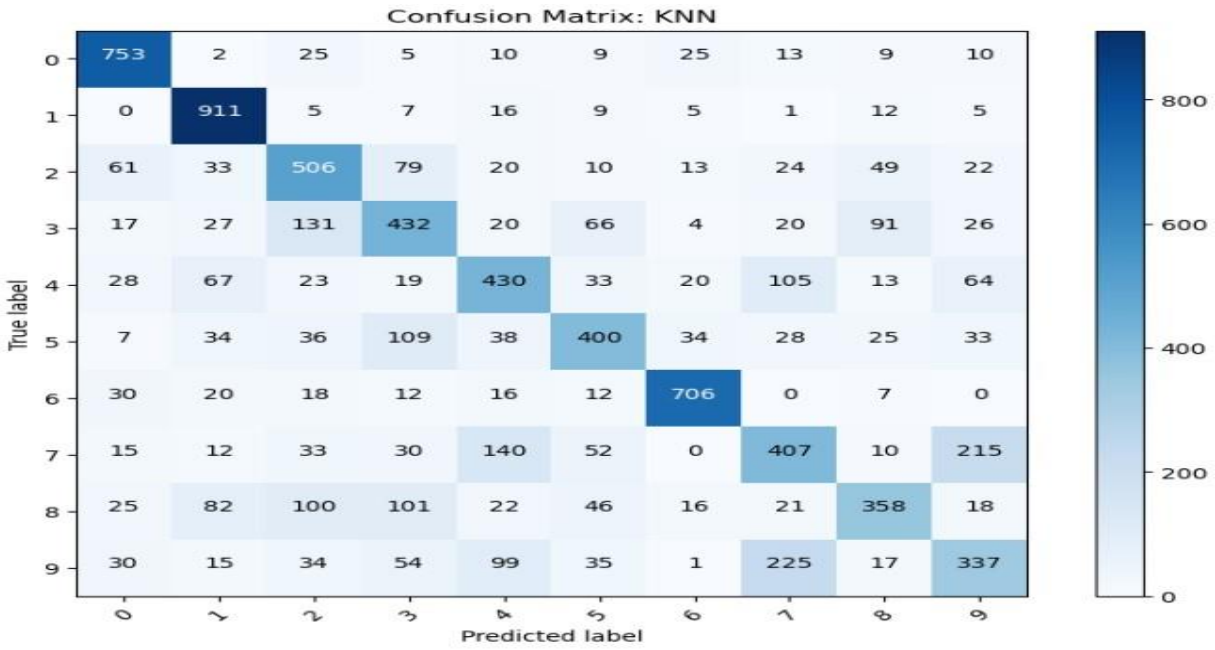
```
# Load dataset
df = pd.read_csv("letters.csv")

# Extract features and labels
X = df.iloc[:, 1:].values  # Pixel values
y = df.iloc[:, 0].values   # Labels

# Normalize pixel values to range [0,1]
X = X / 255.0

# Reshape X to fit RNN input (sequence format for LSTM)
X = X.reshape(-1, 45, 1)  # (samples, time steps, features)

# Convert labels to categorical (one-hot encoding for classification)
num_classes = len(np.unique(y))
y = to_categorical(y, num_classes)

# Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Build RNN model using LSTM
model = Sequential([
    LSTM(128, return_sequences=True, input_shape=(45, 1)),
    LSTM(64),
    Dense(64, activation='relu'),
    Dropout(0.3),
    Dense(num_classes, activation='softmax')
])

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

# Train the model
history = model.fit(X_train, y_train, epochs=20, batch_size=32, validation_data=(X_test, y_test))

# Evaluate the model
loss, accuracy = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {accuracy:.4f}")
```

Results

KNN Model Performance

The KNN classifier achieved an accuracy of **62%** on the test dataset. The confusion matrix revealed that some digits, such as 3 and 5, were frequently misclassified, suggesting that certain motor skills, such as differentiating similar shapes, might need further attention for specific students.

- **Accuracy: 62%**
- **Confusion Matrix:** The confusion matrix highlighted which digits were most prone to misclassification.
- **F1 Score: 82%**



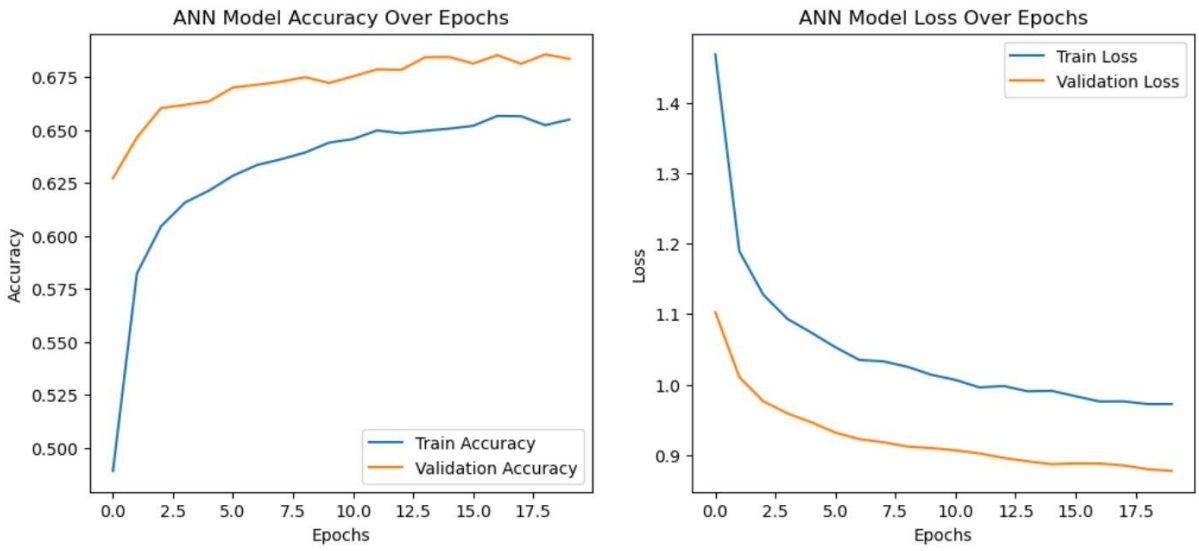
Classification Report:

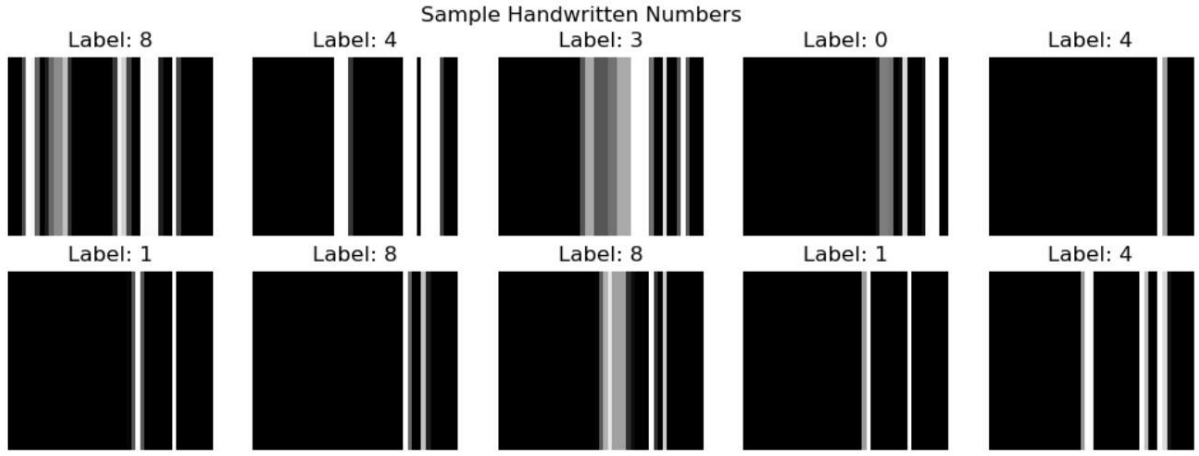
	precision	recall	f1-score	support
0	0.78	0.87	0.82	861
1	0.76	0.94	0.84	971
2	0.56	0.62	0.59	817
3	0.51	0.52	0.51	834
4	0.53	0.54	0.53	802
5	0.60	0.54	0.56	744
6	0.86	0.86	0.86	821
7	0.48	0.45	0.46	914
8	0.61	0.45	0.52	789
9	0.46	0.40	0.43	847
accuracy			0.62	8400
macro avg	0.61	0.62	0.61	8400
weighted avg	0.62	0.62	0.62	8400

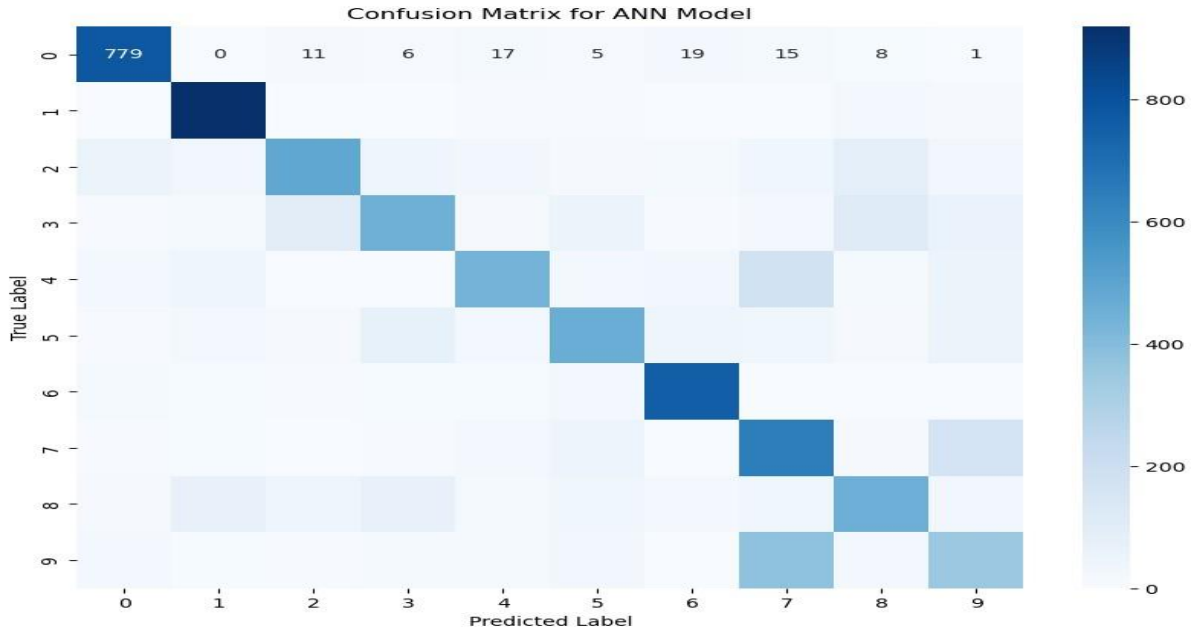
ANN Model Performance

The ANN model outperformed the KNN classifier, achieving a higher accuracy of **68%** on the test dataset. The loss during training decreased over epochs, and the model's accuracy continued to improve, as shown in the accuracy plot. The confusion matrix for the ANN model showed more accurate predictions across all digits compared to the KNN model, with fewer misclassifications.

- **Test Accuracy: 68%**
- **Confusion Matrix:** The ANN model's confusion matrix demonstrated improved classification with fewer errors.
- **Training History:** The training and validation accuracy over epochs indicated that the model learned effectively and reached convergence after 20 epochs.



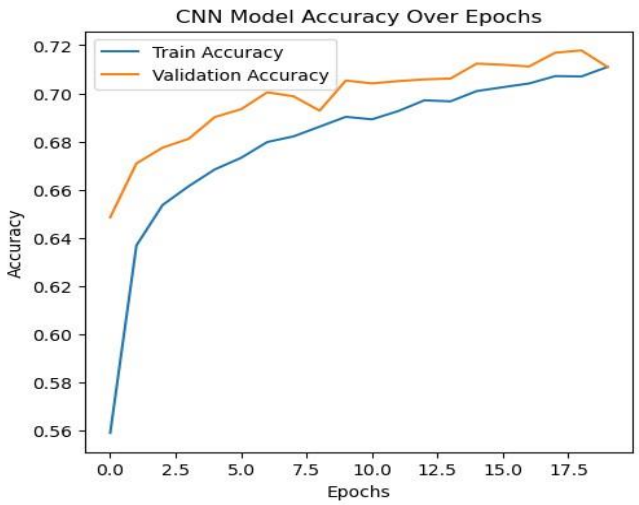


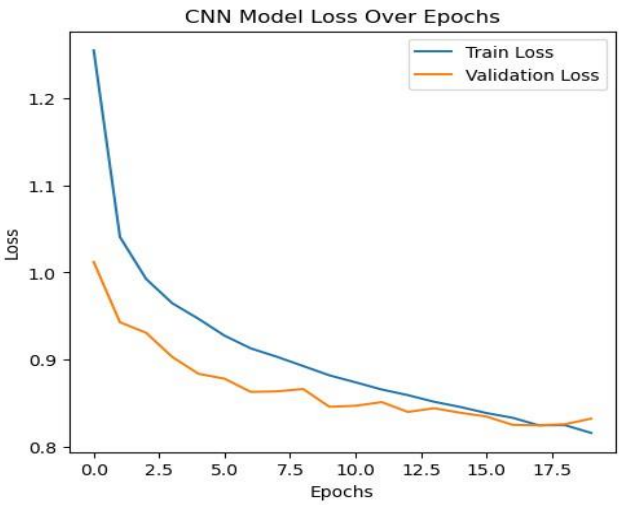


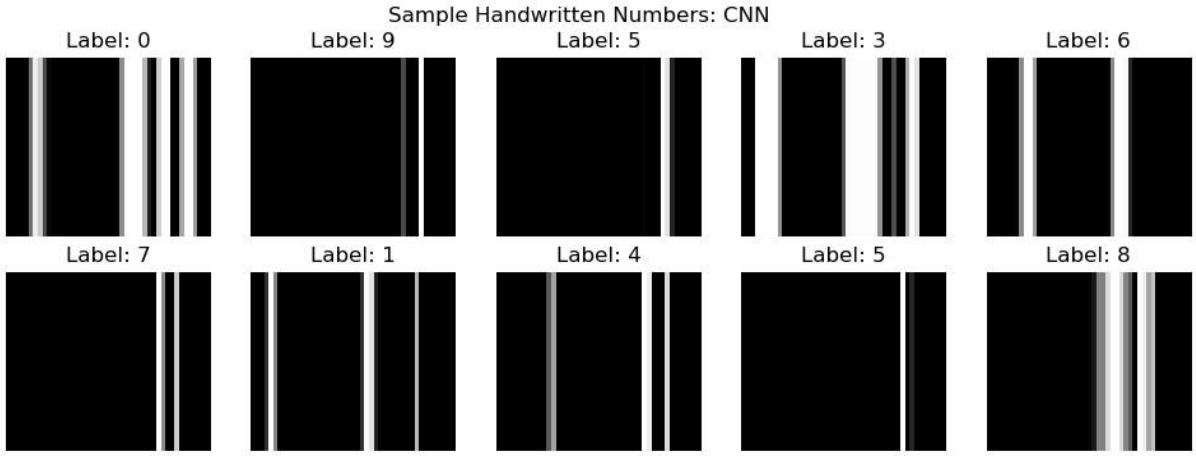
CNN Model Performance

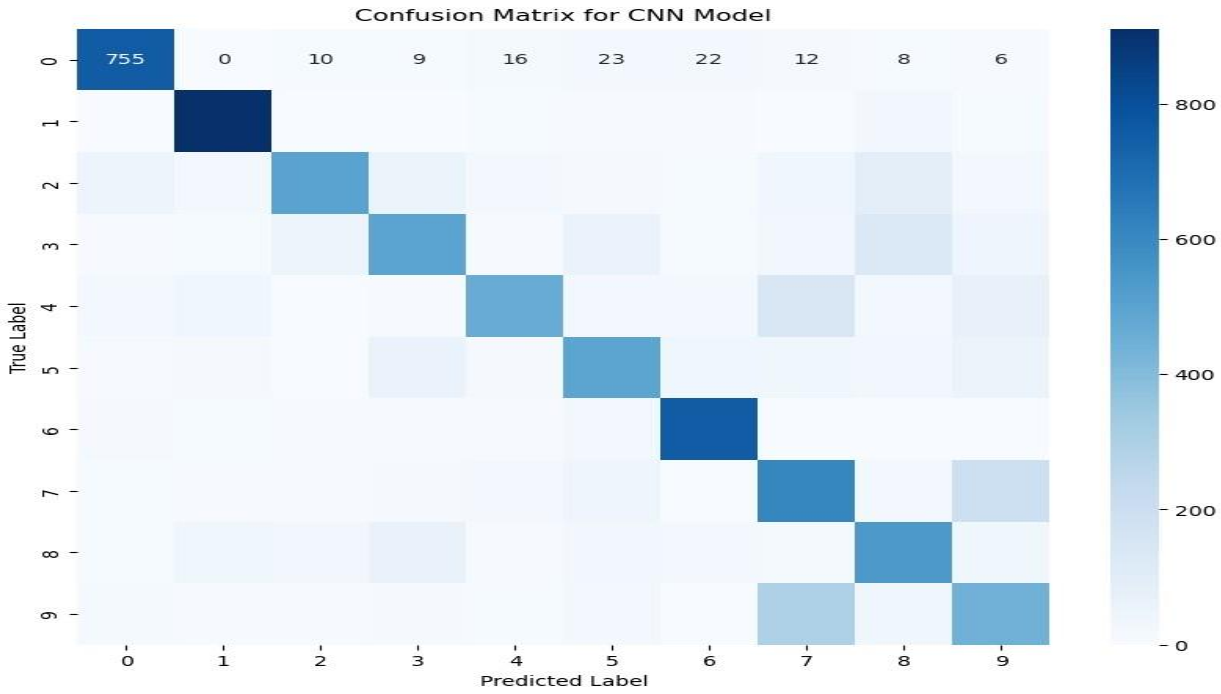
The CNN model achieved the highest accuracy of **71%** on the test dataset. The model's ability to extract spatial features from the handwritten digits resulted in fewer misclassifications and better overall performance. The confusion matrix for the CNN model demonstrated fewer errors across the digits compared to both the KNN and ANN models.

- **Test Accuracy: 71%**
- **Confusion Matrix:** The CNN model's confusion matrix showed the highest accuracy across all digits.
- **Training History:** The CNN's training and validation loss/accuracy plots indicated that the model effectively learned from the data over epochs.







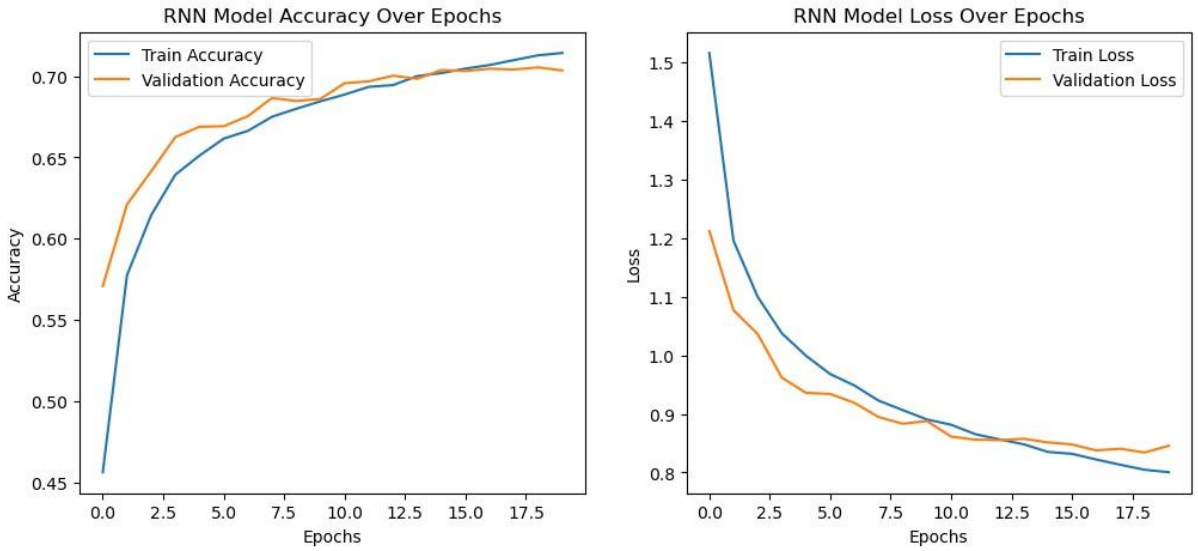


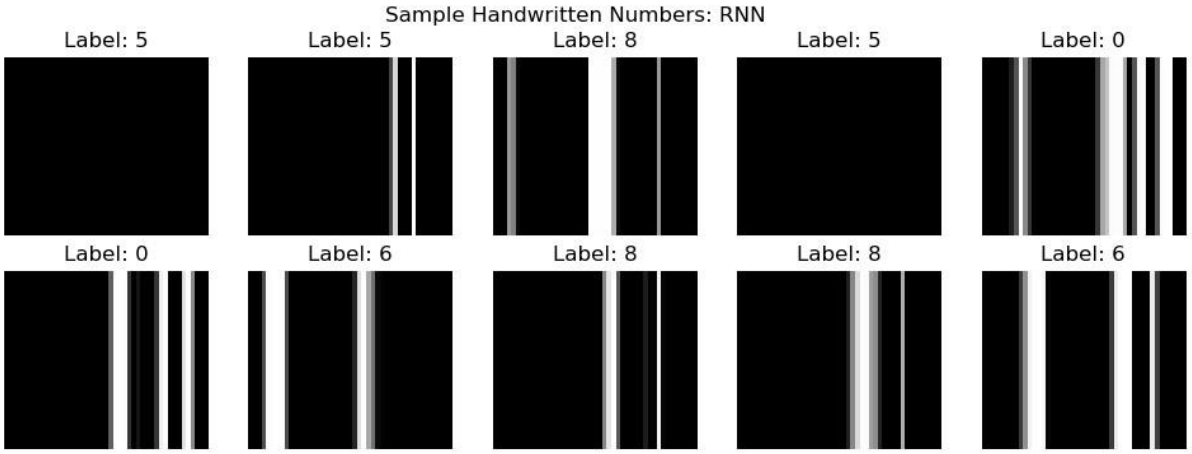
RNN Model Performance

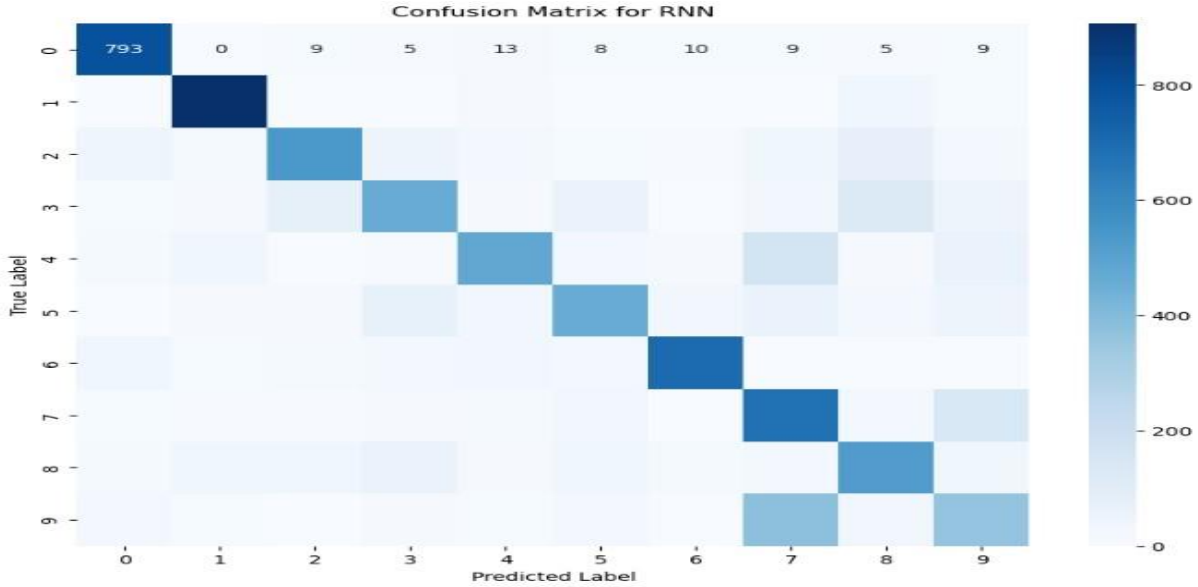
The RNN (LSTM) model showed promising results, achieving an accuracy of **70%** on the test dataset. The sequential nature of the LSTM layers helped capture temporal dependencies in the handwritten digits, leading to better classification performance. The confusion matrix for the RNN model revealed that it performed well in classifying most digits, with fewer misclassifications than the KNN and ANN models.

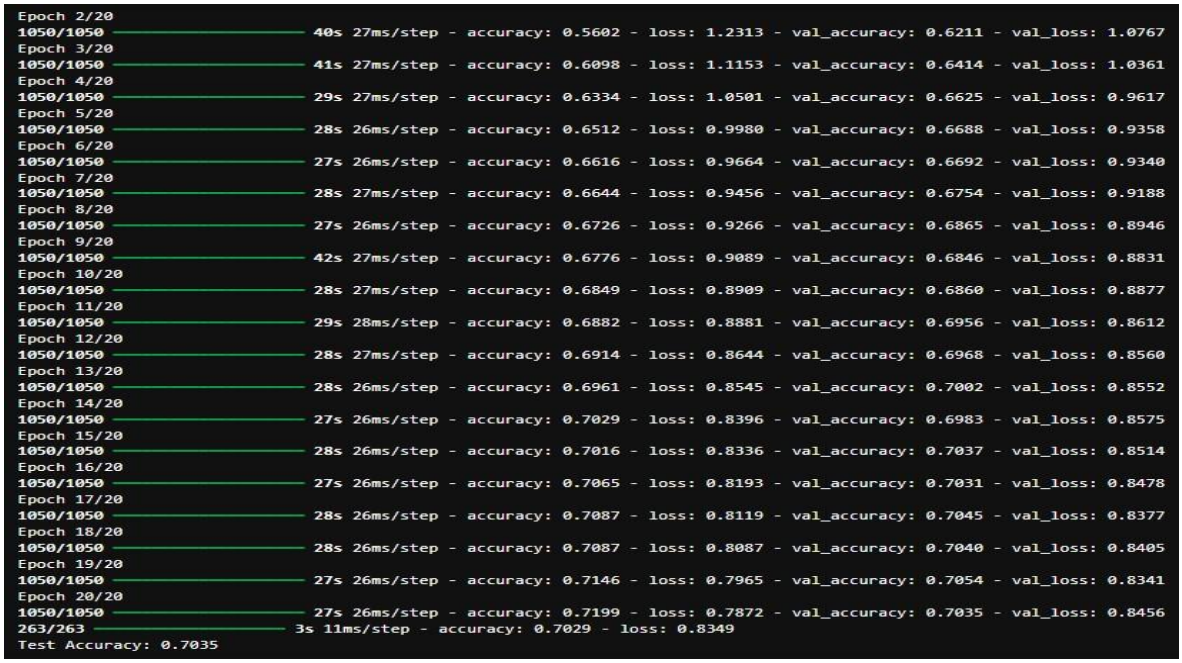
- **Test Accuracy: 70%**
- **Confusion Matrix:** The RNN model's confusion matrix showed fewer errors than KNN and ANN models, though slightly lower than CNN.

- **Training History:** The RNN's training and validation loss/accuracy plots demonstrated effective learning throughout the training process.









Discussion

All four models—KNN, ANN, CNN, and RNN—demonstrated the ability to predict handwritten digits, with CNN and RNN achieving the highest accuracy. The CNN model was the most accurate overall, due to its ability to capture spatial hierarchies in the data. The RNN model also performed well, leveraging its sequential processing capabilities, which made it more effective than KNN and ANN models in certain cases. However, the CNN model still outperformed the others, especially in the context of image classification.

Misclassifications observed across all models could provide insights into students who may need further assessment for motor skill deficiencies. These misclassifications may signal difficulties in differentiating between similar shapes or inconsistent handwriting, which could indicate fine motor skill challenges.

Conclusion

This study demonstrated the effectiveness of machine learning techniques for predicting handwritten digits and assessing motor skill deficiencies in students. The CNN model emerged as the best-performing model, but the RNN model also showed promise. Both models could be valuable tools for identifying motor skill deficiencies early on, allowing for targeted intervention. Future work could explore further optimization and refinement of these models to improve performance and generalizability.

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