Convolutional Neural Network for Image Classification: Model Development and Evaluation

This project aims to build a Convolutional Neural Network (CNN) to classify images from the SVHN dataset. The dataset contains 99289 images categorized into 10. CNNs are particularly well-suited for image classification due to their ability to capture spatial hierarchies in images.

Loading Required packages

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.io import loadmat
from skimage import color
from skimage import io
from sklearn.model_selection import train_test_split

%matplotlib inline
plt.rcParams['figure.figsize'] = (16.0, 4.0)
```

Loading dataset

```
def load_data(path):
    """ Helper function for loading a MAT-File"""
    data = loadmat(path)
    return data['X'], data['y']

X_train, y_train = load_data("/kaggle/input/svhndataset/train_32x32.mat")
X_test, y_test = load_data("/kaggle/input/svhndataset/test_32x32.mat")

print("Training Set", X_train.shape, y_train.shape)
print("Test Set", X_test.shape, y_test.shape)
```

```
Training Set (32, 32, 3, 73257) (73257, 1)
Test Set (32, 32, 3, 26032) (26032, 1)
```

```
# Transpose the image arrays
X_train = X_train.transpose((3,0,1,2))
X_test = X_test.transpose((3,0,1,2))
```

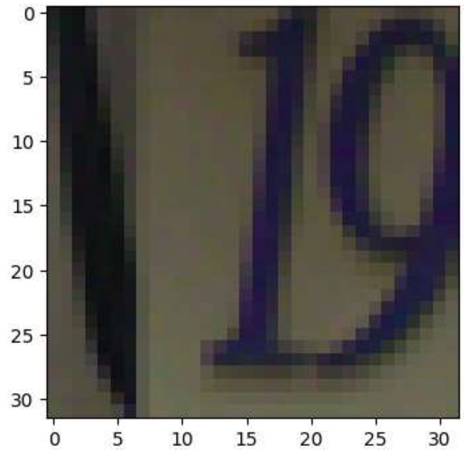
Displaying the Shapes of dataset

```
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(73257, 32, 32, 3)
(73257, 1)
(26032, 32, 32, 3)
(26032, 1)
```

```
plt.imshow(X_train[0])
```

```
<matplotlib.image.AxesImage at 0x7b145c5e1d50>
```



Min Max Scalling

```
# converting to floating point and normalizing pixel values in range [0,1]
X_train = X_train.astype("float32")
X_test = X_test.astype("float32")
X_train /= 255
X_test /= 255
```

```
y_train[y_train == 10] = 0
y_test[y_test == 10] = 0
```

One Hot encoding

```
# Reshaping Labels in One-hot encoding for Multi-class Classification
from keras.utils import to_categorical

y_train = to_categorical(y_train, 10)  # 10 classes (digits 0-9)
y_test = to_categorical(y_test, 10)
# Seeing updated Shapes
print("X_train Shape :", X_train.shape)
print("y_train Shape :", y_train.shape)
print("X_test Shape :", X_test.shape)
print("y_test Shape :", y_test.shape)
```

```
X_train Shape : (73257, 32, 32, 3)
y_train Shape : (73257, 10)
X_test Shape : (26032, 32, 32, 3)
y_test Shape : (26032, 10)
```

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
```

Building the CNN

```
from tensorflow.keras import layers, models, optimizers, callbacks

# Creating Updated Model
model = models.Sequential()

# First Convolution Block
model.add(layers.Conv2D(32, (3, 3), padding='same', activation='relu', input_shape=(32, 32, 3)))
# Batch Normalization after Conv layer
model.add(layers.BatchNormalization())
model.add(layers.Conv2D(32, (3, 3), padding='same', activation='relu'))
model.add(layers.MaxPooling2D(pool_size=(2, 2)))  # Downsampling
```

```
model.add(layers.Dropout(0.3))  # Dropout to avoid overfitting

# Second Convolution Block
model.add(layers.Conv2D(64, (3, 3), padding='same', activation='relu'))
model.add(layers.BatchNormalization())  # Batch Normalization
model.add(layers.Conv2D(64, (3, 3), padding='same', activation='relu'))
model.add(layers.MaxPooling2D(pool_size=(2, 2)))
model.add(layers.Dropout(0.3))

# Third Convolution Block
model.add(layers.Conv2D(128, (3, 3), padding='same', activation='relu'))
model.add(layers.BatchNormalization())  # Batch Normalization
model.add(layers.Conv2D(128, (3, 3), padding='same', activation='relu'))
model.add(layers.MaxPooling2D(pool_size=(2, 2)))
model.add(layers.Dropout(0.4))

# Flatten and Dense Layers
model.add(layers.Flatten())  # Flatten before fully connected layer
model.add(layers.Dense(128, activation='relu'))  # Dense layer with 128 units
model.add(layers.Dropout(0.4))  # Higher dropout for regularization
model.add(layers.Dense(10, activation='softmax'))  # Output layer (for 10 classes)

# Compile the model with Adam optimizer and learning rate scheduler
model.compile(loss='categorical_crossentropy', optimizer='sgd', metrics=['accuracy'])
```

```
model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 32, 32, 32)	896
batch_normalization_3 (BatchNormalization)	(None, 32, 32, 32)	128
conv2d_7 (Conv2D)	(None, 32, 32, 32)	9,248
max_pooling2d_3 (MaxPooling2D)	(None, 16, 16, 32)	0
dropout_4 (Dropout)	(None, 16, 16, 32)	0
conv2d_8 (Conv2D)	(None, 16, 16, 64)	18,496
batch_normalization_4 (BatchNormalization)	(None, 16, 16, 64)	256
conv2d_9 (Conv2D)	(None, 16, 16, 64)	36,928
max_pooling2d_4 (MaxPooling2D)	(None, 8, 8, 64)	0
dropout_5 (Dropout)	(None, 8, 8, 64)	0
conv2d_10 (Conv2D)	(None, 8, 8, 128)	73,856
batch_normalization_5 (BatchNormalization)	(None, 8, 8, 128)	512
conv2d_11 (Conv2D)	(None, 8, 8, 128)	147,584
max_pooling2d_5 (MaxPooling2D)	(None, 4, 4, 128)	0
dropout_6 (Dropout)	(None, 4, 4, 128)	0
flatten_1 (Flatten)	(None, 2048)	0
dense_2 (Dense)	(None, 128)	262,272
dropout_7 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 10)	1,290

Total params: 551,466 (2.10 MB)
Trainable params: 551,018 (2.10 MB)
Non-trainable params: 448 (1.75 KB)

Training the CNN

```
# Training Model
model.fit(X_train, y_train, validation_split= 0.2, epochs=15, batch_size=64, verbose=1)
# model.evaluate(x_test, y_test, verbose=2)
```

```
Epoch 1/15
916/916 ━━━━━━━━━━━━━━━━━━━━ 206s 223ms/step - accuracy: 0.1582 - loss: 2.3647 - val_accuracy: 0.1875 - val_loss: 2.2117
Epoch 2/15
916/916 ━━━━━━━━━━━━━━━━━━━━ 201s 219ms/step - accuracy: 0.1979 - loss: 2.1874 - val_accuracy: 0.3054 - val_loss: 1.9114
Epoch 3/15
916/916 ━━━━━━━━━━━━━━━━━━━━ 203s 220ms/step - accuracy: 0.3726 - loss: 1.7704 - val_accuracy: 0.6941 - val_loss: 0.9511
Epoch 4/15
916/916 ━━━━━━━━━━━━━━━━━━━━ 203s 221ms/step - accuracy: 0.6265 - loss: 1.1321 - val_accuracy: 0.8160 - val_loss: 0.6108
Epoch 5/15
916/916 ━━━━━━━━━━━━━━━━━━━━ 203s 222ms/step - accuracy: 0.7221 - loss: 0.8616 - val_accuracy: 0.7929 - val_loss: 0.6616
Epoch 6/15
916/916 ━━━━━━━━━━━━━━━━━━━━ 203s 221ms/step - accuracy: 0.7744 - loss: 0.7253 - val_accuracy: 0.8574 - val_loss: 0.4712
Epoch 7/15
916/916 ━━━━━━━━━━━━━━━━━━━━ 261s 220ms/step - accuracy: 0.7999 - loss: 0.6516 - val_accuracy: 0.8767 - val_loss: 0.4038
Epoch 8/15
916/916 ━━━━━━━━━━━━━━━━━━━━ 201s 220ms/step - accuracy: 0.8173 - loss: 0.5955 - val_accuracy: 0.8857 - val_loss: 0.3771
Epoch 9/15
916/916 ━━━━━━━━━━━━━━━━━━━━ 203s 221ms/step - accuracy: 0.8323 - loss: 0.5424 - val_accuracy: 0.8875 - val_loss: 0.3769
Epoch 10/15
916/916 ━━━━━━━━━━━━━━━━━━━━ 201s 220ms/step - accuracy: 0.8420 - loss: 0.5206 - val_accuracy: 0.9014 - val_loss: 0.3383
Epoch 11/15
916/916 ━━━━━━━━━━━━━━━━━━━━ 202s 220ms/step - accuracy: 0.8550 - loss: 0.4838 - val_accuracy: 0.9038 - val_loss: 0.3236
Epoch 12/15
916/916 ━━━━━━━━━━━━━━━━━━━━ 202s 220ms/step - accuracy: 0.8637 - loss: 0.4592 - val_accuracy: 0.8995 - val_loss: 0.3342
Epoch 13/15
916/916 ━━━━━━━━━━━━━━━━━━━━ 200s 218ms/step - accuracy: 0.8752 - loss: 0.4181 - val_accuracy: 0.9094 - val_loss: 0.3106
Epoch 15/15
916/916 ━━━━━━━━━━━━━━━━━━━━ 200s 218ms/step - accuracy: 0.8822 - loss: 0.4021 - val_accuracy: 0.9166 - val_loss: 0.2849
<keras.src.callbacks.history.History at 0x7b137ca0aef0>
```

Testing the Model

```
# Import the necessary libraries
from sklearn.metrics import accuracy_score
import numpy as np
import matplotlib.pyplot as plt

# Predict probabilities for the test set using the trained model
y_pred_probs = model.predict(X_test, verbose=0)
y_pred = np.where(y_pred_probs > 0.5, 1, 0)

# Calculate and print the test accuracy using predicted and true labels
test_accuracy = accuracy_score(y_pred, y_test)
print("\nTest accuracy: {}".format(test_accuracy))
```

```
Test accuracy: 0.8921711739397664
```

Start coding or generate with AI.