# 🧠 Overview:

The goal is to **build a CNN (Convolutional Neural Network)** that classifies handwritten digits (0–9) using the **MNIST dataset**.

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## 1. Importing Required Libraries

```
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.optimizers import SGD
import matplotlib.pyplot as plt
import numpy as np
```

- **mnist** → built-in dataset of 70,000 handwritten digit images (28×28 pixels).
- **Sequential** → linear stack model, layer-by-layer CNN.
- **Conv2D, MaxPooling2D, Flatten, Dense** → CNN layers.
- **SGD** → Stochastic Gradient Descent optimizer.
- **matplotlib, numpy** → for visualization and data handling.

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## 2. Loading and Preprocessing the Data

```
(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

- Loads **60,000 training** and **10,000 testing** images with their digit labels.

```
X_train = X_train / 255.0
X_test = X_test / 255.0
```

- Normalizes pixel values (0–255) → (0–1) range for faster training and stability.

```
X_train = X_train.reshape(-1, 28, 28, 1)
X_test = X_test.reshape(-1, 28, 28, 1)
```

- Adds a **channel dimension** (since CNNs expect 4D input: samples × height × width × channels).
  Here, 1 channel = grayscale image.

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### 3. Visualizing Sample Images

```
plt.figure(figsize=(10,4))
for i in range(10):
    plt.subplot(2,5,i+1)
    plt.imshow(X_train[i].reshape(28,28), cmap="gray")
    plt.title(y_train[i])
    plt.axis('off')
plt.show()
```

- Displays first 10 images with their corresponding digit labels.

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### 4. Defining the CNN Architecture

```
model = Sequential([
    Conv2D(32, (3,3), activation='relu', input_shape=(28,28,1)),
    MaxPooling2D(2,2),
    Flatten(),
    Dense(100, activation='relu'),
    Dense(10, activation='softmax')
])
```

Let's break this down:

| Layer | Purpose | Output shape |
|---|---|---|
| **Conv2D(32, (3×3))** | Detects features like edges/corners using 32 filters. | (26, 26, 32) |
| **ReLU** | Removes negative values (keeps non-linearity). | — |
| **MaxPooling2D(2×2)** | Reduces spatial size → keeps strongest feature. | (13, 13, 32) |
| **Flatten()** | Converts 2D feature maps into 1D vector. | (5408,) |
| **Dense(100, ReLU)** | Fully connected layer for learning complex patterns. | (100,) |
| **Dense(10, Softmax)** | Output layer — 10 neurons for 10 classes (0–9). | (10,) |

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### 5. Compiling the Model

```
optimizer = SGD(learning_rate=0.01, momentum=0.9)
model.compile(
    optimizer=optimizer,
    loss="sparse_categorical_crossentropy",
    metrics=["accuracy"]
)
```

- **Optimizer:** SGD adjusts weights after each batch to minimize loss.
    - *learning_rate=0.01*: step size in optimization.
    - *momentum=0.9*: helps speed up convergence and avoid oscillation.
- **Loss:** sparse categorical crossentropy → used for integer labels.
- **Metrics:** accuracy to monitor performance.

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## 6. Training the Model

```
model.fit(X_train, y_train, epochs=10, batch_size=32)
```

- **epoch:** 1 full pass through training data.
- **batch_size:** model sees 32 images before updating weights once.

As shown in your output, accuracy improves with each epoch — reaching **~99.8% training accuracy** by epoch 10.

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## 7. Evaluating on Test Data

```
test_loss, test_acc = model.evaluate(X_test, y_test, verbose=0)
print("Test Accuracy:", test_acc)
print("Test Loss:", test_loss)
```

Results:

```
Test Accuracy: 0.9874 (~98.7%)
Test Loss: 0.0405
```

→ The model generalizes very well, nearly 99% accuracy on unseen data.

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## 8. Making a Random Prediction

```
n = np.random.randint(0, 9999)
plt.imshow(X_test[n])
plt.show()

predicted_value = model.predict(X_test)
```

```
print("Handwritten number in the image is =", np.argmax(predicted_value[n]))
```

- Picks a random image from test set.
- Predicts its class (highest probability index from softmax).
- Prints the predicted digit.

Output example:

```
Handwritten number in the image is = 5
```

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## ✅ Summary

| Step | Purpose |
|---|---|
| Load + Normalize | Prepare data for CNN |
| CNN Layers | Extract features & classify |
| Compile | Define optimizer, loss, and metric |
| Train | Learn from data |
| Evaluate | Measure accuracy on test set |
| Predict | Check individual predictions |

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Would you like me to **rewrite this same code in a slightly simplified, clean version** (e.g., no warnings, clear comments, and modern style using `Input()` layer)?
That would make it better for showing in your report or submission.

**You said:**
Good. Why the -1 here X_train = X_train.reshape(-1, 28, 28, 1) X_test = X_test.reshape(-1, 28, 28, 1)?

**ChatGPT said:**

Excellent question 🔥 — and this is one that **really helps you understand how data is shaped** before going into a CNN.

Let's break it down clearly 👇

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## 🧩 The line:

```
X_train = X_train.reshape(-1, 28, 28, 1)
```

is reshaping your array into **4 dimensions**:

```
(samples, height, width, channels)
```

For **MNIST**, we know:

- Each image = 28×28 pixels
- Grayscale → 1 channel
- There are 60,000 training samples

So ideally, we want the shape to become:

```
(60000, 28, 28, 1)
```

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## ⚙️ Now, what does `-1` do?

The `-1` is a special placeholder in NumPy that says:

> "Figure this dimension out automatically based on the total size of the array."

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## ✅ Example:

Suppose `X_train` initially has shape `(60000, 28, 28)`.

That means total elements =
`60000 × 28 × 28 = 47,040,000`

When you write:

```
X_train.reshape(-1, 28, 28, 1)
```

NumPy checks:

> Okay, total = 47,040,000.
> I know each sample will have `28×28×1 = 784` elements.
> So how many samples are there?
> `47,040,000 ÷ 784 = 60000`

Hence it automatically infers:

```
X_train.shape → (60000, 28, 28, 1)
```

---

## 🧠 Why it's used

Using `-1` makes your code **dynamic and flexible** —
you don’t have to manually write `60000` (or whatever number of samples there are).
If dataset size changes, it still works perfectly.

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### 📊 Quick visual comparison

| Before reshape | After reshape |
|---|---|
| `(60000, 28, 28)` | `(60000, 28, 28, 1)` |
| Missing channel dimension | Now ready for CNN (expects 4D input) |

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In short:

- 🔹 `-1` tells NumPy “figure out the correct number of samples automatically.”
- 🔹 The `(28, 28, 1)` part specifies the shape of each image for CNN input.

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Would you like me to show a **mini demonstration** of this reshape with actual numbers and printed shapes? It’ll visually make the “-1” effect super clear.

**You said:**

plt.figure(figsize=(10,4)) for i in range(10): plt.subplot(2,5,i+1) plt.imshow(X_train[i].reshape(28,28), cmap="gray") plt.title(y_train[i]) plt.axis('off') plt.show() why reshaping here again? Also explain the subplot logic as well.

**ChatGPT said:**

Perfect question again 🔥 — you’re noticing the *small but smart* details that actually make the visualization work properly.

Let’s unpack both parts of your question clearly 👇

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## 🧠 Part 1 — Why `reshape(28, 28)` again?

You’re right — earlier we already reshaped `X_train` as:

```
X_train = X_train.reshape(-1, 28, 28, 1)
```

So, **each image is now 4D**:
`(height, width, channels)` → `(28, 28, 1)`

That last `1` is the **channel dimension** — it’s needed for CNNs,
but **matplotlib’s `imshow()`** doesn’t expect that.

`imshow()` expects a **2D array** for grayscale images — i.e. `(height, width)`.

So this line:

```
plt.imshow(X_train[i].reshape(28,28), cmap="gray")
```

is just flattening back `(28,28,1)` → `(28,28)` temporarily for **display purposes only** (no effect on training data).

In other words:

| Purpose | Shape |
|---|---|
| CNN input | `(28,28,1)` |
| Visualization | `(28,28)` |

If you **omit the reshape**, `imshow()` might still work sometimes, but you could get a warning like:

> “Invalid shape (28,28,1) for image data”

So reshaping ensures it’s shown correctly.

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## 🎨 Part 2 — Understanding the Subplot Logic

The code:

```
plt.figure(figsize=(10,4))
for i in range(10):
    plt.subplot(2,5,i+1)
    plt.imshow(X_train[i].reshape(28,28), cmap="gray")
    plt.title(y_train[i])
    plt.axis('off')
plt.show()
```

### 🔹 `plt.figure(figsize=(10,4))`

Creates a new figure of size **10 inches wide × 4 inches tall**.

### 🔹 `for i in range(10):`

We want to display **10 images**.

### 🔹 `plt.subplot(2, 5, i+1)`

Subplot divides your figure into a **grid of 2 rows × 5 columns**.

So total possible plots = `2 × 5 = 10`.

`i+1` tells matplotlib *which cell in the grid* to place the current image.

So:

| i | subplot(2,5,i+1) | Position |
|---|---|---|
| 0 | subplot(2,5,1) | 1st image |
| 1 | subplot(2,5,2) | 2nd image |
| … | … | … |
| 9 | subplot(2,5,10) | 10th image |

### 🔹 `plt.imshow(X_train[i].reshape(28,28), cmap="gray")`

Displays each digit image in grayscale.

### 🔹 `plt.title(y_train[i])`

Shows its actual label (e.g. 3, 7, 5, etc.) as title.

### 🔹 `plt.axis('off')`

Removes the x/y axes — makes it cleaner.

### 🔹 `plt.show()`

Finally renders the whole grid of images.

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## 🧩 So in short:

| Code part | What it does |
|---|---|
| `reshape(28,28)` | removes channel dimension for display |
| `subplot(2,5,i+1)` | arranges 10 plots (2 rows × 5 columns) |
| `imshow()` | shows image |
| `title()` | shows digit label |
| `axis('off')` | hides axis lines |
| `show()` | displays all |

---

Would you like me to modify this visualization block slightly to show **predicted labels too** (like “Actual: 3, Predicted: 3” under each image)?
It looks really nice when you show sample predictions later.

**You said:**

# b. Defining the model’s architecture model = Sequential([ Conv2D(32, (3,3), activation='relu', input_shape=(28,28,1)), MaxPooling2D(2,2), Flatten(), Dense(100, activation='relu'), Dense(10, activation='softmax') ]) Make this more clear.

**ChatGPT said:**

Absolutely 💪
This is **the heart of your CNN (Convolutional Neural Network)** — where the actual learning structure is defined.
Let’s go through this step-by-step in **clear, visual, human-understandable logic** 👇

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## 🧩 Code Block

```
model = Sequential([
    Conv2D(32, (3,3), activation='relu', input_shape=(28,28,1)),
    MaxPooling2D(2,2),
    Flatten(),
    Dense(100, activation='relu'),
    Dense(10, activation='softmax')
])
```

---

## 🔷1️⃣Sequential Model

```
model = Sequential([...])
```

- **Sequential** means the layers are stacked one after another in a **straight line** —
  the output of one layer is automatically the input to the next.
- Perfect for CNNs where the flow is:
  *Image → Convolution → Pooling → Flatten → Dense Layers → Output.*

Think of it like a **pipeline**:
📸 Input → 🔍 Feature Extraction → 🧠 Decision Making

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## 🔷2️⃣Convolutional Layer

```
Conv2D(32, (3,3), activation='relu', input_shape=(28,28,1))
```

### What it does:

- Detects **features** from the image like edges, corners, and textures.

- The convolution operation slides small **3×3 filters** across the image, multiplying and summing pixel values.

### Parameters:

- **32** → number of filters (each learns a different feature).
- **(3,3)** → filter (kernel) size — small window scanning over the image.
- **activation='relu'** → introduces non-linearity (turns negatives → 0).
- **input_shape=(28,28,1)** → image dimensions (height, width, channels).

### Output shape after this layer:

→ (26, 26, 32)
(because 28×28 image shrinks by 2 pixels on each side due to 3×3 filters).

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## 🔷3️⃣Max Pooling Layer

`MaxPooling2D(2,2)`

### What it does:

- Reduces image size (downsampling) but **keeps the strongest features**.
- Looks at 2×2 pixel blocks and takes the **maximum** value in each block.

This makes:

- Model smaller and faster.
- Features more focused (less sensitive to small shifts in image).

### Output shape after this layer:

→ (13, 13, 32)

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## 🔷4️⃣Flatten Layer

`Flatten()`

### What it does:

- Converts 3D data (height, width, channels) → 1D vector.
- Example: (13, 13, 32) → (5408,)

This is necessary before passing data to the **Dense (fully connected)** layers, which expect 1D input.

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## 🔷5️⃣ Fully Connected Layer (Hidden Layer)

```
Dense(100, activation='relu')
```

### What it does:

- Standard **neural network layer** with 100 neurons.
- Each neuron learns patterns combining all features extracted by CNN.
- **ReLU** again adds non-linearity so the model can learn complex relationships.

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## 🔷6️⃣ Output Layer

```
Dense(10, activation='softmax')
```

### What it does:

- The final prediction layer.
- **10 neurons** → one for each digit (0–9).
- **Softmax activation** converts raw scores → probabilities that sum to 1.

Example output for an image:

```
[0.01, 0.00, 0.95, 0.01, 0.00, 0.01, 0.00, 0.01, 0.00, 0.01]
```

→ Model predicts **digit 2** (highest probability 0.95).

---

## 🧠 In summary:

| Layer | Type | Function |
|---|---|---|
| 1 | Conv2D(32, 3×3) | Extracts features (edges, textures) |

| | | |
|---|---|---|
| 2 | MaxPooling2D(2×2) | Reduces image size, keeps key info |
| 3 | Flatten() | Converts 3D → 1D |
| 4 | Dense(100, ReLU) | Learns complex feature combinations |
| 5 | Dense(10, Softmax) | Outputs probabilities for digits 0–9 |

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## 🔁 Complete Flow Visualization:

```
28×28×1 Image
   ↓
[Conv2D → feature maps: 26×26×32]
   ↓
[MaxPooling2D → smaller maps: 13×13×32]
   ↓
[Flatten → 5408 values]
   ↓
[Dense(100) → learn patterns]
   ↓
[Dense(10, Softmax) → predict digit]
```

---

Would you like me to make a **small diagram (image)** showing this CNN structure visually (like a flowchart from input to output)? It really helps in reports and viva prep.