# handwritting_simple_ANN_zenuni

May 12, 2025

## 0.1 Digit Recognition Demo Notebook

**Author: Bledar Blake Zenuni - May 2025** A. For demonstration purposes only, inspired by the Oxford AI Programme 2025 (which I highly recommend!) – no copyright materials or modules are shared.

B. This notebook demonstrates a simple artificial neural network (ANN) built to recognise handwritten digits using a standard dataset.

C. Challenges discussed in the accompanying essay are drawn from reflecting on my own handwriting; the implementation here uses publicly available data for reproducibility and technical demonstration.

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### 1 - Importing Python Libs, Loading and Visualizing Sample Digits

[13]:
```
# importing libs
from sklearn.datasets import load_digits
import matplotlib.pyplot as plt
from sklearn.neural_network import MLPClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix as cm, ConfusionMatrixDisplay
from yellowbrick.classifier import ConfusionMatrix as YBConfusionMatrix

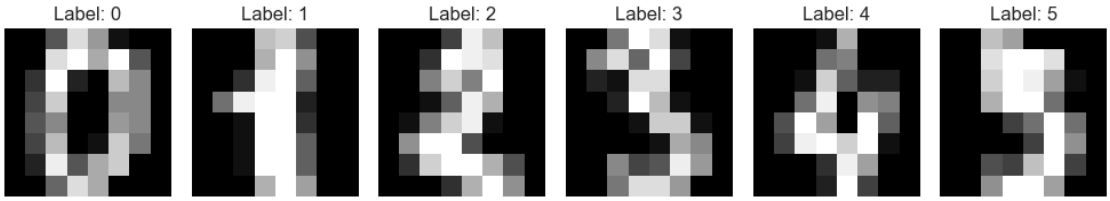
#load and visualise sample digits

digits = load_digits()

# see dataset shape
print(f"Data shape: {digits.data.shape}")
print(f"Target shape: {digits.target.shape}")

# plotting first 6 images
fig, axes = plt.subplots(1, 6, figsize=(10, 3))
for i, ax in enumerate(axes):
    ax.imshow(digits.images[i], cmap='gray')
    ax.set_title(f"Label: {digits.target[i]}")
    ax.axis('off')
plt.tight_layout()
plt.show()
```

```
Data shape: (1797, 64)
Target shape: (1797,)
```




- Sample digits show structure and consistent spacing; this is useful for training but less representative of real handwriting variability
- This lets the model learn basic visual features like loops, straight lines, and stroke angles

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**2 - Preprocessing Data and Creating Train-Test Split**

[14]:
```
# preprocess data and create train-test split
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler

# flatten image data and scale to [0, 1]
X = digits.data
y = digits.target
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)

# train-test split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,␣
 ↪random_state=42)

print(f"Training samples: {X_train.shape[0]}")
print(f"Test samples: {X_test.shape[0]}")
```

```
Training samples: 1437
Test samples: 360
```

- This is "feature scaling" and it ensures uniform input for the network, reducing bias from pixel intensity variation
- We tried to generate a clean train-test split to allow us to evaluate the model's ability to generalise; this is a core concern when handling messy handwriting; reflecting on my own handwritting (Question 1), this is a concern sometimes also when I scribble digits down quickly
- Lastly, preprocessing is critical for addressing variation and inconsistency, key challenges highlighted in the assignment

### 3 - Defining and Training a Simple ANN Model

[15]:
```
# define and train a simple ANN model
from sklearn.neural_network import MLPClassifier

# defines
model = MLPClassifier(hidden_layer_sizes=(64,), activation='relu',␣
 ↪solver='adam',
                      max_iter=300, random_state=42)

# trains
model.fit(X_train, y_train)

# outputs that training is complete
print("Model training complete.")
```

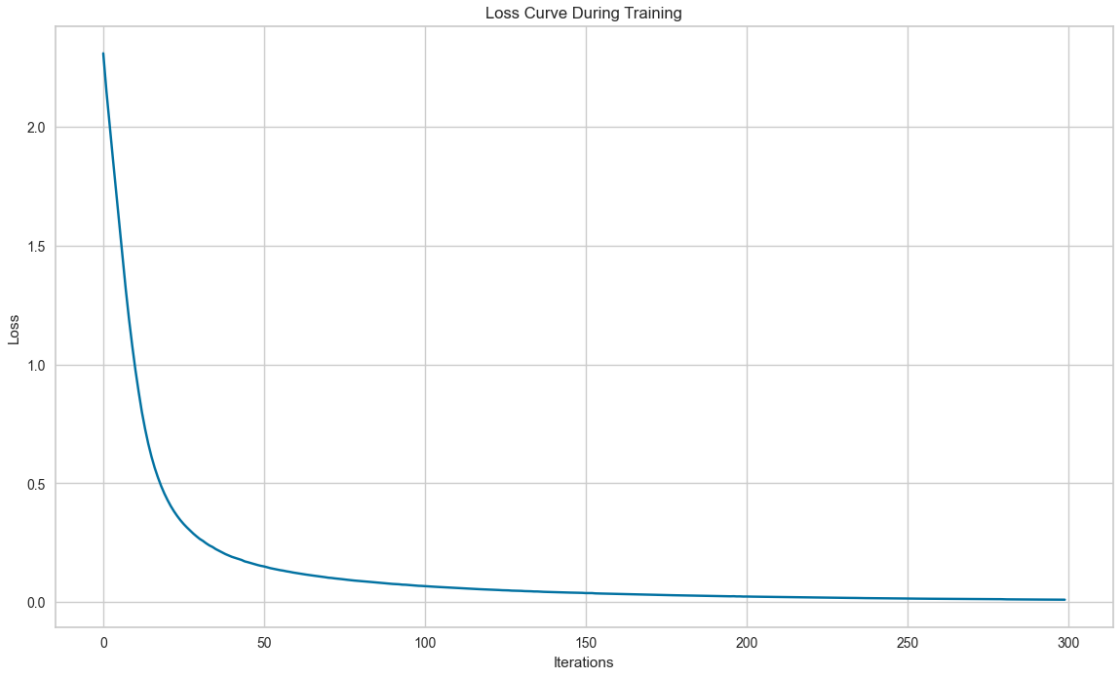
```
Model training complete.

C:\Users\blake\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n
2kfra8p0\LocalCache\local-packages\Python310\site-
packages\sklearn\neural_network\_multilayer_perceptron.py:690:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (300) reached and
the optimization hasn't converged yet.
  warnings.warn(
```

- This model should have (behind the scenes) a single hidden layer with ReLU activation that captures non-linear patterns in the digit images
- It then learns internal weights to distinguish visual differences between digits, such as loops and angles
- Though the training completes in seconds, the learning reflects core ANN principles discussed in Questions 2 and 3.

Nota Bene (NB): Since the model was trained with `verbose=false` we can still access it by plotting the loss curve after training:

[16]:
```
plt.figure(figsize=(14, 8))
plt.plot(model.loss_curve_)
plt.title("Loss Curve During Training")
plt.xlabel("Iterations")
plt.ylabel("Loss")
plt.grid(True)
plt.show()
```




- Loss curve shows us rapid initial improvement, followed by convergence
- It indicates the model successfully learned meaningful patterns and minimised error over time

NB: To see more during training, we can enable `verbose` – we should see the model improve after each iteration:

[17]:
```
# model with verbose output
model = MLPClassifier(hidden_layer_sizes=(64,), activation='relu',␣
 ↪solver='adam',
                      max_iter=300, random_state=42, verbose=True)

model.fit(X_train, y_train)
```

```
Iteration 1, loss = 2.30923323
Iteration 2, loss = 2.14782517
Iteration 3, loss = 2.00492474
Iteration 4, loss = 1.86583888
Iteration 5, loss = 1.72770651
Iteration 6, loss = 1.58793817
Iteration 7, loss = 1.44879617
Iteration 8, loss = 1.31601078
Iteration 9, loss = 1.19185759
Iteration 10, loss = 1.08003923
Iteration 11, loss = 0.97710348
Iteration 12, loss = 0.88556016
Iteration 13, loss = 0.80098396
```

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Iteration 14, loss = 0.72942595
Iteration 15, loss = 0.66617108
Iteration 16, loss = 0.61204547
Iteration 17, loss = 0.56517691
Iteration 18, loss = 0.52489484
Iteration 19, loss = 0.48870926
Iteration 20, loss = 0.45702367
Iteration 21, loss = 0.42920171
Iteration 22, loss = 0.40410001
Iteration 23, loss = 0.38203623
Iteration 24, loss = 0.36239515
Iteration 25, loss = 0.34452361
Iteration 26, loss = 0.32864073
Iteration 27, loss = 0.31445408
Iteration 28, loss = 0.30122791
Iteration 29, loss = 0.28845802
Iteration 30, loss = 0.27690421
Iteration 31, loss = 0.26600429
Iteration 32, loss = 0.25751614
Iteration 33, loss = 0.24743899
Iteration 34, loss = 0.23860286
Iteration 35, loss = 0.23184010
Iteration 36, loss = 0.22301143
Iteration 37, loss = 0.21576449
Iteration 38, loss = 0.20903109
Iteration 39, loss = 0.20204898
Iteration 40, loss = 0.19655575
Iteration 41, loss = 0.19059257
Iteration 42, loss = 0.18618747
Iteration 43, loss = 0.18185880
Iteration 44, loss = 0.17749748
Iteration 45, loss = 0.17130142
Iteration 46, loss = 0.16782849
Iteration 47, loss = 0.16381840
Iteration 48, loss = 0.15956677
Iteration 49, loss = 0.15607615
Iteration 50, loss = 0.15266033
Iteration 51, loss = 0.15016761
Iteration 52, loss = 0.14627333
Iteration 53, loss = 0.14283890
Iteration 54, loss = 0.14008030
Iteration 55, loss = 0.13722922
Iteration 56, loss = 0.13450842
Iteration 57, loss = 0.13237152
Iteration 58, loss = 0.12959312
Iteration 59, loss = 0.12740655
Iteration 60, loss = 0.12465134
Iteration 61, loss = 0.12241327
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Iteration 62, loss = 0.12004347
Iteration 63, loss = 0.11833410
Iteration 64, loss = 0.11601698
Iteration 65, loss = 0.11397188
Iteration 66, loss = 0.11221115
Iteration 67, loss = 0.11041439
Iteration 68, loss = 0.10902420
Iteration 69, loss = 0.10695074
Iteration 70, loss = 0.10489426
Iteration 71, loss = 0.10272188
Iteration 72, loss = 0.10165531
Iteration 73, loss = 0.09985785
Iteration 74, loss = 0.09860522
Iteration 75, loss = 0.09701296
Iteration 76, loss = 0.09521440
Iteration 77, loss = 0.09379509
Iteration 78, loss = 0.09211076
Iteration 79, loss = 0.09084608
Iteration 80, loss = 0.08976813
Iteration 81, loss = 0.08867083
Iteration 82, loss = 0.08715935
Iteration 83, loss = 0.08637522
Iteration 84, loss = 0.08504772
Iteration 85, loss = 0.08378522
Iteration 86, loss = 0.08264116
Iteration 87, loss = 0.08166050
Iteration 88, loss = 0.08004740
Iteration 89, loss = 0.07863067
Iteration 90, loss = 0.07783857
Iteration 91, loss = 0.07653359
Iteration 92, loss = 0.07582119
Iteration 93, loss = 0.07501950
Iteration 94, loss = 0.07348460
Iteration 95, loss = 0.07310465
Iteration 96, loss = 0.07189302
Iteration 97, loss = 0.07079802
Iteration 98, loss = 0.06975308
Iteration 99, loss = 0.06864095
Iteration 100, loss = 0.06812815
Iteration 101, loss = 0.06711607
Iteration 102, loss = 0.06622928
Iteration 103, loss = 0.06551979
Iteration 104, loss = 0.06455606
Iteration 105, loss = 0.06391040
Iteration 106, loss = 0.06315942
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Iteration 108, loss = 0.06154876
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Iteration 110, loss = 0.06013367
Iteration 111, loss = 0.05945543
Iteration 112, loss = 0.05872138
Iteration 113, loss = 0.05811693
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Iteration 116, loss = 0.05585242
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Iteration 118, loss = 0.05441967
Iteration 119, loss = 0.05390122
Iteration 120, loss = 0.05368127
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Iteration 122, loss = 0.05256749
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Iteration 124, loss = 0.05091970
Iteration 125, loss = 0.05010649
Iteration 126, loss = 0.04990565
Iteration 127, loss = 0.04931173
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Iteration 129, loss = 0.04806415
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Iteration 147, loss = 0.03982262
Iteration 148, loss = 0.03928668
Iteration 149, loss = 0.03902027
Iteration 150, loss = 0.03892574
Iteration 151, loss = 0.03803100
Iteration 152, loss = 0.03778441
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Iteration 154, loss = 0.03680585
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Iteration 156, loss = 0.03604223
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Iteration 158, loss = 0.03525340
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Iteration 160, loss = 0.03468836
Iteration 161, loss = 0.03419625
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Iteration 163, loss = 0.03382553
Iteration 164, loss = 0.03328388
Iteration 165, loss = 0.03292777
Iteration 166, loss = 0.03260180
Iteration 167, loss = 0.03228899
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Iteration 199, loss = 0.02413422
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Iteration 201, loss = 0.02353797
Iteration 202, loss = 0.02312058
Iteration 203, loss = 0.02303956
Iteration 204, loss = 0.02285554
Iteration 205, loss = 0.02259705
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Iteration 206, loss = 0.02274328
Iteration 207, loss = 0.02237112
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Iteration 241, loss = 0.01657173
Iteration 242, loss = 0.01625667
Iteration 243, loss = 0.01616079
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Iteration 245, loss = 0.01585614
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Iteration 247, loss = 0.01566350
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Iteration 250, loss = 0.01527702
Iteration 251, loss = 0.01504929
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Iteration 253, loss = 0.01476483
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Iteration 254, loss = 0.01466720
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Iteration 257, loss = 0.01432167
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Iteration 280, loss = 0.01246345
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Iteration 282, loss = 0.01170391
Iteration 283, loss = 0.01150491
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Iteration 286, loss = 0.01138836
Iteration 287, loss = 0.01168132
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Iteration 290, loss = 0.01117328
Iteration 291, loss = 0.01082161
Iteration 292, loss = 0.01078207
Iteration 293, loss = 0.01064193
Iteration 294, loss = 0.01055466
Iteration 295, loss = 0.01046398
Iteration 296, loss = 0.01040367
Iteration 297, loss = 0.01043060
Iteration 298, loss = 0.01042094
Iteration 299, loss = 0.01039797
Iteration 300, loss = 0.01019975
```

```
C:\Users\blake\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n
2kfra8p0\LocalCache\local-packages\Python310\site-
packages\sklearn\neural_network\_multilayer_perceptron.py:690:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (300) reached and
the optimization hasn't converged yet.
  warnings.warn(
```

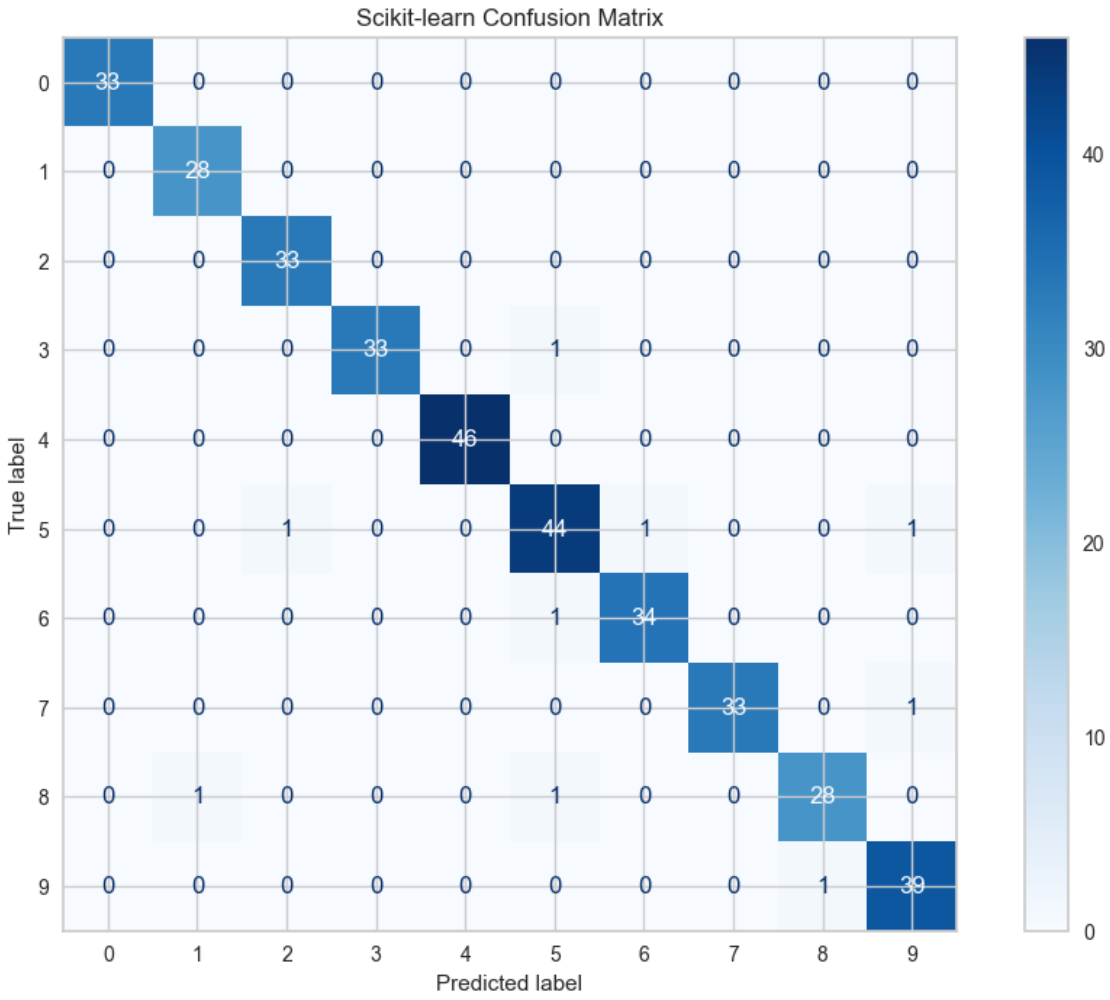
[17]:
```
MLPClassifier(hidden_layer_sizes=(64,), max_iter=300, random_state=42,
              verbose=True)
```

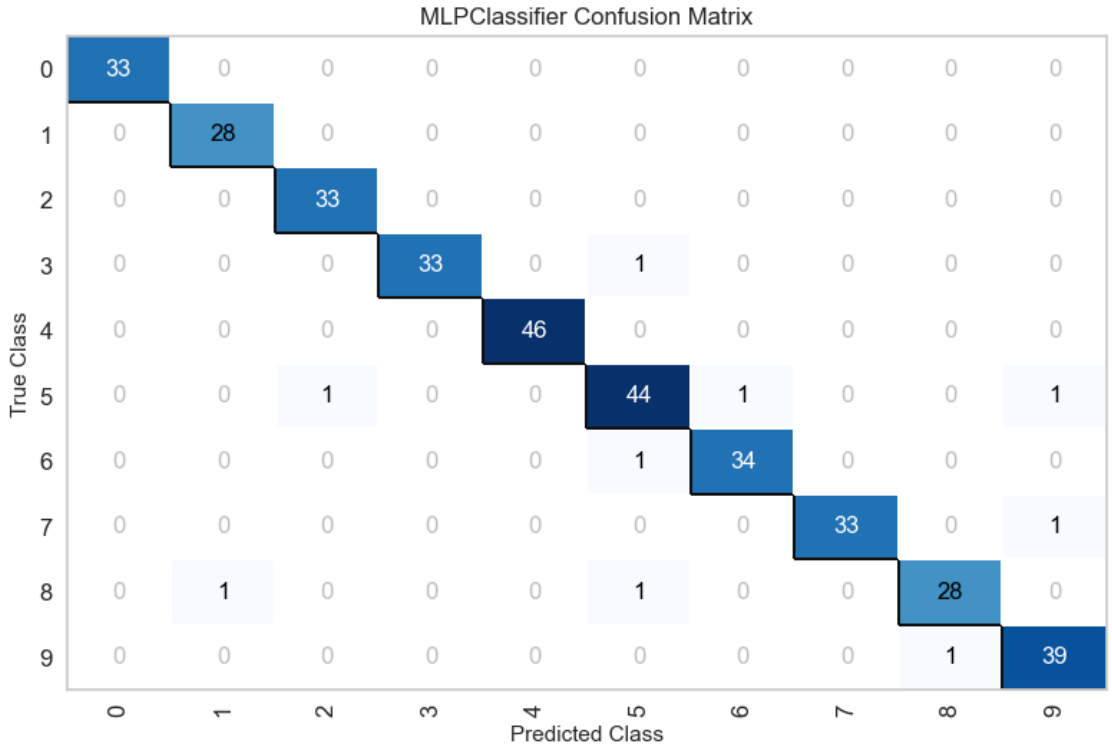
---

**4 - Evaluating the Model on Test Set**

[18]:
```
y_pred = model.predict(X_test)
# sklearn version - confusion matrix to evaluate
cm = confusion_matrix(y_test, y_pred)
fig, ax = plt.subplots(figsize=(12, 8))
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=digits.
 ↪target_names)
disp.plot(cmap='Blues', values_format='d', ax=ax)
plt.title("Scikit-learn Confusion Matrix")
plt.show()

# yellowbrick version (annotated, precision/recall included)
yb_cm = YBConfusionMatrix(model, classes=digits.target_names, cmap='Blues')
yb_cm.fit(X_train, y_train)
yb_cm.score(X_test, y_test)
yb_cm.show()
```


Scikit-learn Confusion Matrix
True label
Predicted label
0 1 2 3 4 5 6 7 8 9
33 0 0 0 0 0 0 0 0 0
0 28 0 0 0 0 0 0 0 0
0 0 33 0 0 0 0 0 0 0
0 0 0 33 0 1 0 0 0 0
0 0 0 0 46 0 0 0 0 0
0 0 1 0 0 44 1 0 0 1
0 0 0 0 0 1 34 0 0 0
0 0 0 0 0 0 0 33 0 1
0 1 0 0 0 1 0 0 28 0
0 0 0 0 0 0 0 0 1 39
40
30
20
10
0




[18]: `<Axes: title={'center': 'MLPClassifier Confusion Matrix'}, xlabel='Predicted Class', ylabel='True Class'>`

- The Scikit-learn version gives control over layout and aesthetics
- The Yellowbrick matrix, developed by faculty at Georgetown, (from whom I learned data science) adds precision/recall support and integrates smoothly with scikit-learn models — helpful for interpretability in academic and production settings
- Both the scikit-learn and Yellowbrick confusion matrices show strong diagonal dominance, indicating high classification accuracy across all digits.
- Misclassifications are minimal and mostly isolated — e.g., occasional confusion between 5 and 6 or 8 and 9, likely due to shared curvature and loop structure.
- Yellowbrick adds clarity by integrating precision/recall metrics, enhancing interpretability — particularly useful when evaluating how well the model handles digits with similar strokes.

---

**5 - Closing Down the Pub** This notebook illustrated a simple ANN's ability to learn patterns from handwritten digits; instead of intuition (which is what is built into us humans), the machine needs to recognize it through iteration.

The model improved by seeing its own error and adjusting with each pass.

The loss curve, like a learner's arc, bent toward clarity. Each confusion matrix showed not perfection, but progress.

In the spirit of Condorcet, learning is not a leap but a series of steps. And like Locke's blank slate, the model began knowing nothing; yet over many interations it came to recognise form, loop, and line.

Not to say that we can extrapolate to all ANNs from this, but in this case these are both the advantanges and the weaknesses of this simple Artificial Neural Nets.