Semi-supervised Clustering in Image Analysis

```
# Aesthetics
import warnings
import sklearn.exceptions
warnings.filterwarnings('ignore', category=DeprecationWarning)
warnings.filterwarnings('ignore', category=FutureWarning)
warnings.filterwarnings("ignore", category=sklearn.exceptions.UndefinedMetricWarning)
# General
import pandas as pd
pd.set_option('display.max_columns', None)
import numpy as np
import os
import random
# Visualization
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set(style="whitegrid")
from plotly import graph_objs as go
import plotly.express as px
# Machine Learning
# Dimensionality Reduction
from sklearn.manifold import Isomap, TSNE
from sklearn.decomposition import PCA
# Clustering
from sklearn.cluster import KMeans
from sklearn.semi_supervised import LabelSpreading
# Metrics
from sklearn import metrics
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score, adjusted_ranc
from sklearn.model_selection import train_test_split
from sklearn.mixture import GaussianMixture

import tensorflow as tf
from tensorflow.keras import layers, models
import plotly.io as pio

pio.renderers.default = 'notebook'
```

```
RANDOM_SEED = 42
def seed_everything(seed=RANDOM_SEED):
    os.environ['PYTHONHASHSEED'] = str(seed)
    np.random.seed(seed)
    random.seed(seed)
seed_everything()
```

```
data_path = '/Users/akshatha/Desktop/Data_Science_Sem3/master_thesis/Master_Thesis/Dataset'

train_file_path = os.path.join(data_path, 'train.csv')
test_file_path = os.path.join(data_path, 'test.csv')

print(f'Training File path: {train_file_path}')
print(f'Test Files path: {test_file_path}')
```

```
train_df = pd.read_csv(train_file_path)
test_df = pd.read_csv(test_file_path)
```

```
Training File path:
/Users/akshatha/Desktop/Data_Science_Sem3/master_thesis/Master_Thesis/Dataset/train.csv
Test Files path:
/Users/akshatha/Desktop/Data_Science_Sem3/master_thesis/Master_Thesis/Dataset/test.csv
```

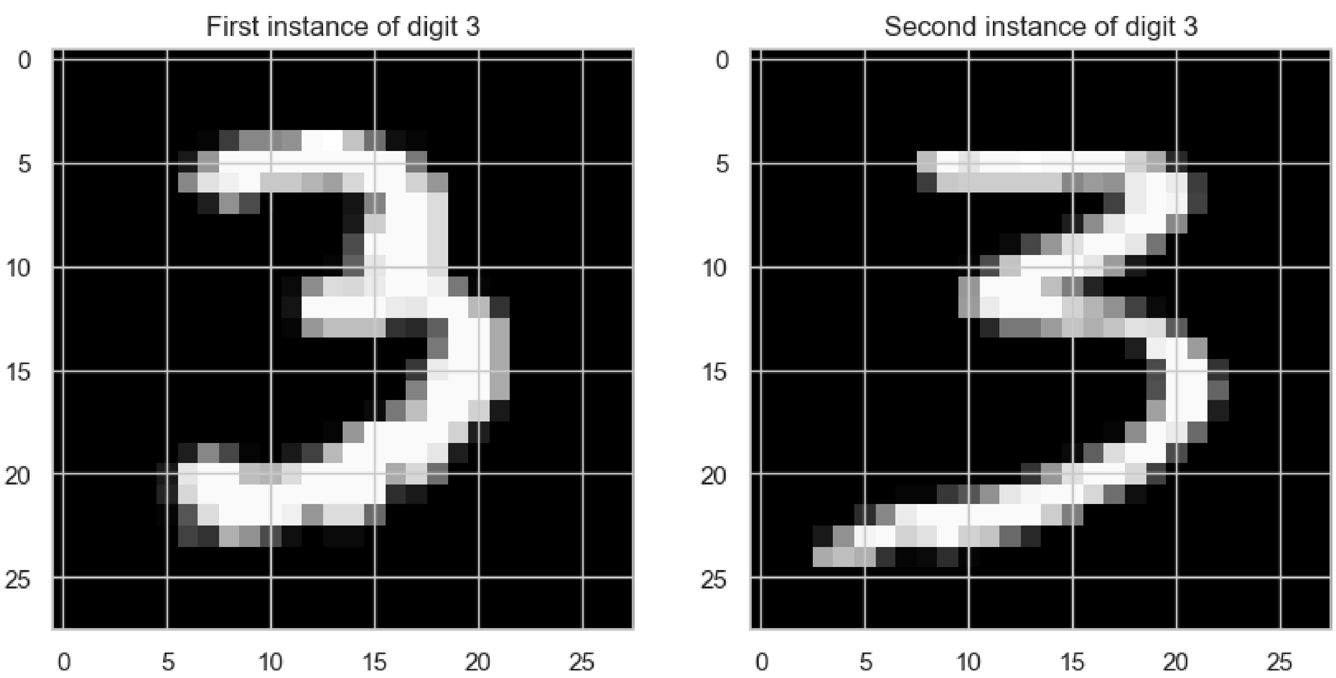
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 42000 entries, 0 to 41999
Columns: 785 entries, label to pixel783
dtypes: int64(785)
memory usage: 251.5 MB
```

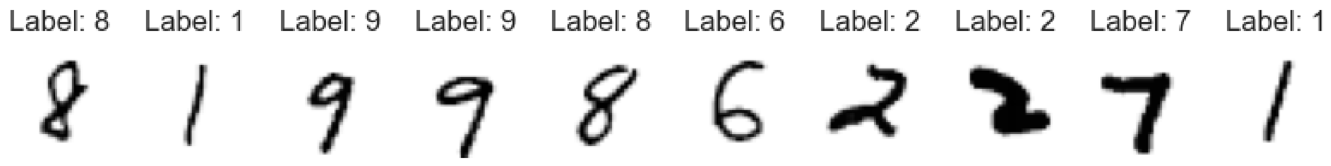
```
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 28000 entries, 0 to 27999
Columns: 784 entries, pixel0 to pixel783
dtypes: int64(784)
memory usage: 167.5 MB
```

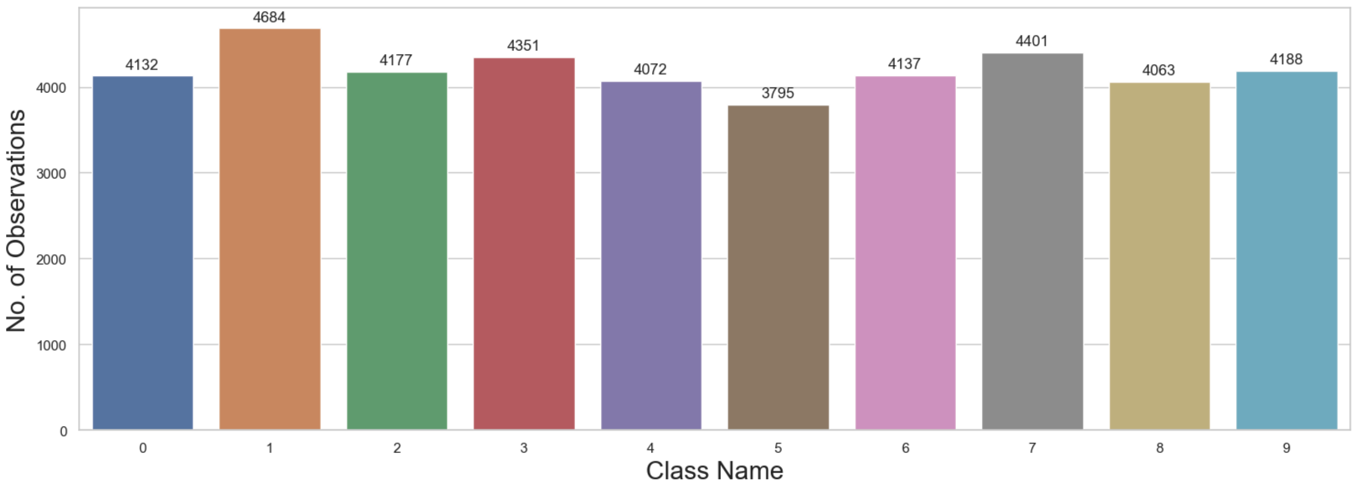
```
image1 = train_df.iloc[9,1:].values.reshape(28,28)
image2 = train_df.iloc[25,1:].values.reshape(28,28)

plt.figure(figsize=(10,5))

plt.subplot(1,2,1)
plt.imshow(image1, cmap='gray')
plt.title('First instance of digit 3')

plt.subplot(1,2,2)
plt.imshow(image2, cmap='gray')
plt.title('Second instance of digit 3')

plt.show()
```



```
train_labels = train_df['label'].values
train_data = train_df.drop(['label'], axis=1).values
num_examples = 10
random_indices = np.random.choice(train_data.shape[0], num_examples, replace=False)
plt.figure(figsize=(10, 10))
for i, idx in enumerate(random_indices):
    plt.subplot(1, num_examples, i+1)
    plt.imshow(train_data[idx].reshape(28, 28), cmap='Greys')
    plt.title(f"Label: {train_labels[idx]}")
    plt.axis('off')
plt.show()
```



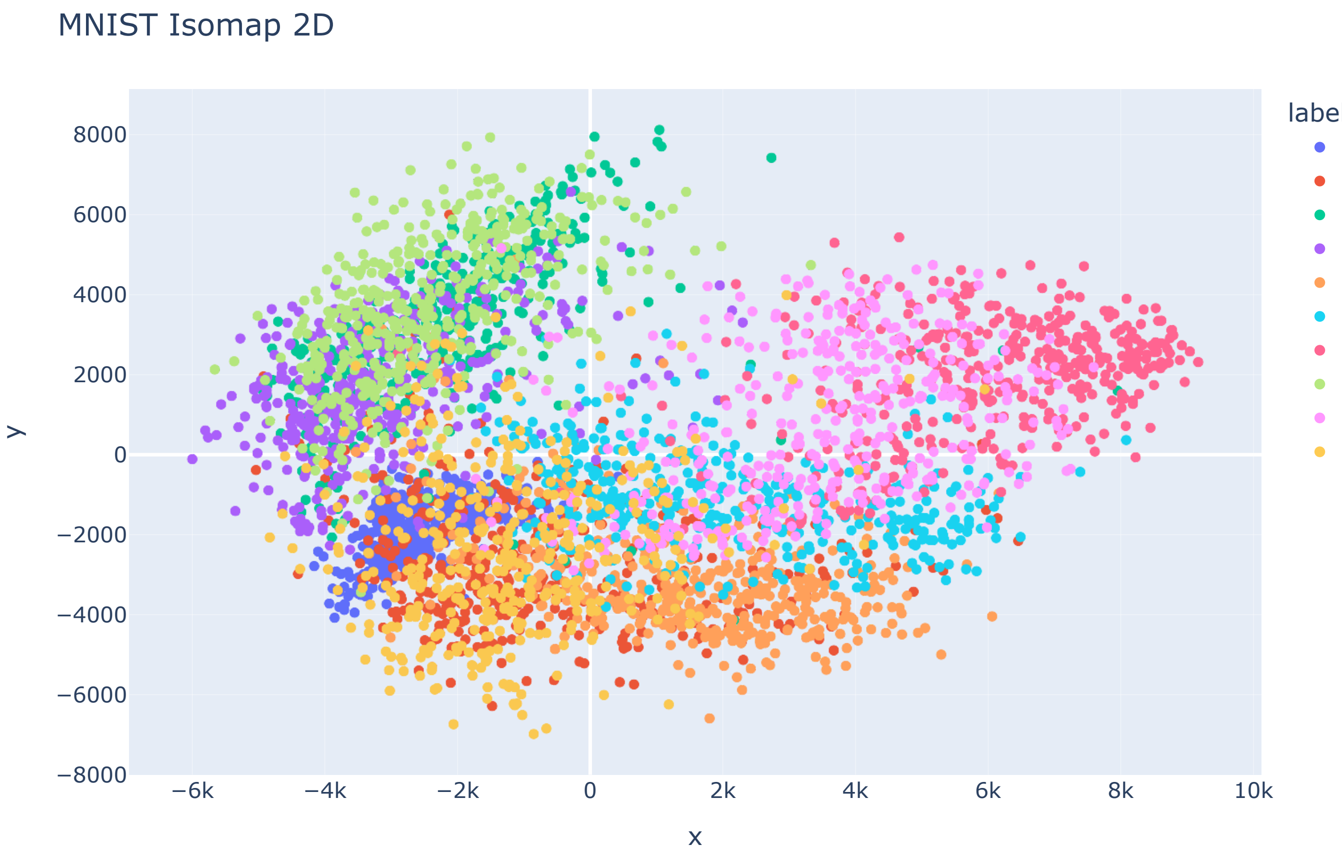

```
ax = plt.subplots(figsize=(18, 6))
sns.set_style("whitegrid")
bar_plot = sns.countplot(x='label', data=train_df)
plt.ylabel("No. of Observations", size=20)
plt.xlabel("Class Name", size=20)

for container in bar_plot.containers:
    bar_plot.bar_label(container, fmt='%.0f', label_type='edge', fontsize=12, padding=3)

plt.show()
```




```
iso = Isomap(n_components=2)

# Using only 1/10 of the data as full data takes a lot of time to run
iso.fit(train_df.drop(['label'], axis=1)[::10])
data_2d = iso.transform(train_df.drop(['label'], axis=1)[::10])

iso_df = pd.DataFrame(data_2d)
iso_df['label'] = train_df.label.values[::10]
iso_df.columns = ['x', 'y', 'label']
# Converting label to string to get discrete colors in plot
iso_df['label'] = iso_df['label'].astype(str)
iso_df.head()
```

	x	y	label
0	-3164.522146	-2876.064133	1
1	-1392.993977	-3268.073825	8
2	-505.836838	-2730.492689	8
3	-1892.122937	-2603.238878	8
4	-1155.536391	-2238.244455	9

```
fig = px.scatter(iso_df, x='x', y='y', color='label', hover_data=['label'])
fig.update_layout(title='MNIST Isomap 2D')
fig.show()
```



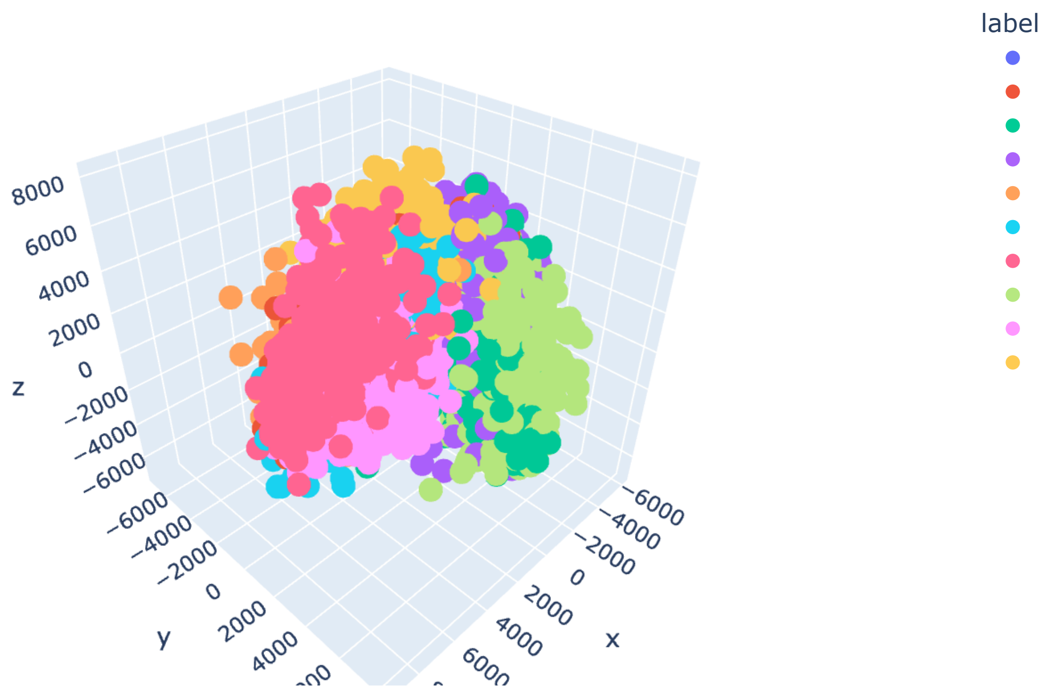

```
iso = Isomap(n_components=3)

# Using only 1/10 of the data as full data takes a lot of time to run
iso.fit(train_df.drop(['label'], axis=1)[::10])
data_3d = iso.transform(train_df.drop(['label'], axis=1)[::10])

iso_df = pd.DataFrame(data_3d)
iso_df['label'] = train_df.label.values[::10]
iso_df.columns = ['x', 'y', 'z', 'label']
# Converting label to string to get discrete colors in plot
iso_df['label'] = iso_df['label'].astype(str)
iso_df.head()
```

	x	y	z	label
0	-3164.522146	-2876.064133	2769.434567	1

	x	y	z	label
1	-1392.993977	-3268.073825	2537.656185	8
2	-505.836838	-2730.492689	1403.573999	8
3	-1892.122937	-2603.238878	1973.673223	8
4	-1155.536391	-2238.244455	-2228.778622	9

```
fig = px.scatter_3d(iso_df, x='x', y='y', z='z', color='label', hover_data=['label'])
fig.update_layout(title ='MNIST Isomap 3D')
fig.show()
```

MNIST Isomap 3D




```
pca = PCA(n_components=2)

# Using only 1/5 of the data as full data takes a lot of time to run
pca.fit(train_df.drop(['label'], axis=1)[::5])
data_2d = pca.transform(train_df.drop(['label'], axis=1)[::5])

pca_df = pd.DataFrame(data_2d)
pca_df['label'] = train_df.label.values[::5]
pca_df.columns = ['x', 'y', 'label']
# Converting label to string to get discrete colors in plot
pca_df['label'] = pca_df['label'].astype(str)
pca_df.head()
```

	x	y	label
0	-689.649976	-684.843619	1
1	492.013847	194.769615	0
2	251.532408	368.983271	8

	x	y	label
3	-965.636424	-269.214044	1
4	-253.193349	-244.224089	8

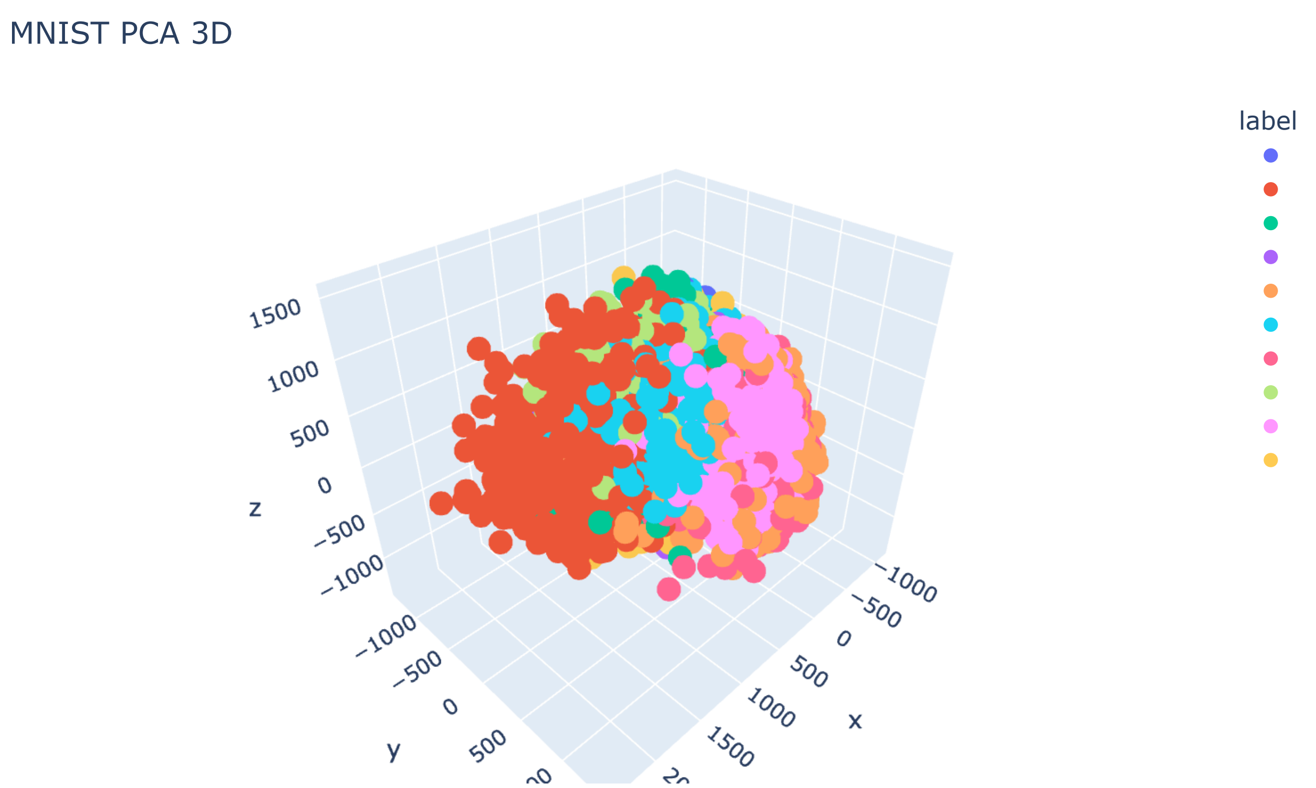
```
fig = px.scatter(pca_df, x='x', y='y', color='label',
                 hover_data=['label'])
fig.update_layout(title = 'MNIST PCA 2D')
fig.show()
```


```
pca = PCA(n_components=3)

# Using only 1/5 of the data as full data takes a lot of time to run
pca.fit(train_df.drop(['label'], axis=1)[::5])
data_3d = pca.transform(train_df.drop(['label'], axis=1)[::5])

pca_df = pd.DataFrame(data_3d)
pca_df['label'] = train_df.label.values[::5]
pca_df.columns = ['x', 'y', 'z', 'label']
# Converting label to string to get discrete colors in plot
pca_df['label'] = pca_df['label'].astype(str)
pca_df.head()
```

	x	y	z	label
0	-689.649371	-684.842103	180.441962	1
1	492.014066	194.773127	29.496154	0
2	251.532825	368.980792	517.974140	8
3	-965.636714	-269.212459	-18.302643	1

	x	y	z	label
4	-253.192783	-244.221331	306.334444	8

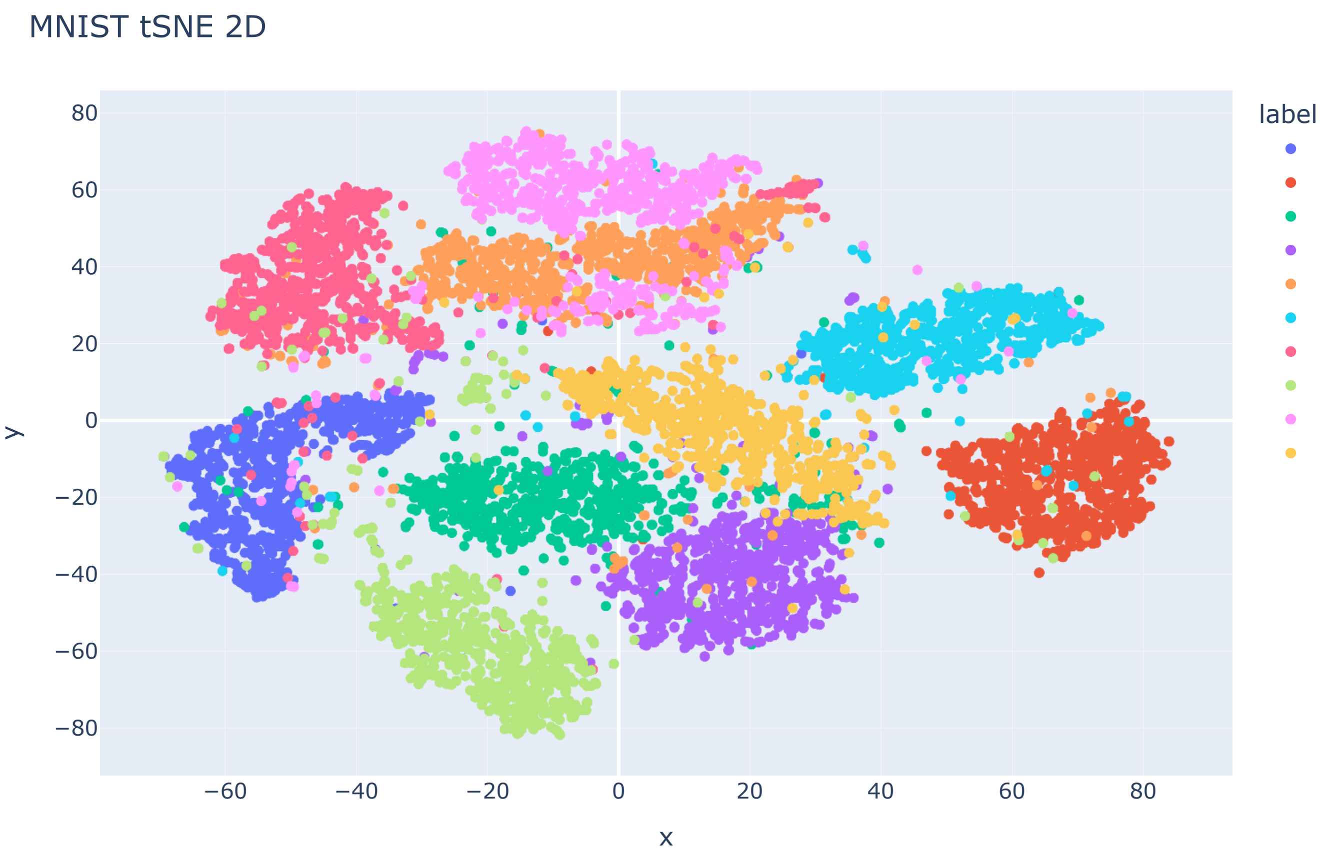
```
fig = px.scatter_3d(pca_df, x='x', y='y', z='z', color='label',
                    hover_data=['label'])
fig.update_layout(title = 'MNIST PCA 3D')
fig.show()
```




```
tsne = TSNE(n_components=2, random_state=RANDOM_SEED)

# Using only 1/5 of the data as full data takes a lot of time to run
data_2d = tsne.fit_transform(train_df.drop(['label'], axis=1)[::5])

tsne_df = pd.DataFrame(data_2d)
tsne_df['label'] = train_df.label.values[::5]
tsne_df.columns = ['x', 'y', 'label']
# Converting label to string to get discrete colors in plot
tsne_df['label'] = tsne_df['label'].astype(str)
tsne_df.head()
```

	x	y	label
0	-54.973747	-39.513020	1
1	59.208115	-13.389258	0
2	-21.755135	-11.108450	8
3	-50.486458	-12.374542	1
4	-17.735485	-25.174314	8

```
fig = px.scatter(tsne_df, x='x', y='y', color='label',
                 hover_data=['label'])
fig.update_layout(title = 'MNIST tSNE 2D')
fig.show()
```

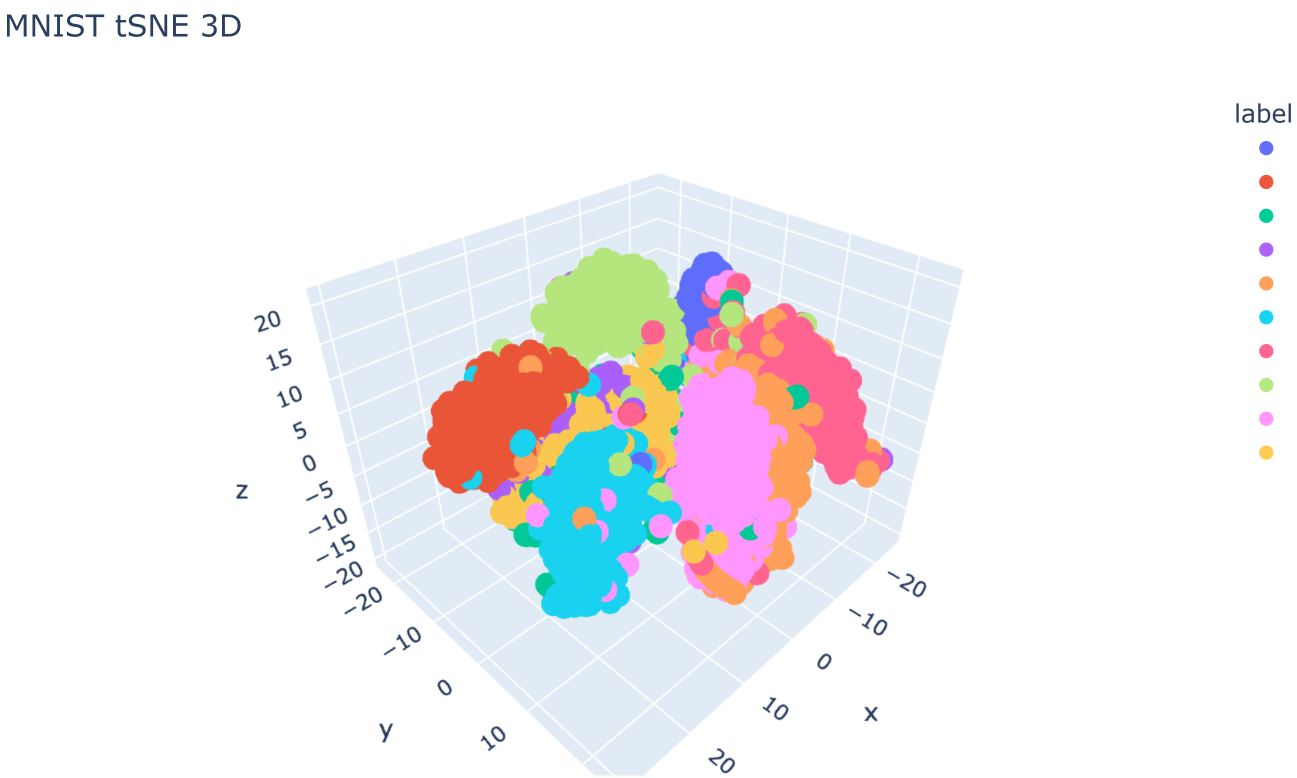



```
tsne = TSNE(n_components=3, random_state=RANDOM_SEED)

# Using only 1/5 of the data as full data takes a lot of time to run
data_3d = tsne.fit_transform(train_df.drop(['label'], axis=1)[::5])

tsne_df = pd.DataFrame(data_3d)
tsne_df['label'] = train_df.label.values[::5]
tsne_df.columns = ['x', 'y', 'z', 'label']
# Converting label to string to get discrete colors in plot
tsne_df['label'] = tsne_df['label'].astype(str)
tsne_df.head()
```

	x	y	z	label
0	-13.878677	-5.060273	14.828371	1
1	18.223419	-11.924116	7.233977	0
2	-5.197411	-1.964661	-5.070707	8
3	-13.127986	-1.138468	0.515834	1
4	-6.714522	-9.224581	-5.961275	8

```
fig = px.scatter_3d(tsne_df, x='x', y='y', z='z', color='label',
                    hover_data=['label'])
```

```
fig.update_layout(title = 'MNIST tSNE 3D')
fig.show()
```



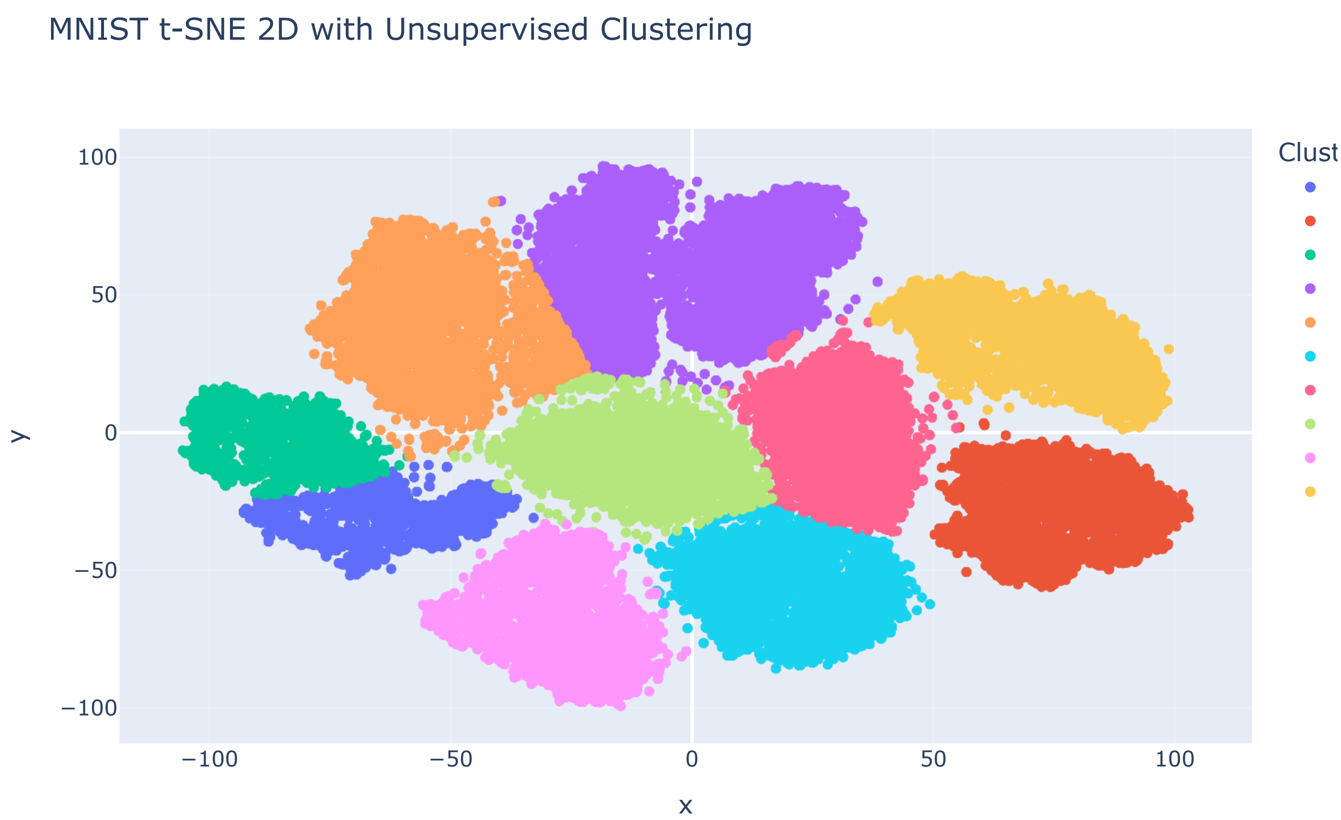

```
labels = train_df['label'].values
features = train_df.drop(columns=['label']).values
features = features / 255.0
```

```
tsne = TSNE(n_components=2, random_state=42)
reduced_features = tsne.fit_transform(features)
```

```
gmm = GaussianMixture(n_components=10, random_state=42)
cluster_labels = gmm.fit_predict(reduced_features)
```

```
def map_cluster_to_label(cluster_labels, true_labels):
    label_mapping = {}
    for cluster in np.unique(cluster_labels):
        mask = cluster_labels == cluster
        most_common = np.bincount(true_labels[mask]).argmax()
        label_mapping[cluster] = most_common
    return np.vectorize(label_mapping.get)(cluster_labels)

# Map the cluster labels to the true labels
predicted_labels = map_cluster_to_label(cluster_labels, labels)
```

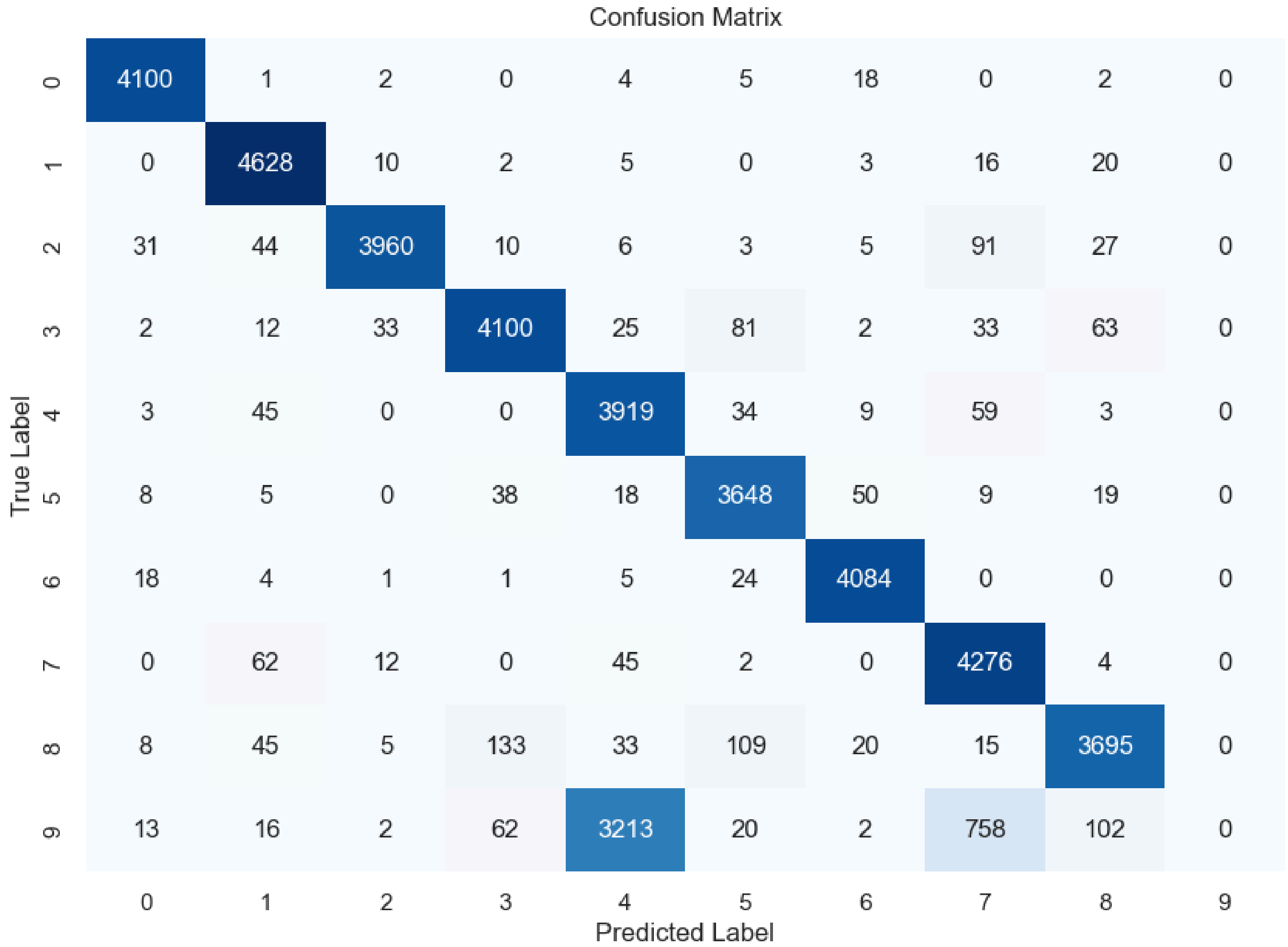
```
reduced_df = pd.DataFrame(reduced_features, columns=['x', 'y'])
reduced_df['Cluster'] = cluster_labels.astype(str)

fig = px.scatter(reduced_df, x='x', y='y', color='Cluster', title='MNIST t-SNE 2D with Unsupervise
fig.show()
```




```
accuracy = accuracy_score(labels, predicted_labels)
ari = adjusted_rand_score(labels, cluster_labels)
print(f'Clustering Accuracy: {accuracy * 100:.2f}%')
print(f'Adjusted Rand Index: {ari:.2f}')
```

```
Clustering Accuracy: 86.69%
Adjusted Rand Index: 0.78
```

```
# Confusion matrix
conf_matrix = confusion_matrix(labels, predicted_labels)
plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```



Supervised Learning

```
X = train_df.drop(columns=['label']).values.reshape(-1, 28, 28, 1)  # Reshape for CNN
y = train_df['label'].values
X = X / 255.0
X_train, X_val, y_train, y_val = train_test_split(X, labels, test_size=0.2, random_state=42)
```

```
# Defining the CNN model
model = models.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(10, activation='softmax')
])
```

```
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/site-
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.
```

```
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
```

```
              metrics=['accuracy'])
history = model.fit(X_train, y_train, epochs=10, validation_data=(X_val, y_val))
```

```
Epoch 1/10
1050/1050 ━━━━━━━━━━━━━━━━━━━━ 8s 7ms/step - accuracy: 0.8569 - loss: 0.4711 - val_accuracy:
0.9786 - val_loss: 0.0681
Epoch 2/10
1050/1050 ━━━━━━━━━━━━━━━━━━━━ 7s 7ms/step - accuracy: 0.9806 - loss: 0.0598 - val_accuracy:
0.9858 - val_loss: 0.0442
Epoch 3/10
1050/1050 ━━━━━━━━━━━━━━━━━━━━ 7s 7ms/step - accuracy: 0.9868 - loss: 0.0399 - val_accuracy:
0.9857 - val_loss: 0.0480
Epoch 4/10
1050/1050 ━━━━━━━━━━━━━━━━━━━━ 8s 7ms/step - accuracy: 0.9887 - loss: 0.0324 - val_accuracy:
0.9863 - val_loss: 0.0422
Epoch 5/10
1050/1050 ━━━━━━━━━━━━━━━━━━━━ 7s 7ms/step - accuracy: 0.9929 - loss: 0.0227 - val_accuracy:
0.9870 - val_loss: 0.0439
Epoch 6/10
1050/1050 ━━━━━━━━━━━━━━━━━━━━ 7s 7ms/step - accuracy: 0.9939 - loss: 0.0177 - val_accuracy:
0.9860 - val_loss: 0.0466
Epoch 7/10
1050/1050 ━━━━━━━━━━━━━━━━━━━━ 7s 7ms/step - accuracy: 0.9951 - loss: 0.0160 - val_accuracy:
0.9860 - val_loss: 0.0489
Epoch 8/10
1050/1050 ━━━━━━━━━━━━━━━━━━━━ 7s 7ms/step - accuracy: 0.9946 - loss: 0.0149 - val_accuracy:
0.9912 - val_loss: 0.0311
Epoch 9/10
1050/1050 ━━━━━━━━━━━━━━━━━━━━ 7s 7ms/step - accuracy: 0.9971 - loss: 0.0093 - val_accuracy:
0.9863 - val_loss: 0.0545
Epoch 10/10
1050/1050 ━━━━━━━━━━━━━━━━━━━━ 8s 7ms/step - accuracy: 0.9974 - loss: 0.0104 - val_accuracy:
0.9900 - val_loss: 0.0345
```

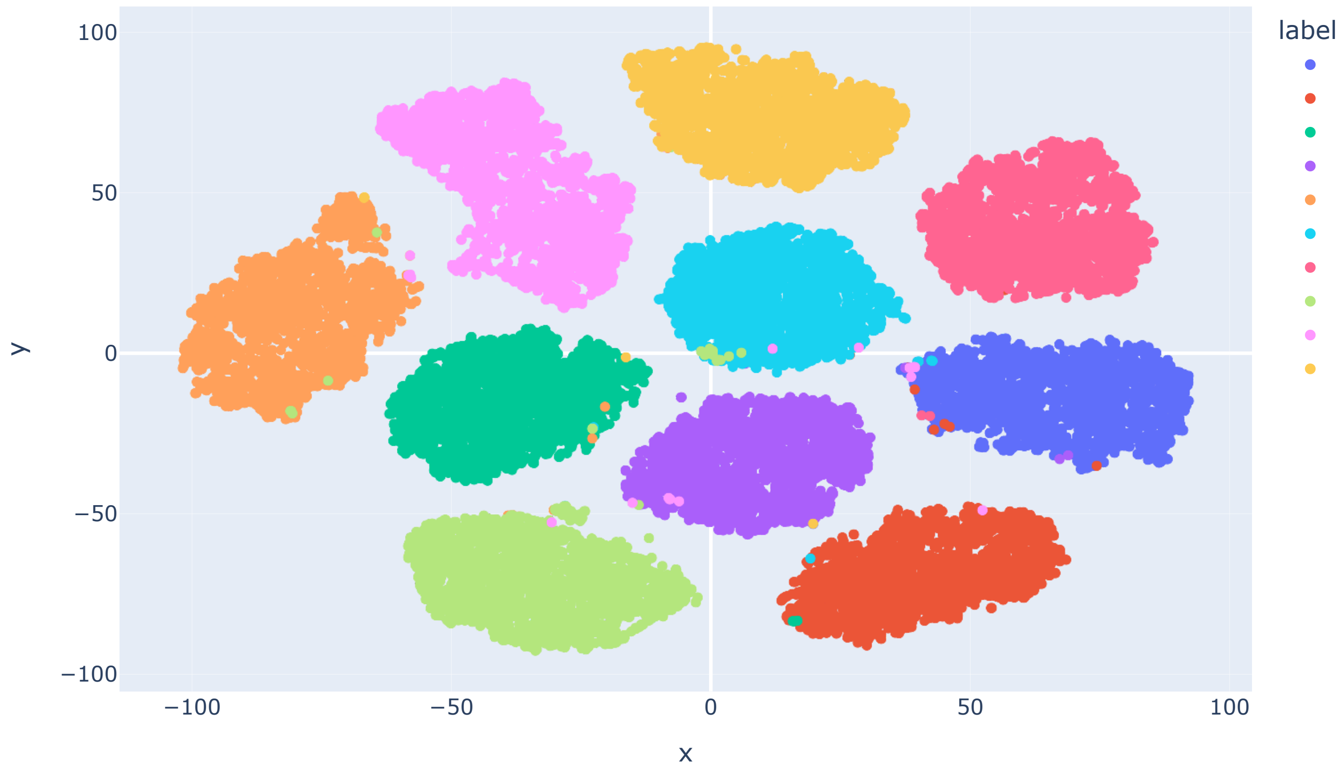
```
feature_extractor = models.Model(inputs=model.inputs,
                                 outputs=model.layers[-2].output)
# Extracting features from the training data
features = feature_extractor.predict(X_train)

# Applying KMeans clustering to the extracted features
n_clusters = 10  # Number of clusters (since we have 10 digits)
kmeans = KMeans(n_clusters=n_clusters, random_state=42)
clusters = kmeans.fit_predict(features)
```

```
1050/1050 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step
```

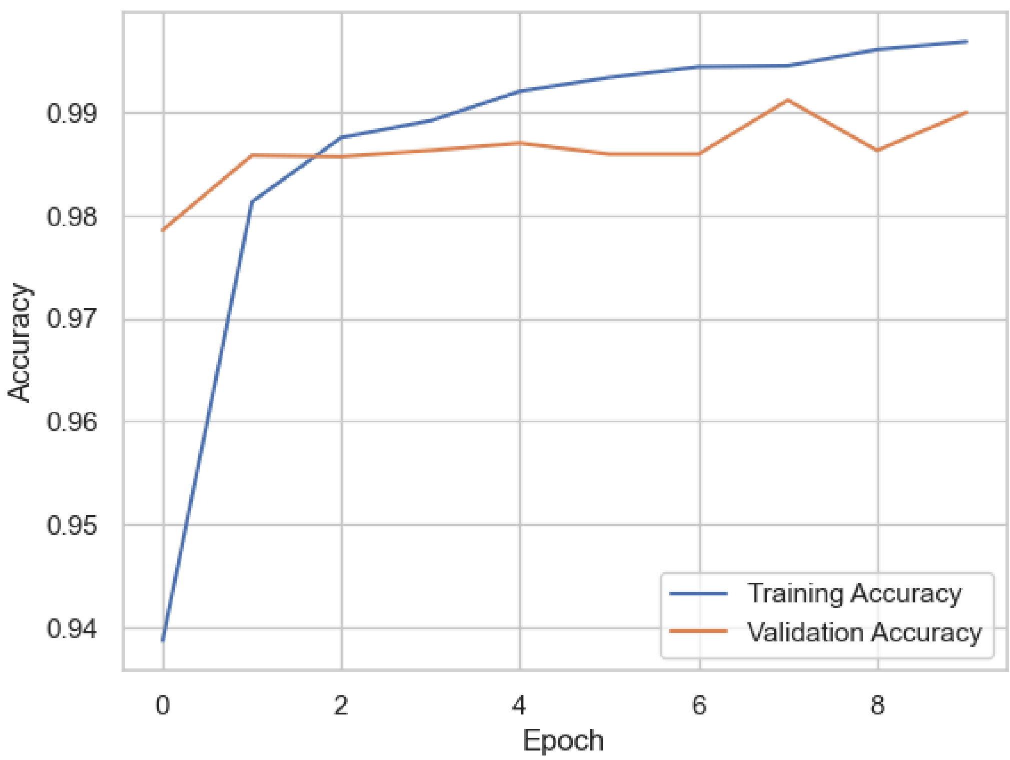
```
# Dimensionality reduction using t-SNE
tsne_sem = TSNE(n_components=2, random_state=42)
features_tsne = tsne_sem.fit_transform(features)
```

```
tsne_df_sem = pd.DataFrame(features_tsne, columns=['x', 'y'])
tsne_df_sem['label'] = clusters.astype(str)

fig = px.scatter(tsne_df_sem, x='x', y='y', color='label', hover_data=['label'])
fig.update_layout(title='MNIST t-SNE 2D with Supervised Clustering')
fig.show()
```

MNIST t-SNE 2D with Supervised Clustering




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



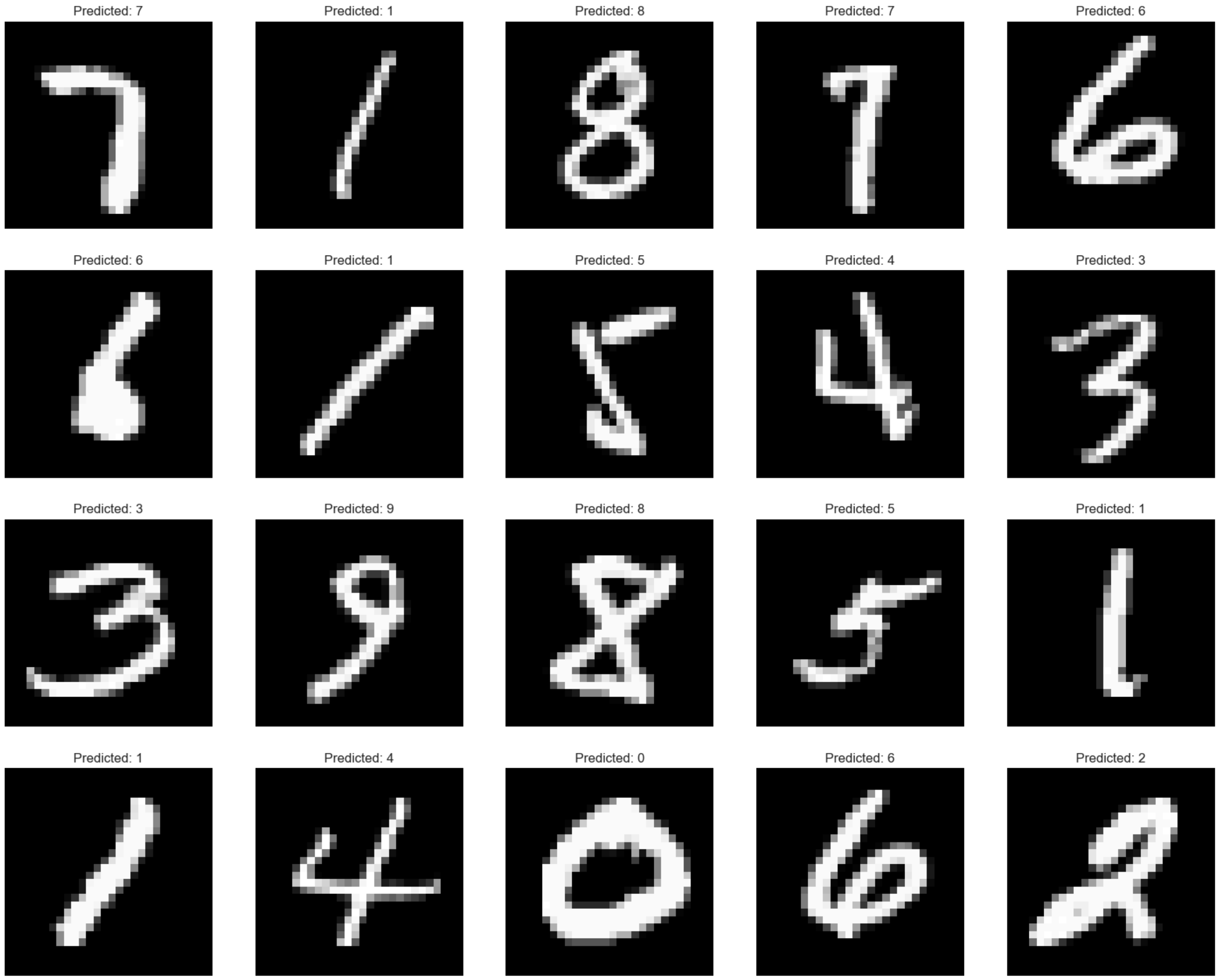

```
X_test = test_df.values.reshape(-1, 28, 28, 1)  # Reshape for CNN
X_test = X_test / 255.0
```

```
y_pred = np.argmax(model.predict(X_test), axis=-1)
```

```
875/875 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step
```

```
X_test = test_df.values.reshape(-1, 28, 28, 1) / 255.0
y_pred = np.argmax(model.predict(X_test), axis=-1)

num_examples = 20
random_indices = np.random.choice(X_test.shape[0], num_examples, replace=False)
plt.figure(figsize=(20, 20))

for i, idx in enumerate(random_indices):
    plt.subplot(5, 5, i + 1)
    plt.imshow(X_test[idx].reshape(28, 28), cmap='gray')
    plt.title(f'Predicted: {y_pred[idx]}')
    plt.axis('off')
plt.show()
```

```
875/875 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step
```



Semi-supervised Clustering with LabelSpreading

```
# Preprocessing the data
X = train_df.drop(columns=['label']).values.astype(float)
y = train_df['label'].values
```

```
# Normalizing the features
X = X / 255.0
# Split labeled and unlabeled data
labeled_size = 0.1
RANDOM_SEED = 42
X_labeled, X_unlabeled, y_labeled, y_unlabeled_true = train_test_split(X, y, train_size=labeled_si
```

```
# Combine labeled and unlabeled data
X_combined = np.vstack((X_labeled, X_unlabeled))
y_combined = np.concatenate([y_labeled, [-1]*len(X_unlabeled)])

pca = PCA(n_components=50, random_state=RANDOM_SEED)
X_combined_pca = pca.fit_transform(X_combined)
```

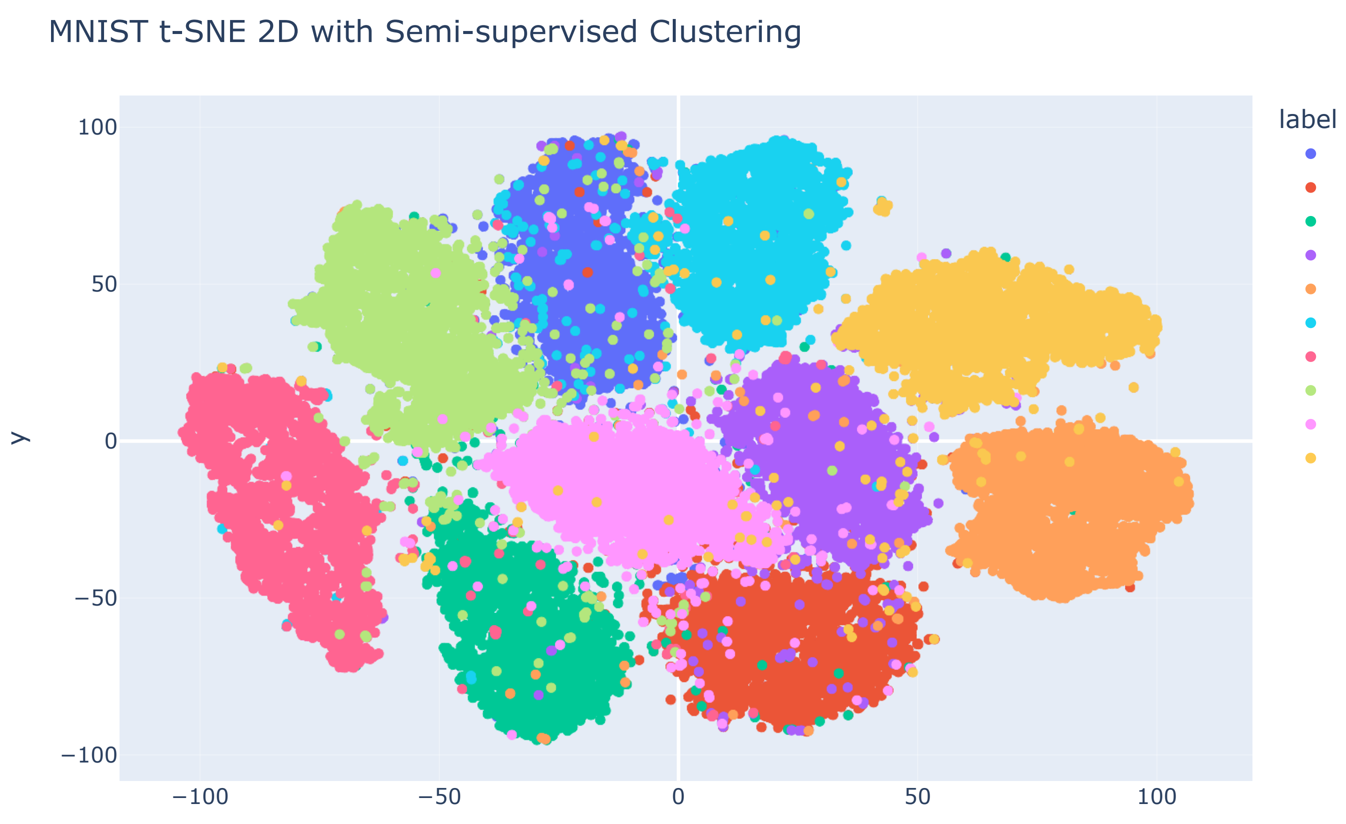
```
label_spread = LabelSpreading(kernel='knn', alpha=0.2)
label_spread.fit(X_combined_pca, y_combined)
```

▾ LabelSpreading

LabelSpreading(kernel='knn')

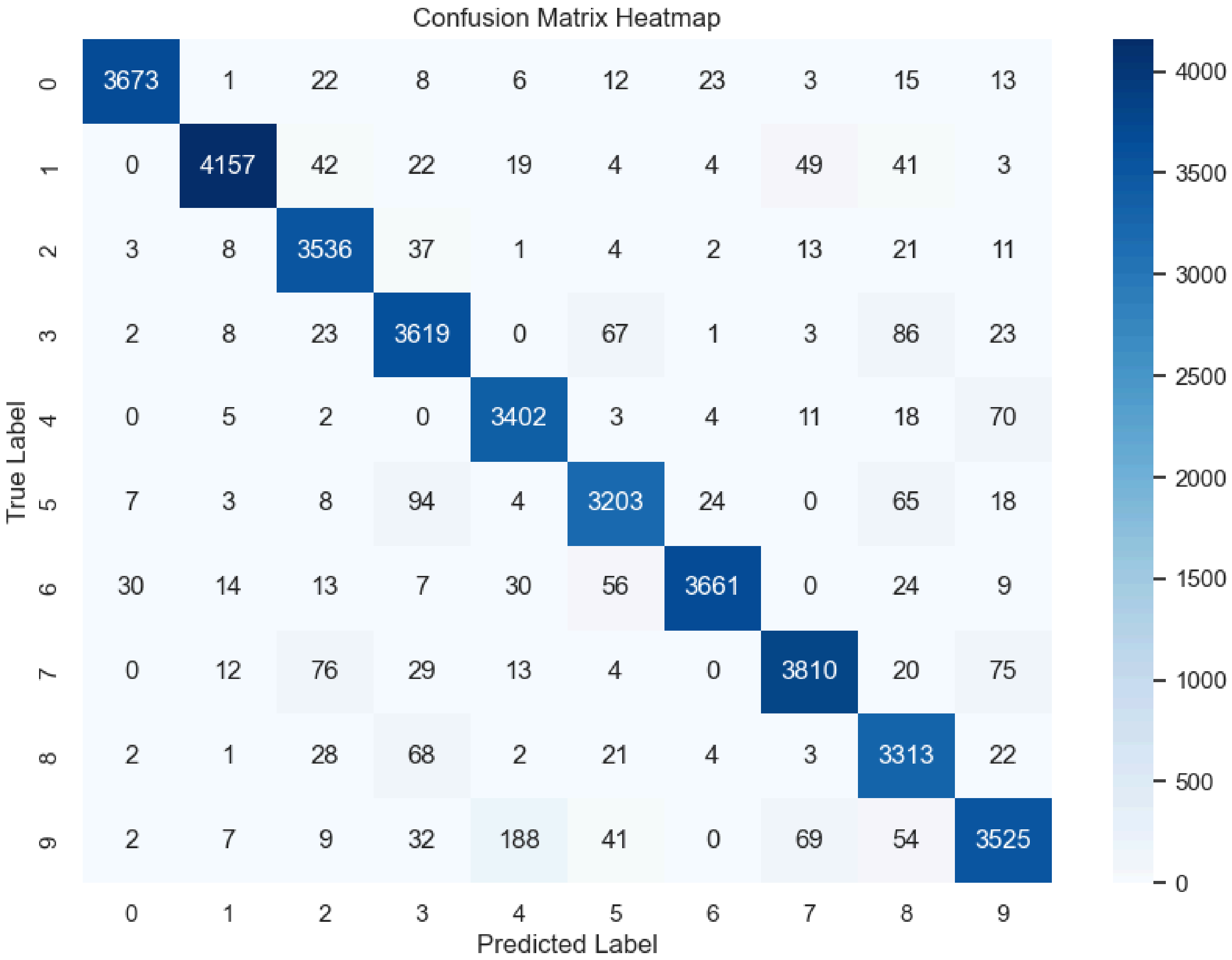
```
y_combined_pred = label_spread.transduction_
y_unlabeled_pred = y_combined_pred[-len(X_unlabeled):]
y_labeled_pred = y_combined_pred[:len(X_labeled)]
tsne = TSNE(n_components=2, random_state=RANDOM_SEED)
X_combined_tsne = tsne.fit_transform(X_combined_pca)
```

```
tsne_df = pd.DataFrame(X_combined_tsne, columns=['x', 'y'])
tsne_df['label'] = y_combined_pred.astype(str)
fig = px.scatter(tsne_df, x='x', y='y', color='label', hover_data=['label'])
fig.update_layout(title='MNIST t-SNE 2D with Semi-supervised Clustering')
fig.show()
```



```
accuracy = accuracy_score(y_unlabeled_true, y_unlabeled_pred)

print("Accuracy Score:", accuracy)
print("Classification Report:\n", classification_report(y_unlabeled_true, y_unlabeled_pred))
conf_matrix = confusion_matrix(y_unlabeled_pred, y_unlabeled_true)
plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix Heatmap')
plt.show()
```

```
Accuracy Score: 0.9497089947089947
Classification Report:
               precision    recall  f1-score   support

           0       0.97      0.99      0.98      3719
           1       0.96      0.99      0.97      4216
           2       0.97      0.94      0.96      3759
           3       0.94      0.92      0.93      3916
           4       0.97      0.93      0.95      3665
           5       0.93      0.94      0.94      3415
           6       0.95      0.98      0.97      3723
           7       0.94      0.96      0.95      3961
           8       0.96      0.91      0.93      3657
           9       0.90      0.94      0.92      3769

    accuracy                           0.95     37800
   macro avg       0.95      0.95      0.95     37800
weighted avg       0.95      0.95      0.95     37800
```




```python
num_examples = 10
random_indices = np.random.choice(len(X_unlabeled), num_examples, replace=False)
plt.figure(figsize=(10, 10))
for i, idx in enumerate(random_indices):
    plt.subplot(1, num_examples, i+1)
    plt.imshow(X_unlabeled[idx].reshape(28, 28), cmap='Greys')
    plt.title(f"Pred: {y_unlabeled_pred[idx]}")
    plt.axis('off')
plt.show()
```