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MNIST Dataset

The MNIST database of handwritten digits (http://yann.lecun.com)

Data Card Code (225) Discussion (0) Suggestions (0)

About Dataset

Context

MNIST is a subset of a larger set available from NIST (it's copied from http://yann.lecun.com/exdb/mnist/)

Content

The MNIST database of handwritten digits has a training set of 60,000 examples, and a test set of 10,000 examples. .

Four files are available:

- train-images-idx3-ubyte.gz: training set images (9912422 bytes)
- train-labels-idx1-ubyte.gz: training set labels (28881 bytes)
- t10k-images-idx3-ubyte.gz: test set images (1648877 bytes)
- t10k-labels-idx1-ubyte.gz: test set labels (4542 bytes)

How to read

See sample MNIST reader

Usability

7.50

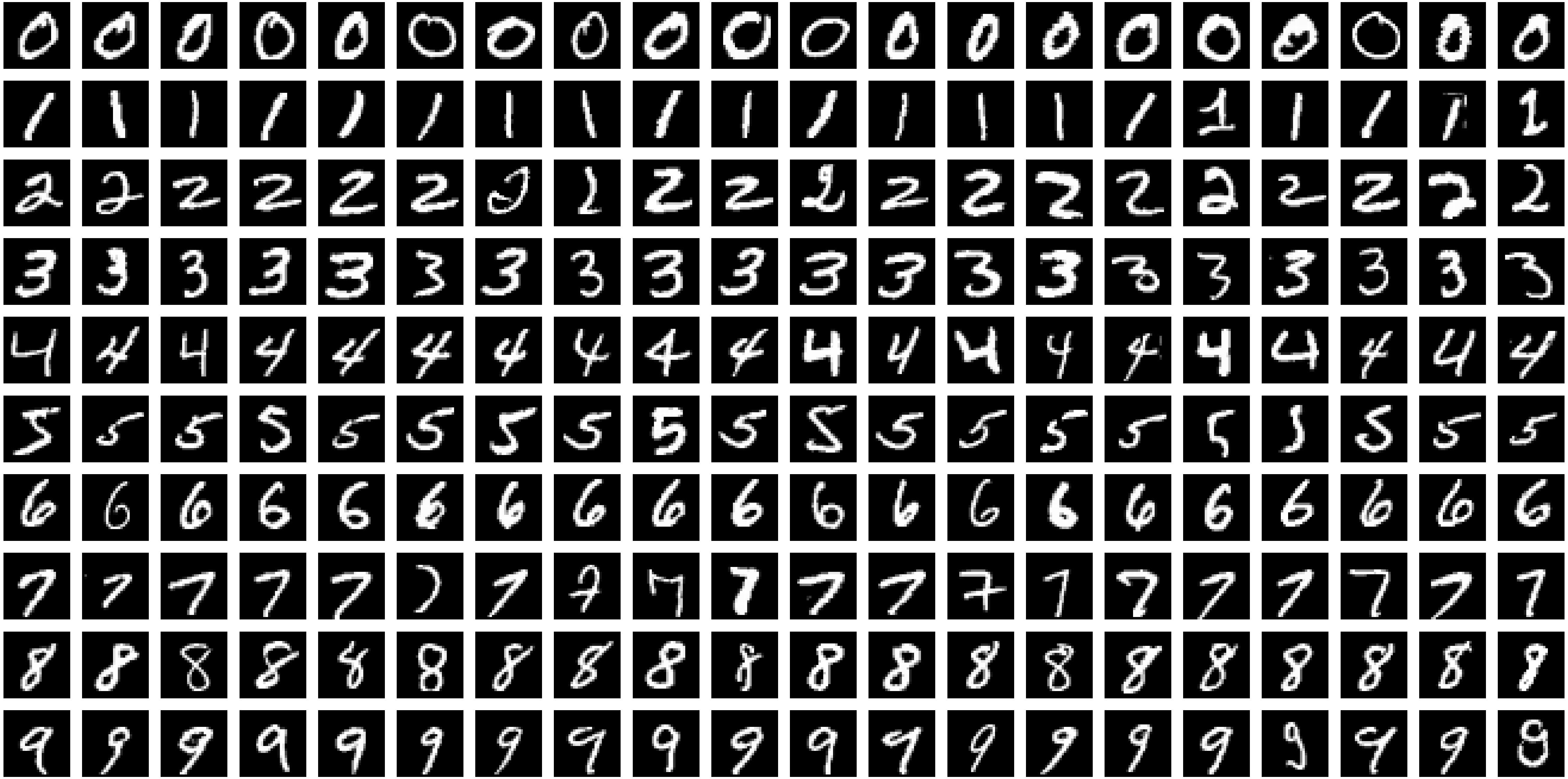
License

Expected update frequency

Not specified

Tags

Computer Science Image Multiclass Classification



Trianing Data

- 60,000 images of handwritten digits from 250 individuals. Among these, 50% are high school students and the other 50% are employees from the Census Bureau.
- All images are composed of 224×224 pixels. Each image also has a corresponding label indicating the digit represented in the image.

Testing Data

- The test data contains 10,000 images of handwritten digits, also sourced from U.S. high school students and Census Bureau employees.
- These images come from a different set of 250 individuals than those whose handwriting was included in the training data.

Why MNIST Dataset?

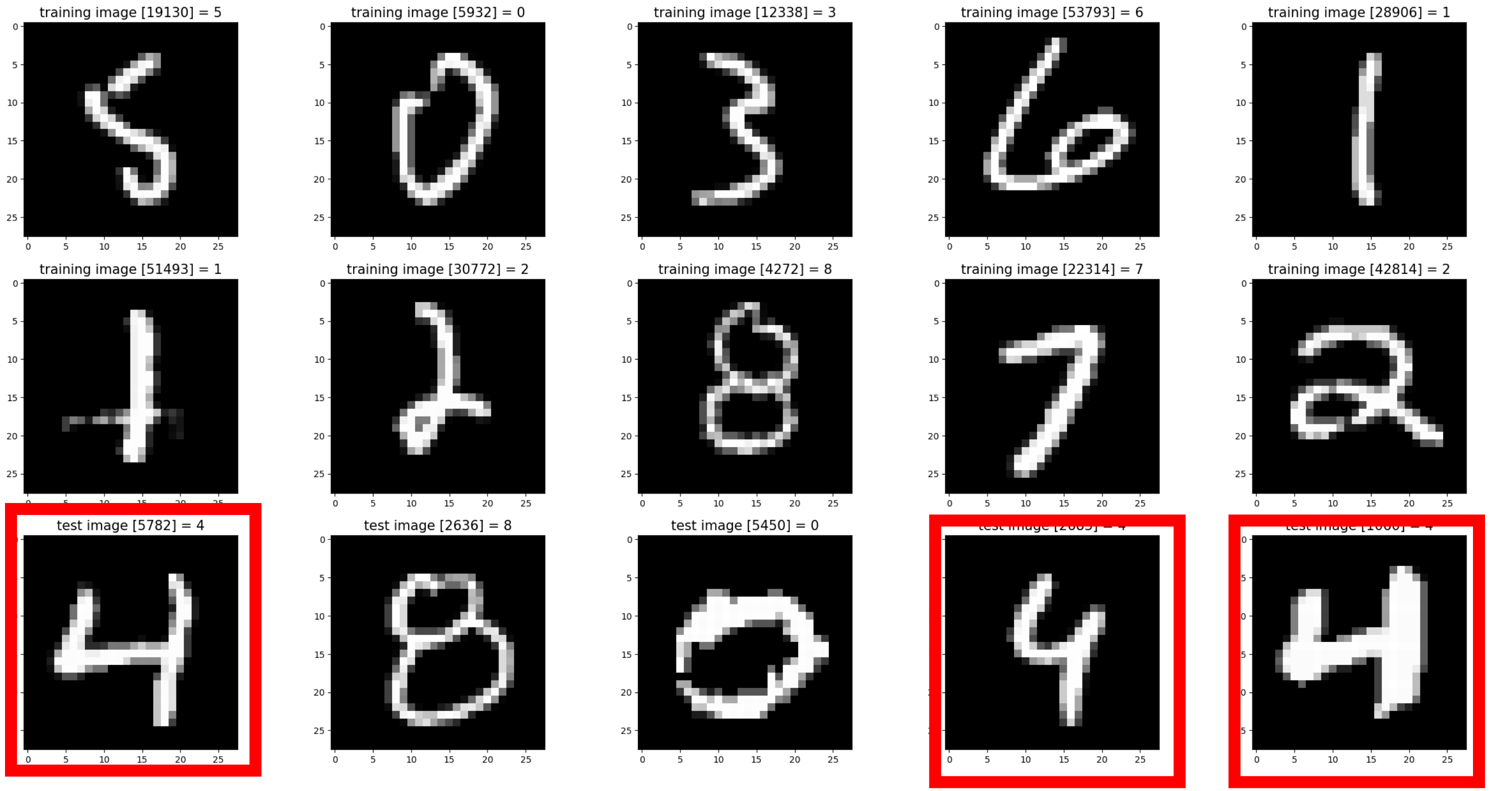
- **Data Availability**: The MNIST dataset, which stands for the Modified National Institute of Standards and Technology dataset, is widely used for training and testing in the field of machine learning. It is a large database of handwritten digits that is publicly available and thus easy to access.
- **Well-defined Problem**: Since the dataset and problem (digit recognition) are well-defined, you can focus more on the modeling aspects rather than spending a lot of time in the data gathering and cleaning stages.

Identify a Supervised Learning Problem

- Why supervised machine learning?
  - MNist is a labeled dataset
  - Room for improvement: top deep learning methods like CNN achieved over 99% accuracy. There is little room for improvement.
  - Faster than deep learning: Compared to CNN, supervised machine learning methods like SVM has shorter run time.

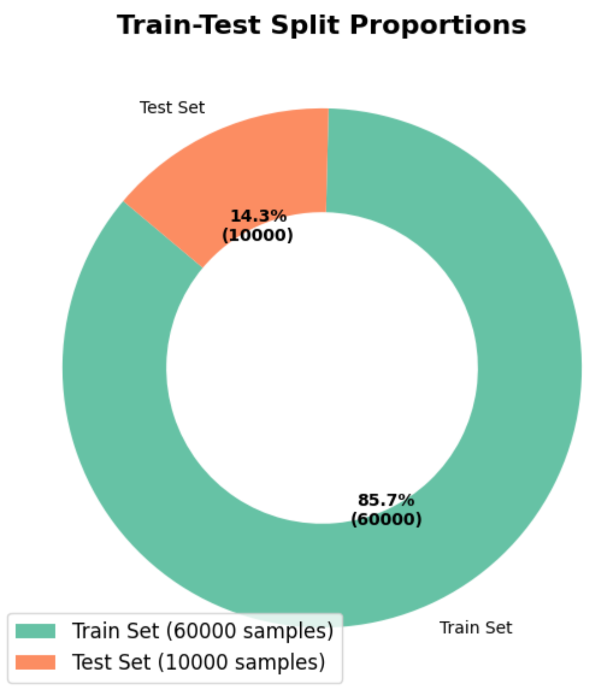
EDA

- I first take a look into the input data
- Most of the handwritings are easy to identify by human eyes
- But I do see a variety of writing styles



EDA

- Each input picture is 224x224x3
  - Most pixels are black and do not contain much information
- Dataset is well balanced among all 10 digits
- Pre-defined test/train split
- At first glance, I believe no transform is required, as MNist is a clean dataset



Models & Results & Analysis: Supervised Method

- Directly apply linear kernel SVM on MNist dataset
  - Full Features: 224*224*3=150528
  - Acc: 91%
  - Run time: 20 mins
  - Session was shut down several times due to excessive memory usage.

Supervised Machine learning: SVM

```python
from sklearn import svm
from sklearn import metrics
svm_linear = svm.SVC(kernel='linear')
print("Full Features: ",X_train_tsne.shape)
print(X_val.shape)
y_val_label=np.argmax(y_val,axis=1)
```

```
Full Features:  (4800, 150528)
(1200, 224, 224, 3)
```

+ Code + Markdown

```python
# fit
svm_linear.fit(X_train_tsne, y_train_label)
predictions_SVM = svm_linear.predict(X_val.reshape(1200,-1))
correct=0
for i in range(len(predictions_SVM)):
    if(predictions_SVM[i]==y_val_label[i]):
        correct+=1
print(correct/len(predictions_SVM))
```

```
0.9141666666666667
```

+ Code + Markdown

Models & Results & Analysis: Supervised Method with PCA Dimension Reduction

- Use PCA to reduce feature size to 20 per image
  - Lower feature size(~5) produces low accuracy (~66%)
- Apply SVM on the reduced features
  - Acc: 91%
  - Run time: 11 s

Supervised Machine learning: SVM with PCA dimension reduction

+ Code + Markdown

[21]:
```
from sklearn.decomposition import PCA
pca = PCA(n_components = 20)
pca.fit(X_train_tsne)
X_train_pca = pca.transform(X_train_tsne)
print(X_train_pca.shape)
```
```
(4800, 20)
```

[22]:
```
from sklearn import svm
svm_linear2 = svm.SVC(kernel='linear')
start = timeit.default_timer()
# fit
svm_linear2.fit(X_train_pca, y_train_label)

print("train_complete")
X_val_pca = pca.transform(X_val.reshape(1200,-1))
print(X_val_pca.shape)
predictions_pca = svm_linear2.predict(X_val_pca)

correct=0
for i in range(len(predictions_pca)):
    if(predictions_pca[i]==y_val_label[i]):
        correct+=1
print(correct/len(predictions_pca))

stop = timeit.default_timer()
print('Time: ', stop - start)
```
```
train_complete
(1200, 20)
0.9108333333333334
Time:  11.623891282000159
```

Models & Results & Analysis: Supervised Method with Hyperparameter Tuning

- Apply grid search on C, gamma
  - Best combination:
    - C=5, gamma=0.001
  - Accuracy 94%

Supervised Machine learning: SVM hyperparameter tuning

[23]:
```
from sklearn.model_selection import GridSearchCV
parameters = {'C': [1, 5, 10],
          'gamma': [0.001, 0.01, 1]}
model_SVM_GS = svm.SVC()
grid = GridSearchCV(estimator=model_SVM_GS, param_grid=parameters)
grid.fit(X_train_pca, y_train_label)
print(grid)
# summarize the results of the grid search
print(grid.best_score_)
print(grid.best_estimator_)
```

```
GridSearchCV(estimator=SVC(),
             param_grid={'C': [1, 5, 10], 'gamma': [0.001, 0.01, 1]})
0.944375
SVC(C=5, gamma=0.001)
```

[24]:
```
predictions_grid = grid.predict(X_val_pca)

correct=0
for i in range(len(predictions_grid)):
    if(predictions_grid[i]==y_val_label[i]):
        correct+=1
print(correct/len(predictions_grid))
```

```
0.9483333333333334
```

Models & Results & Analysis: Unsupervised Method

- Unsupervised methods can also be applied on this dataset
- We use first TSNE to perform dimension reduction
- Followed by GMM clustering
- Ended with label permutation to match with ground truth

```
X_train_tsne=X_train.reshape(4800,-1)
print(X_train_tsne.shape)
tsne = TSNE(n_components=3,
            n_jobs=-1)
digits_proj = tsne.fit_transform(X_train_tsne)
gmm = GaussianMixture(
    n_components=10)
clusters = gmm.fit_predict(digits_proj)
```

Models & Results & Analysis: Unsupervised Method Performance

- The accuracy is 83.6%
- Run time ~ 2 min
- Increasing TSNE component does not improve accuracy

```
stop = timeit.default_timer()

print('Time: ', stop - start)
```

```
(4800, 224, 224, 3)
(4800, 150528)
Time:  157.55008647299974
```

```
voter=np.zeros(shape=(10,10))
y_train_label=np.argmax(y_train,axis=1)
for i in range(len(clusters)):
    #print(clusters[i],y_train_label[i])
    voter[clusters[i]][y_train_label[i]]+=1
print(voter)
trans=np.argmax(voter,axis=1)
correct=0
for i in range(len(clusters)):
    if y_train_label[i]==trans[clusters[i]]:
        correct+=1
print(correct/len(clusters))
```

```
[[  1.   1.   6. 448.   0.  29.   0.   0.  33.   7.]
 [  0.   3.   9.   4.  13.   0.   0. 470.   1. 159.]
 [  1.   0.   3.   2.  10.   7. 479.   0.   3.   1.]
 [476.   0.   1.   1.   0.   1.   3.   0.   7.   5.]
 [  0. 206.   8.   3.   4.   1.   1.   4.   5.   0.]
 [  0.   2. 429.   1.   1.   1.   0.   4.   2.   0.]
 [  0.   1.   2.   7.   0.   1.   0.   0. 347.   0.]
 [  5.   1.   3.   8.   0. 366.   4.   1.  32.   0.]
 [  0.   1.   1.   3. 472.  10.   1.  25.   8. 299.]
 [  1. 322.   4.   4.   4.   1.   1.   5.   2.   2.]]
0.8364583333333333
```

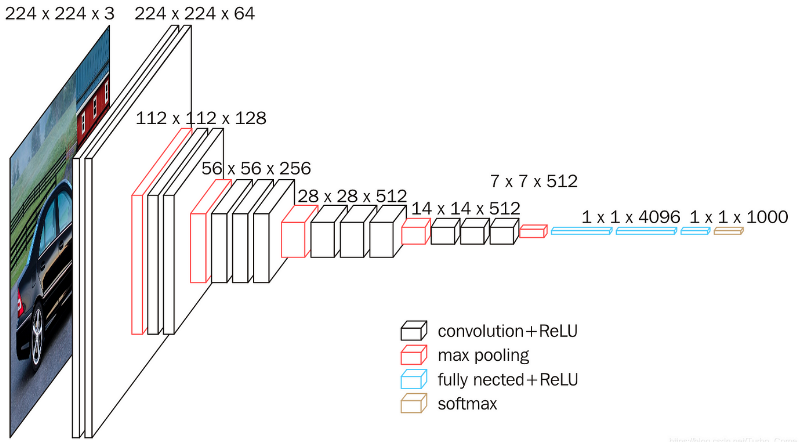
Models & Results & Analysis: Unsupervised Method using less training data

- Although the accuracy is lower, unsupervised methods is less sensitive to insufficient training data
- We experiment using only half of the training set for training
- Accuracy drops from 83.6% to 83.2%
- While run time drops from 2 min to less than 1 min

```
(2400, 150528)
Time:  54.03585478500008
[[  1.   2.   0.   4. 243.   7.   2.  10.   3. 174.]
 [  0.   0.   5.   7.   0. 170.   4.   1.   2.   0.]
 [232.   0.   0.   0.   0.   0.   2.   0.   1.   1.]
 [  0.   1.   5. 223.   0.  23.   0.   0.  10.   3.]
 [  1. 147.   3.   0.   0.   1.   0.   5.   1.   0.]
 [  0.   2.   9.   1.  13.   0.   0. 220.   0.  41.]
 [  0.   1. 218.   6.   0.   0.   0.   3.   5.   0.]
 [  0.   0.   1.   2.   6.   6. 241.   0.   4.   0.]
 [  0. 110.   3.   2.   2.   0.   0.   3.   2.   0.]
 [  0.   0.   0.   7.   0.   4.   0.   0. 194.   0.]]
0.8325
```

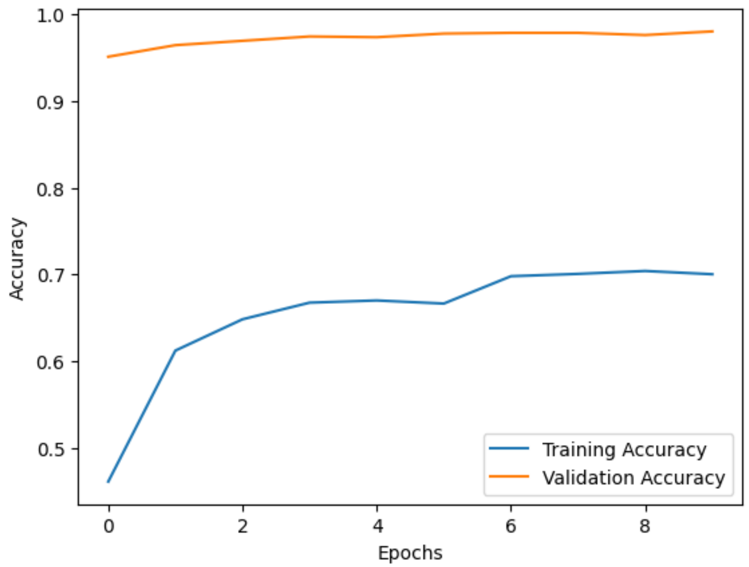
Models & Results & Analysis: Deep-Learning Method

- Since CNN is the king of 2D image processing, I decided to include it in the comparison
- Since 224x224 is the input size of the famous VGG16, we use the pre-trained model provided in Keras to solve the problem.
- Below is the architecture of VGG16. The schematic consists of hierarchical CNN feature extractor and fully-connected classifier.



Models & Results & Analysis: Deep-Learning Method Performance

- Achieved 99.5% accuracy
- Accuracy is almost 90% at the beginning of training, thanks to the pretrained weight.
- Run time is ~15min



Conclusion

- Raw input, even cleaned, may still need transform like dimension reduction for the following reasons
  - Shorter run time
  - Lower hardware requirement (smaller memory usage)
- Deep learning methods outperforms traditional methods, at the price of higher computing cost
- Hyperparameter selection is crucial regarding model performance

```python
import numpy as np
import pandas as pd

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
/kaggle/input/mnist-dataset/train-images.idx3-ubyte
/kaggle/input/mnist-dataset/t10k-labels.idx1-ubyte
/kaggle/input/mnist-dataset/t10k-images.idx3-ubyte
/kaggle/input/mnist-dataset/train-labels.idx1-ubyte
/kaggle/input/mnist-dataset/t10k-labels-idx1-ubyte/t10k-labels-idx1-
ubyte
/kaggle/input/mnist-dataset/t10k-images-idx3-ubyte/t10k-images-idx3-
ubyte
/kaggle/input/mnist-dataset/train-labels-idx1-ubyte/train-labels-idx1-
ubyte
/kaggle/input/mnist-dataset/train-images-idx3-ubyte/train-images-idx3-
ubyte
```

Libraries to be used

```python
import tensorflow as tf
from keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten,
Dense, Dropout
from tensorflow.keras.utils import to_categorical
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
```

Load Data

```python
(train_images, train_labels), (test_images, test_labels) =
mnist.load_data()
train_images, test_images = train_images / 255.0, test_images / 255.0
# normalising the dimensions of images to increase the performance of
cnn

# Load the MNIST dataset
(train_images, train_labels), (test_images, test_labels) =
mnist.load_data()

# Normalize the images
train_images, test_images = train_images / 255.0, test_images / 255.0
```

```
# Use only 60% of the dataset
train_images, train_labels = train_images[:int(0.1 *
len(train_images))], train_labels[:int(0.1 * len(train_labels))]

# Convert images to 3-channel (RGB) and resize to 224x224 for VGG16
def preprocess_images(images):
    images = tf.expand_dims(images, axis=-1)  # Add channel dimension
    images = tf.image.grayscale_to_rgb(images)  # Convert to RGB
    images = tf.image.resize(images, [224, 224])  # Resize to 224x224
    return images.numpy()

train_images = preprocess_images(train_images)
test_images = preprocess_images(test_images)

# Convert labels to one-hot encoding
train_labels = to_categorical(train_labels, num_classes=10)
test_labels = to_categorical(test_labels, num_classes=10)

# Split train data into train and validation sets (80-20 split of 60%
dataset)
X_train, X_val, y_train, y_val = train_test_split(train_images,
train_labels, test_size=0.2, random_state=42)

random_index = np.random.randint(0,len(train_images))
random_image = train_images[random_index]
random_label = train_labels[random_index]
```

EDA

```
temp=np.argmax(train_labels, axis=1)
d={}
for i in range(10):
    d[i]=0
for q in temp:
    d[q]+=1
print(d)
#balanced dataset
```

```
{0: 592, 1: 671, 2: 581, 3: 608, 4: 623, 5: 514, 6: 608, 7: 651, 8:
551, 9: 601}
```

```
for i in range(20):
    random_index = np.random.randint(0, len(train_images))
    random_image = train_images[random_index]
    random_label = train_labels[random_index]

    plt.imshow(random_image, cmap='gray')  # Use 'gray' for MNIST
images
```

```
    plt.axis('off')
    plt.title(np.argmax(random_label))  # Convert one-hot label back to a class index
    plt.show()
```

1

4

8

8

2

8

7

0

4

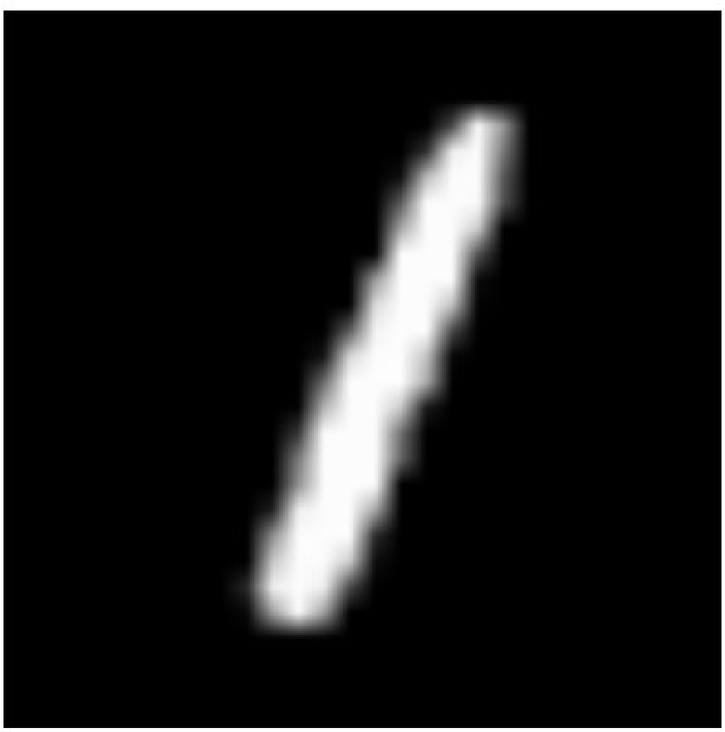
9

2

8

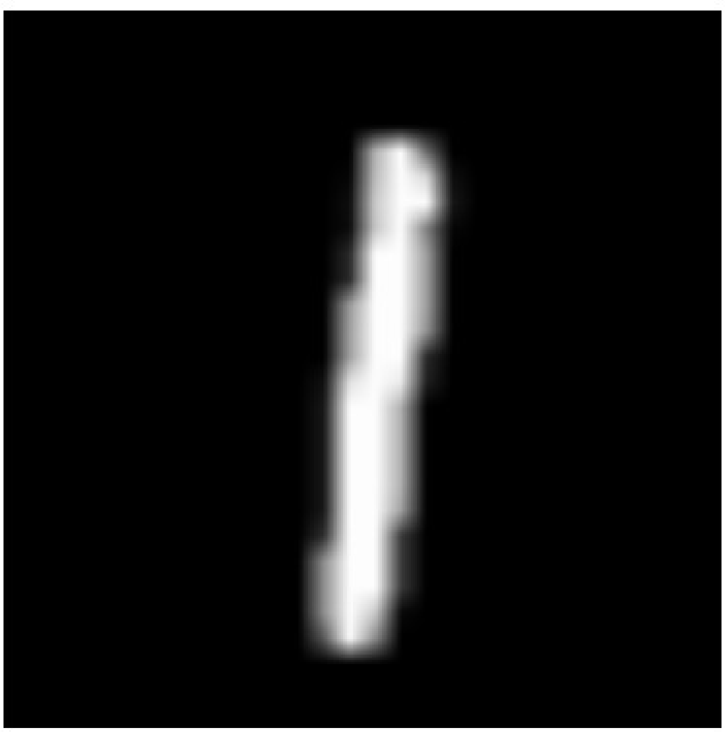
4

1



4

1



8

0

1

```
random_image.shape
```

```
(224, 224, 3)
```

```
labels = str(list(range(0,10)))
labels
```

```
'[0, 1, 2, 3, 4, 5, 6, 7, 8, 9]'
```

```
num_samples = 12
random_indices = np.random.choice(train_images.shape[0], num_samples,
replace=False)
sample_images = train_images[random_indices]
sample_labels = train_labels[random_indices]
```

```
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)
```

Deep learning: VGG16 Network

```
from tensorflow.keras.applications import VGG16
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Flatten, Dense, Dropout
vgg_base = VGG16(weights='imagenet', include_top=False,
input_shape=(224, 224, 3))
```

```python
# Freeze the VGG16 base layers
for layer in vgg_base.layers:
    layer.trainable = False

# Add custom layers on top of VGG16
x = Flatten()(vgg_base.output)
x = Dense(128, activation='relu')(x)
x = Dropout(0.5)(x)
output = Dense(10, activation='softmax')(x)  # 10 classes for MNIST

# Create final model
model = Model(inputs=vgg_base.input, outputs=output)
# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', 
metrics=['accuracy'])

# Train the model without using ImageDataGenerator
##change to true if train CNN
if False:
    history = model.fit(
        X_train, y_train,  # Directly use the training data
        validation_data=(X_val, y_val),  # Directly use the validation 
data
        epochs=10,
        batch_size=32  # Set batch size here
    )
```

Unsupervised method: TSNE+GMM

```python
from sklearn.manifold import Isomap, TSNE
from sklearn.decomposition import PCA
# Clustering
from sklearn.mixture import GaussianMixture
import timeit



print(X_train.shape)
X_train_tsne=X_train.reshape(4800,-1)
print(X_train_tsne.shape)
y_train_label=np.argmax(y_train,axis=1)
y_val_label=np.argmax(y_val,axis=1)
```

```
(4800, 224, 224, 3)
(4800, 150528)
```

```python
if True:#change to true if you want to run GMM
    start = timeit.default_timer()
```

```
    tsne = TSNE(n_components=3,
                n_jobs=-1)
    digits_proj = tsne.fit_transform(X_train_tsne)
    gmm = GaussianMixture(
        n_components=10)
    clusters = gmm.fit_predict(digits_proj)
    #Your statements here

    stop = timeit.default_timer()

    print('Time: ', stop - start)
    voter=np.zeros(shape=(10,10))

    for i in range(len(clusters)):
        #print(clusters[i],y_train_label[i])
        voter[clusters[i]][y_train_label[i]]+=1
    print(voter)
    trans=np.argmax(voter,axis=1)
    correct=0
    for i in range(len(clusters)):
        if y_train_label[i]==trans[clusters[i]]:
            correct+=1
    print(correct/len(clusters))
```

```
Time:  157.3312752239999
[[  0.   0.   1.   0. 267.   0.   0.  26.   2. 264.]
 [  0. 219.   7.   3.   4.   1.   1.   4.   4.   0.]
 [476.   0.   0.   1.   0.   1.   3.   0.   4.   5.]
 [  1. 308.   2.   3.   4.   1.   1.   5.   3.   1.]
 [  0.   2.   9.   3.   1.   0.   0. 441.   1.  10.]
 [  5.   1.   5.  13.   3. 247.  12.   1. 358.   0.]
 [  0.   3. 430.   2.   1.   1.   0.   3.   2.   0.]
 [  1.   1.   4.   2.   7.   4. 471.   0.   2.   1.]
 [  1.   1.   7. 450.   0. 155.   1.   0.  59.   7.]
 [  0.   2.   1.   4. 217.   7.   0.  29.   5. 185.]]
0.7577083333333333
```

Unsupervised method: reduce training data

```
start = timeit.default_timer()

X_train_tsne2=X_train_tsne[:2400][:]
y_train_label2=np.argmax(y_train,axis=1)[:2400]
print(X_train_tsne2.shape)
tsne2 = TSNE(n_components=3,
            n_jobs=-1)
digits_proj2 = tsne2.fit_transform(X_train_tsne2)
gmm2 = GaussianMixture(
```

```
    n_components=10)
clusters2 = gmm2.fit_predict(digits_proj2)
#Your statements here

stop = timeit.default_timer()

print('Time: ', stop - start)

voter2=np.zeros(shape=(10,10))

for i in range(len(clusters2)):
    #print(clusters[i],y_train_label[i])
    voter2[clusters2[i]][y_train_label2[i]]+=1
print(voter2)
trans2=np.argmax(voter2,axis=1)
correct2=0
for i in range(len(clusters2)):
    if y_train_label2[i]==trans2[clusters2[i]]:
        correct2+=1
print(correct2/len(clusters2))
```

```
(2400, 150528)
Time:  56.688194474000284
[[  1. 147.   3.   0.   0.   1.   0.   5.   1.   0.]
 [  0.   1.   5. 223.   0.  28.   0.   0.   8.   3.]
 [  0.   0.   1.   2.   6.   7. 241.   0.   4.   0.]
 [  1.   2.   1.   4. 244.   7.   2.  13.   3. 182.]
 [  0.   1. 219.   6.   0.   0.   0.   3.   5.   0.]
 [  0. 110.   3.   2.   2.   0.   0.   3.   2.   0.]
 [  0.   0.   0.   7.   0.   4.   0.   0. 196.   0.]
 [  0.   2.   8.   1.  12.   0.   0. 217.   0.  33.]
 [  0.   0.   4.   7.   0. 164.   4.   1.   2.   0.]
 [232.   0.   0.   0.   0.   0.   2.   0.   1.   1.]]
0.8304166666666667
```

Supervised Machine learning: SVM

```
from sklearn import svm
from sklearn import metrics
svm_linear = svm.SVC(kernel='linear')
print("Full Features: ",X_train_tsne.shape)
print(X_val.shape)
y_val_label=np.argmax(y_val,axis=1)
```

```
Full Features:  (4800, 150528)
(1200, 224, 224, 3)
```

```
# fit
if False: #change to True if you want to apply SVM on raw data
    svm_linear.fit(X_train_tsne, y_train_label)
    predictions_SVM = svm_linear.predict(X_val.reshape(1200,-1))
    correct=0
    for i in range(len(predictions_SVM)):
        if(predictions_SVM[i]==y_val_label[i]):
            correct+=1
    print(correct/len(predictions_SVM))
```

Supervised Machine learning: SVM with PCA dimension reduction

```
from sklearn.decomposition import PCA
pca = PCA(n_components = 20)
pca.fit(X_train_tsne)
X_train_pca = pca.transform(X_train_tsne)
print(X_train_pca.shape)
```

```
(4800, 20)
```

```
from sklearn import svm
svm_linear2 = svm.SVC(kernel='linear')
start = timeit.default_timer()
# fit
svm_linear2.fit(X_train_pca, y_train_label)

print("train_complete")
X_val_pca = pca.transform(X_val.reshape(1200,-1))
print(X_val_pca.shape)
predictions_pca = svm_linear2.predict(X_val_pca)

correct=0
for i in range(len(predictions_pca)):
    if(predictions_pca[i]==y_val_label[i]):
        correct+=1
print(correct/len(predictions_pca))

stop = timeit.default_timer()
print('Time: ', stop - start)
```

```
train_complete
(1200, 20)
0.9083333333333333
Time:  13.015603397999712
```

Supervised Machine learning: SVM hyperparameter tuning

```
from sklearn.model_selection import GridSearchCV
parameters = {'C': [1, 5, 10],
          'gamma': [0.001, 0.01, 1]}
model_SVM_GS = svm.SVC()
grid = GridSearchCV(estimator=model_SVM_GS, param_grid=parameters)
grid.fit(X_train_pca, y_train_label)
print(grid)
# summarize the results of the grid search
print(grid.best_score_)
print(grid.best_estimator_)
```

```
GridSearchCV(estimator=SVC(),
             param_grid={'C': [1, 5, 10], 'gamma': [0.001, 0.01, 1]})
0.9441666666666666
SVC(C=5, gamma=0.001)
```

```
predictions_grid = grid.predict(X_val_pca)

correct=0
for i in range(len(predictions_grid)):
    if(predictions_grid[i]==y_val_label[i]):
        correct+=1
print(correct/len(predictions_grid))
```

```
0.9483333333333334
```

Deep learning: other analysis

```
from tensorflow.keras.optimizers import Adagrad

# Modeling
model.compile(optimizer='Adagrad', loss='categorical_crossentropy',
metrics=['accuracy'])

model.summary()
```

```
Model: "functional_3"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━
━━━━━┓
┃ Layer (type)                     ┃ Output Shape           ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━
━━━━━┩
```

```
│ input_layer_1 (InputLayer)      │ (None, 224, 224, 3)    │
0 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ block1_conv1 (Conv2D)           │ (None, 224, 224, 64)   │
1,792 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ block1_conv2 (Conv2D)           │ (None, 224, 224, 64)   │
36,928 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ block1_pool (MaxPooling2D)      │ (None, 112, 112, 64)   │
0 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ block2_conv1 (Conv2D)           │ (None, 112, 112, 128)  │
73,856 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ block2_conv2 (Conv2D)           │ (None, 112, 112, 128)  │
147,584 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ block2_pool (MaxPooling2D)      │ (None, 56, 56, 128)    │
0 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ block3_conv1 (Conv2D)           │ (None, 56, 56, 256)    │
295,168 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ block3_conv2 (Conv2D)           │ (None, 56, 56, 256)    │
590,080 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ block3_conv3 (Conv2D)           │ (None, 56, 56, 256)    │
590,080 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ block3_pool (MaxPooling2D)      │ (None, 28, 28, 256)    │
0 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ block4_conv1 (Conv2D)           │ (None, 28, 28, 512)    │
1,180,160 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ block4_conv2 (Conv2D)           │ (None, 28, 28, 512)    │
```

```
2,359,808 │
├─────────────────────────────────┼─────────────────────────┼──────────
───────┤
│ block4_conv3 (Conv2D)           │ (None, 28, 28, 512)     │
2,359,808 │
├─────────────────────────────────┼─────────────────────────┼──────────
───────┤
│ block4_pool (MaxPooling2D)      │ (None, 14, 14, 512)     │
0 │
├─────────────────────────────────┼─────────────────────────┼──────────
───────┤
│ block5_conv1 (Conv2D)           │ (None, 14, 14, 512)     │
2,359,808 │
├─────────────────────────────────┼─────────────────────────┼──────────
───────┤
│ block5_conv2 (Conv2D)           │ (None, 14, 14, 512)     │
2,359,808 │
├─────────────────────────────────┼─────────────────────────┼──────────
───────┤
│ block5_conv3 (Conv2D)           │ (None, 14, 14, 512)     │
2,359,808 │
├─────────────────────────────────┼─────────────────────────┼──────────
───────┤
│ block5_pool (MaxPooling2D)      │ (None, 7, 7, 512)       │
0 │
├─────────────────────────────────┼─────────────────────────┼──────────
───────┤
│ flatten_1 (Flatten)             │ (None, 25088)           │
0 │
├─────────────────────────────────┼─────────────────────────┼──────────
───────┤
│ dense_2 (Dense)                 │ (None, 128)             │
3,211,392 │
├─────────────────────────────────┼─────────────────────────┼──────────
───────┤
│ dropout_1 (Dropout)             │ (None, 128)             │
0 │
├─────────────────────────────────┼─────────────────────────┼──────────
───────┤
│ dense_3 (Dense)                 │ (None, 10)              │
1,290 │
└─────────────────────────────────┴─────────────────────────┴──────────
───────┘

 Total params: 17,927,370 (68.39 MB)

 Trainable params: 3,212,682 (12.26 MB)

 Non-trainable params: 14,714,688 (56.13 MB)
```

```python
loss,accuracy = model.evaluate(X_train,y_train)
print(f"The model accuracy is : {accuracy} \n the model loss :
{loss}")
```

```
WARNING: All log messages before absl::InitializeLog() is called are
written to STDERR
I0000 00:00:1733920451.204469     102 service.cc:145] XLA service
0x7dc46000cf40 initialized for platform CUDA (this does not guarantee
that XLA will be used). Devices:
I0000 00:00:1733920451.204534     102 service.cc:153]   StreamExecutor
device (0): Tesla T4, Compute Capability 7.5
I0000 00:00:1733920451.204540     102 service.cc:153]   StreamExecutor
device (1): Tesla T4, Compute Capability 7.5

  1/150 ━━━━━━━━━━━━━━━━━━━━ 36:33 15s/step - accuracy: 0.0625 - loss:
2.5141

I0000 00:00:1733920465.297473     102 device_compiler.h:188] Compiled
cluster using XLA!  This line is logged at most once for the lifetime
of the process.

150/150 ━━━━━━━━━━━━━━━━━━━━ 33s 124ms/step - accuracy: 0.0936 - loss:
2.3835
The model accuracy is : 0.10104166716337204
 the model loss : 2.377922773361206
```

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

```
----------------------------------------------------------------------
-----
NameError                                 Traceback (most recent call
last)
Cell In[52], line 1
----> 1 plt.plot(history.history['accuracy'],label='Training
Accuracy')
      2 plt.plot(history.history['val_accuracy'], label = 'Validation
Accuracy')
      3 plt.xlabel("Epochs")

NameError: name 'history' is not defined
```

```python
plt.plot(history.history['loss'],label='Training Loss')
plt.plot(history.history['val_loss'],label='Validation Loss')
plt.xlabel("Epoche")
plt.ylabel("Loss")
```

```
plt.legend()
plt.show()

import numpy as np

# Predict the class probabilities for the test dataset
predictions = model.predict(X_val)

# Convert probabilities to class labels
predicted_labels = np.argmax(predictions, axis=1)
true_labels = np.argmax(y_val, axis=1)  # Convert one-hot to class
indices

from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Generate the confusion matrix
true_labels = np.argmax(y_val, axis=1)  # Convert one-hot encoded to
class indices
predicted_labels = np.argmax(predictions, axis=1)  # Already
converting probabilities to class indices
correct=0
for i in range(len(true_labels)):
    if true_labels[i]==predicted_labels[i]:
        correct+=1
print(correct/len(true_labels))
from sklearn.metrics import confusion_matrix

# Generate confusion matrix
conf_matrix = confusion_matrix(true_labels, predicted_labels)

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