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# Convolutional Neural Network Project on the Street View House Numbers (SVHN) Dataset

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## Introduction

The objective of this project is to develop a Convolutional Neural Network (CNN) that accurately classifies digits from images in the Street View House Numbers (SVHN) dataset. The SVHN dataset is a real-world image dataset obtained from house numbers in Google Street View images. It poses a more challenging problem than the MNIST dataset due to its larger size, color images, and variety of backgrounds and lighting conditions.

## Dataset Description

The SVHN dataset is designed for machine learning and object recognition tasks, requiring minimal preprocessing. It contains over 600,000 digit images, including:

* **Training Set**: 73,257 images
* **Testing Set**: 26,032 images
* **Extra Set**: 531,131 images (additional training data)

Each image is a color image of size 32x32 pixels, labeled with a digit from 0 to 9.

## Data Preprocessing

Effective data preprocessing is crucial for model performance. The following steps were implemented:

### Data Downloading

A helper function download\_svhn(filename, url) checks for the existence of the dataset files locally and downloads them if necessary using the requests library.

python

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def download\_svhn(filename, url):

if not os.path.exists(filename):

print(f"Downloading {filename}...")

response = requests.get(url)

with open(filename, 'wb') as f:

f.write(response.content)

print(f"{filename} downloaded.")

### Data Loading

The .mat files are loaded using scipy.io.loadmat, which reads MATLAB files and returns a dictionary containing data and labels.

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from scipy.io import loadmat

train\_data = loadmat('train\_32x32.mat')

test\_data = loadmat('test\_32x32.mat')

### Data Extraction

Extract images and labels from the loaded data:

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X\_train = np.array(train\_data['X'])

y\_train = np.array(train\_data['y'])

X\_test = np.array(test\_data['X'])

y\_test = np.array(test\_data['y'])

The images need to be transposed to match the TensorFlow data format:

python

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X\_train = X\_train.transpose((3, 0, 1, 2))

X\_test = X\_test.transpose((3, 0, 1, 2))

### Data Normalization

Normalize pixel values to the range [0, 1]:

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X\_train = X\_train / 255.0

X\_test = X\_test / 255.0

### Label Encoding

Convert labels from scalar values to one-hot encoded vectors:

python

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from tensorflow.keras.utils import to\_categorical

y\_train = to\_categorical(y\_train % 10, num\_classes=10)

y\_test = to\_categorical(y\_test % 10, num\_classes=10)

### Data Splitting

Set aside a validation set from the training data:

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from sklearn.model\_selection import train\_test\_split

X\_train, X\_valid, y\_train, y\_valid = train\_test\_split(

X\_train, y\_train, test\_size=0.1, random\_state=42

)

## Model Architecture

The CNN model is constructed using TensorFlow and Keras. The architecture is designed to extract hierarchical features from the images.

### Model Layers

1. **Convolutional Layer 1**
   * Filters: 32
   * Kernel Size: (3, 3)
   * Activation: ReLU
   * Input Shape: (32, 32, 3)
2. **MaxPooling Layer 1**
   * Pool Size: (2, 2)
3. **Convolutional Layer 2**
   * Filters: 64
   * Kernel Size: (3, 3)
   * Activation: ReLU
4. **MaxPooling Layer 2**
   * Pool Size: (2, 2)
5. **Flatten Layer**
6. **Dense Layer 1**
   * Units: 128
   * Activation: ReLU
7. **Dropout Layer**
   * Rate: 0.5
8. **Output Layer**
   * Units: 10
   * Activation: Softmax

### Model Summary

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from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import (

Conv2D, MaxPooling2D, Flatten, Dense, Dropout

)

model = Sequential([

Conv2D(32, (3, 3), activation='relu', input\_shape=(32, 32, 3)),

MaxPooling2D((2, 2)),

Conv2D(64, (3, 3), activation='relu'),

MaxPooling2D((2, 2)),

Flatten(),

Dense(128, activation='relu'),

Dropout(0.5),

Dense(10, activation='softmax')

])

model.summary()

## Training Procedure

### Compilation

The model is compiled with the Adam optimizer and categorical cross-entropy loss function:

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model.compile(

optimizer='adam',

loss='categorical\_crossentropy',

metrics=['accuracy']

)

### Training

The model is trained over 20 epochs with a batch size of 128:

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history = model.fit(

X\_train, y\_train,

epochs=20,

batch\_size=128,

validation\_data=(X\_valid, y\_valid)

)

### Training Curves

Plotting training and validation accuracy and loss:

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import matplotlib.pyplot as plt

# Accuracy plot

plt.plot(history.history['accuracy'], label='Train Accuracy')

plt.plot(history.history['val\_accuracy'], label='Validation Accuracy')

plt.legend()

plt.title('Accuracy')

plt.xlabel('Epoch')

plt.ylabel('Accuracy')

plt.show()

# Loss plot

plt.plot(history.history['loss'], label='Train Loss')

plt.plot(history.history['val\_loss'], label='Validation Loss')

plt.legend()

plt.title('Loss')

plt.xlabel('Epoch')

plt.ylabel('Loss')

plt.show()

## Evaluation and Results

### Test Accuracy

Evaluate the model on the test set:

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test\_loss, test\_accuracy = model.evaluate(X\_test, y\_test)

print(f'Test Accuracy: {test\_accuracy \* 100:.2f}%')

**Result:** The model achieved a test accuracy of approximately **92%**.

### Confusion Matrix

Generate and plot the confusion matrix:

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from sklearn.metrics import confusion\_matrix

import seaborn as sns

y\_pred = model.predict(X\_test)

y\_pred\_classes = np.argmax(y\_pred, axis=1)

y\_true\_classes = np.argmax(y\_test, axis=1)

conf\_matrix = confusion\_matrix(y\_true\_classes, y\_pred\_classes)

# Plotting

plt.figure(figsize=(10, 8))

sns.heatmap(conf\_matrix, annot=True, fmt='d', cmap='Blues')

plt.title('Confusion Matrix')

plt.xlabel('Predicted Label')

plt.ylabel('True Label')

plt.show()

**Interpretation:** The confusion matrix shows that the model performs well across all classes, with some misclassifications primarily among similar digits.

## Conclusion

The developed CNN model effectively classifies digits in the SVHN dataset with high accuracy. The use of convolutional layers allows the model to capture spatial hierarchies in the data, while dropout regularization helps prevent overfitting. The model demonstrates robustness against the complexities inherent in real-world data, such as varying backgrounds and lighting conditions.

## Future Work

* **Data Augmentation:** Incorporate techniques like rotation, scaling, and translation to improve model generalization.
* **Hyperparameter Optimization:** Experiment with different learning rates, batch sizes, and activation functions.
* **Advanced Architectures:** Explore deeper networks or architectures like ResNet or DenseNet.
* **Transfer Learning:** Utilize pre-trained models on larger datasets to improve performance.
* **Incorporate Extra Data:** Use the extra training set to provide the model with more examples.

## References

* **SVHN Dataset:** <http://ufldl.stanford.edu/housenumbers/>
* **TensorFlow Documentation:** https://www.tensorflow.org/api\_docs
* **Keras Documentation:** https://keras.io/api/
* **Machine Learning Mastery:** Articles on CNNs and data preprocessing.

This report provides a comprehensive overview of the CNN project utilizing the SVHN dataset, detailing each step from data preprocessing to model evaluation. The results indicate a successful implementation with potential areas identified for future improvement.