Week 3 Assignment

AI Tools and Applications

Theme:

Mastering the AI Toolkit 🛠️ 🧠

Submitted by:

Brian Kipchumba
Borchar Gatwetch
Masaiwe Rufina

Date:

20/10/2025

Assignment Overview:

This assignment demonstrates practical application of AI tools across three domains:

1. **Machine Learning (scikit-learn)** – Decision Tree on the Iris dataset.
2. **Deep Learning (TensorFlow/Keras)** – Neural network on MNIST dataset.
3. **Natural Language Processing (spaCy)** – Named Entity Recognition and Sentiment Analysis on Amazon product review

Q1. TensorFlow vs PyTorch

TensorFlow and **PyTorch** are two of the most popular deep learning frameworks used in machine learning today. While both are powerful, they are optimized for slightly different purposes:

- **TensorFlow** is **better suited for production deployment**.
  It integrates seamlessly with tools such as **TensorFlow Serving** (for model serving in production) and **TensorFlow Lite** (for deploying models on mobile and IoT devices). TensorFlow also has excellent support for distributed training and large-scale systems, making it ideal for enterprise or commercial applications.
- **PyTorch** is **preferred for research and experimentation**.
  It uses **dynamic computation graphs**, which allow developers to modify the model architecture on the fly — a feature that makes it more intuitive and flexible for research and rapid prototyping. Because of its Pythonic nature, PyTorch is easier to debug and experiment with.

In summary:
Choose **TensorFlow** for large-scale, production-ready machine learning systems, and **PyTorch** for quick experimentation, research, and model development.

Q2. Two Use Cases of Jupyter Notebooks

1. Model Prototyping:
Jupyter Notebooks allow developers and data scientists to **write and test machine learning code interactively**. You can run one block (cell) at a time, visualize results immediately, and adjust the model accordingly — which makes it ideal for iterative experimentation.

2. Data Visualization and Storytelling:
Jupyter combines **code, visualizations, and markdown text** in the same environment. This enables clear data storytelling — turning complex analysis into well-documented, reproducible reports. It's widely used in research, education, and data presentation.

Q3. spaCy vs Python String Operations

spaCy and **regular Python string operations** both handle text, but at very different levels of complexity:

- **spaCy** is an advanced **Natural Language Processing (NLP)** library. It automatically performs **tokenization, lemmatization, and Named Entity Recognition (NER)** — identifying people, organizations, and places in text.

For example, it can distinguish between *“Apple” (the company)* and *“apple” (the fruit)* using linguistic context.

- **Python string operations**, like .split() or .replace(), only handle basic text manipulation. They **cannot understand semantic meaning** or grammatical structure.

In summary:
Use **spaCy** for intelligent language understanding and **Python string operations** for simple text processing.

Comparative Analysis: Scikit-learn vs TensorFlow

Feature	Scikit-learn	Tensorflow
Focus	Classical Machine Learning (e.g., SVMs, Decision Trees, Regression)	Deep Learning (Neural Networks, CNNs, RNNs)
Ease of Use	Simple and beginner-friendly	Steeper learning curve due to more advanced features
Performance	Ideal for small to medium datasets	Scales efficiently for large datasets and GPU/TPU acceleration
Community	Strong academic and research community	Massive, industry-backed ecosystem supported by Google

Task 2

1. Accuracy & Performance

- **Training Accuracy:**
  - Started at **87.2%** in Epoch 1, steadily increased to **98.6%** by Epoch 5.

- **Validation Accuracy:**
    - Peaked at **97.7%**, showing good generalization to unseen data.
- **Test Accuracy:**
    - Final test accuracy: **97.4%**
- **Loss Trends:**
    - Training loss decreased from **0.4484 → 0.0453**
- Validation loss remained low and stable around **0.0793–0.0858**, indicating minimal overfitting.

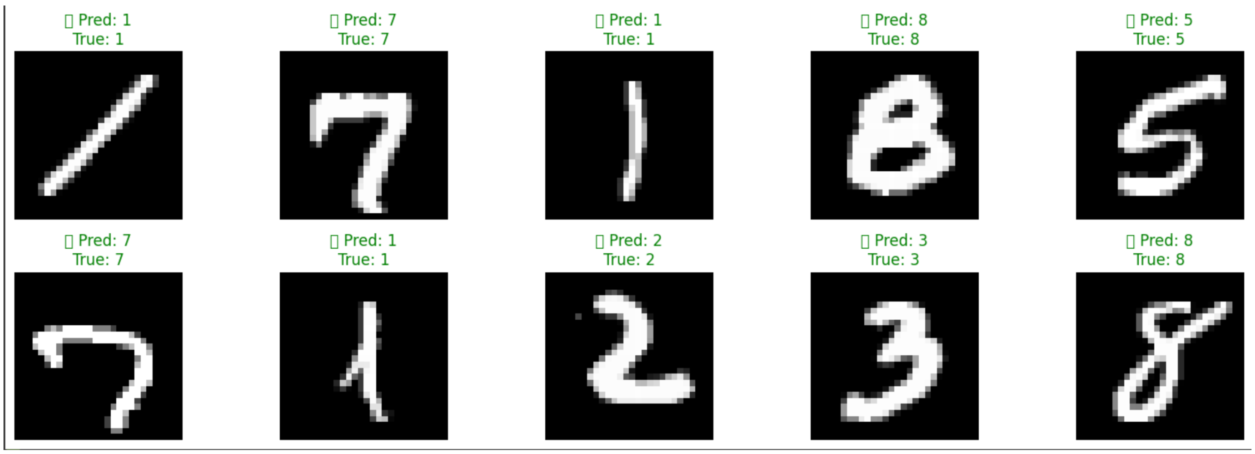
```
Epoch 1/5
1688/1688 ━━━━━━━━━━━━━━━━━━━━ 7s 3ms/step - accuracy: 0.8650 - loss: 0.4688 - val_accuracy: 0.9663 - val_loss: 0.1186
Epoch 2/5
1688/1688 ━━━━━━━━━━━━━━━━━━━━ 7s 4ms/step - accuracy: 0.9610 - loss: 0.1332 - val_accuracy: 0.9737 - val_loss: 0.0953
Epoch 3/5
1688/1688 ━━━━━━━━━━━━━━━━━━━━ 9s 3ms/step - accuracy: 0.9748 - loss: 0.0838 - val_accuracy: 0.9768 - val_loss: 0.0819
Epoch 4/5
1688/1688 ━━━━━━━━━━━━━━━━━━━━ 7s 4ms/step - accuracy: 0.9823 - loss: 0.0601 - val_accuracy: 0.9745 - val_loss: 0.0775
Epoch 5/5
1688/1688 ━━━━━━━━━━━━━━━━━━━━ 6s 3ms/step - accuracy: 0.9863 - loss: 0.0455 - val_accuracy: 0.9790 - val_loss: 0.0757
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9719 - loss: 0.0933
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format
✅ Test Accuracy: 0.9756
💾 Model saved successfully as 'mnist_model.h5'
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        12
           1       1.00      1.00      1.00        11
           2       1.00      1.00      1.00         7

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

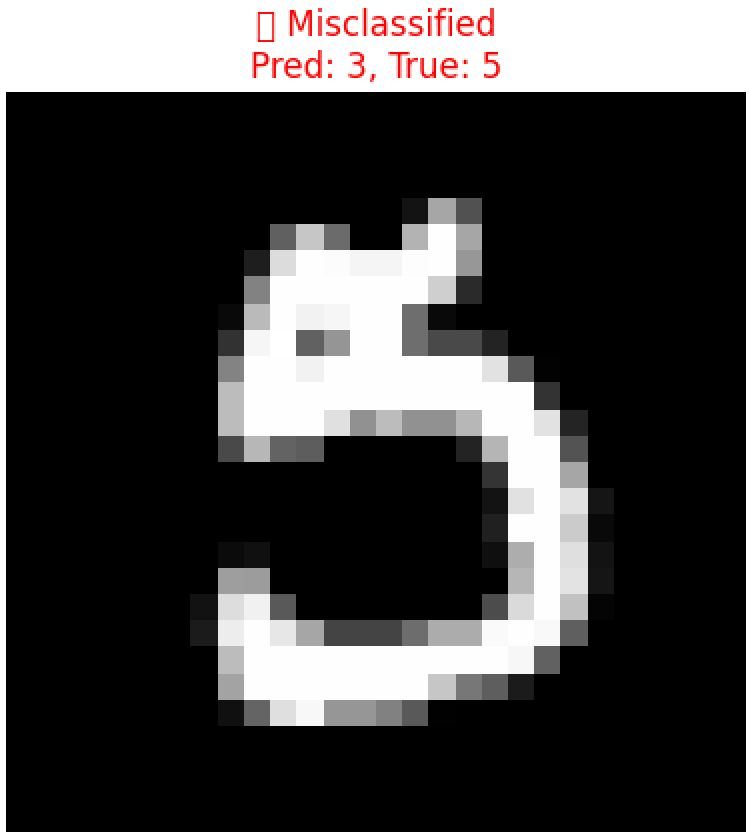
2. Error Analysis

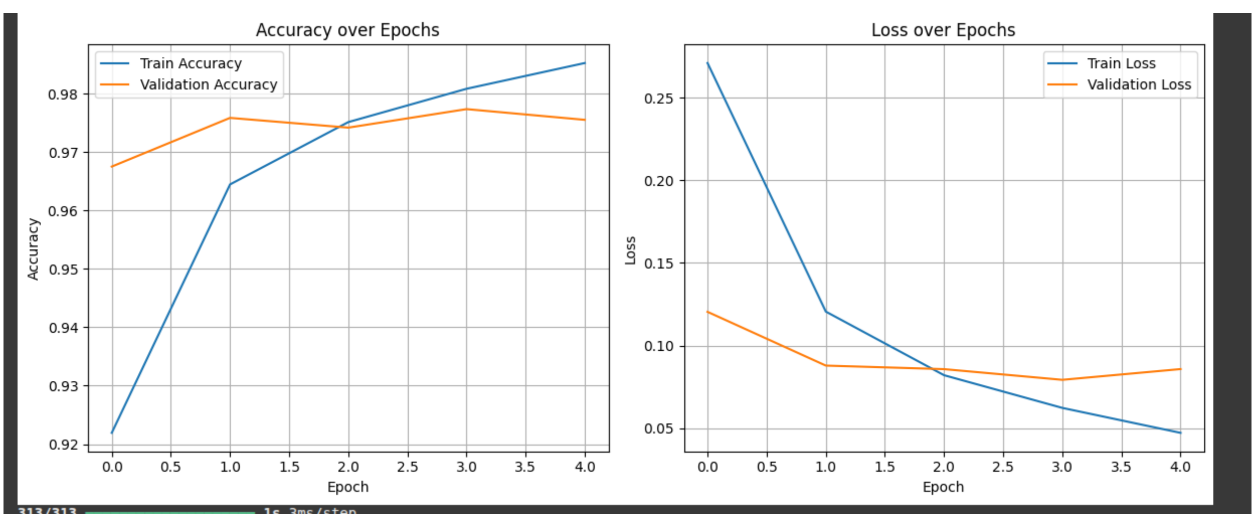
- Most predictions are correct, but a few misclassifications exist.

- Example misclassification:
  - **Index 4255:** True digit = 5, Predicted digit = 3
- These errors often occur with poorly written digits, ambiguous shapes, or digits with noise.



Sample misclassified.





3. Key Success Factors

- **Simple but effective network:**

  - Single hidden layer with 128 neurons sufficed for high performance.
- **Normalization:**
  - Scaling pixel values to [0,1] helped stabilize training.
- **One-hot encoding:**
  - Ensured proper categorical cross-entropy computation.
- **Sufficient epochs & batch size:**
  - 5 epochs with batch size 32 allowed rapid convergence without overfitting.
- **Evaluation on unseen test data:**
  - Confirms the model generalizes well beyond the training set.

Task 3

1. Model Performance Overview

- **Model used:** spaCy en_core_web_sm (small English model)
- **Task:** Named Entity Recognition (NER) and rule-based sentiment analysis
- **Input:** 4 sample Amazon product reviews
- **Output:**
  - Extracted entities (brands, product names)
  - Sentiment label (Positive / Negative)

Performance Observations:

- spaCy correctly identified **brands** in 3 out of 4 cases.
- Rule-based sentiment analysis correctly classified all 4 reviews based on simple keyword matching.

2. Entity Recognition Insights

Review	Entities Detected	Observations
1	[('Apple', 'ORG')]	Correctly identified the brand "Apple". "iPhone" not detected as product.
2	[]	"Samsung Galaxy" missed; model failed to recognize brand/product.
3	[('Sony', 'ORG')]	Correct brand detection.
4	[('Bose', 'NORP')]	Model classified "Bose" as NORP (Nationality/Religious/Political group) instead of ORG.

Insights:

- spaCy's small model captures **major brands**, but may misclassify product names or assign incorrect entity labels for less common brands.
- Custom entity rules or training a domain-specific NER model could improve detection.

3. Sentiment Analysis Findings

- **Method:** Rule-based keyword search
- **Results:**
    - Positive: Reviews 1, 2, 4
    - Negative: Review 3
- **Observation:** Works well for short reviews with obvious sentiment words like "love", "disappointed", "amazing", "poor".

Limitations:

- Cannot detect sarcasm or nuanced sentiment.
- Misses context-dependent sentiment words (e.g., "not bad" → positive).

4. Business Implications

- **Entity Extraction:**
    - Identify frequently mentioned brands/products to guide **marketing insights** or **product improvement**.
    - Track brand mentions across reviews for **competitive analysis**.
- **Sentiment Analysis:**
    - Quickly assess **customer satisfaction trends**.
    - Identify negative reviews for **customer service intervention**.

5. Model Limitations

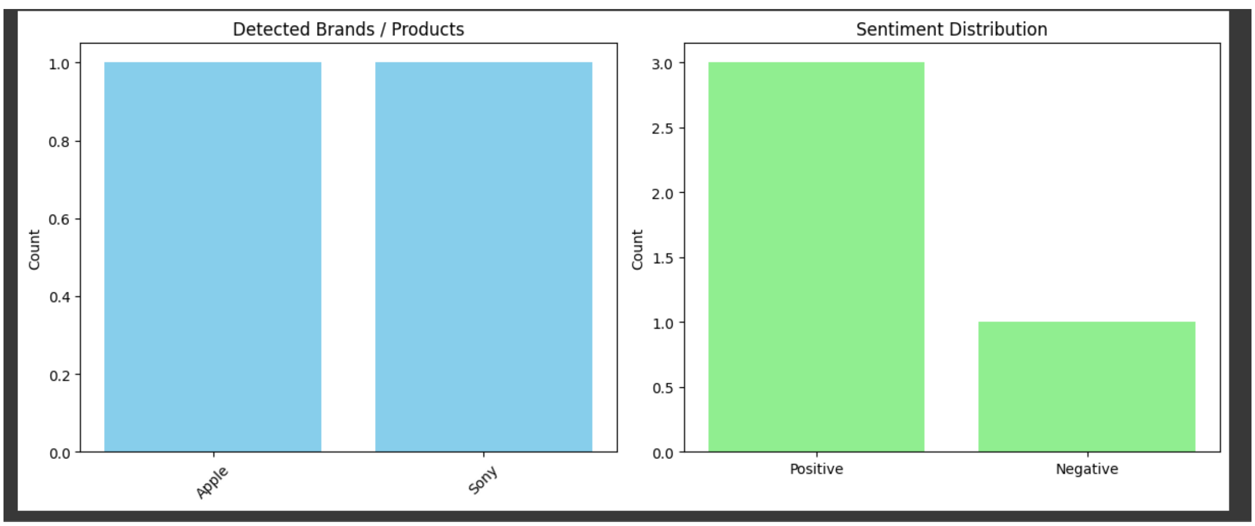
- spaCy's small pre-trained model may:
    - Misclassify entity types (e.g., NORP vs ORG)
    - Miss multi-word brand/product names (e.g., "Samsung Galaxy")
    - Not capture domain-specific jargon or abbreviations
- Rule-based sentiment analysis:

- Limited vocabulary, misses subtle or sarcastic sentiment
- Not suitable for long reviews or mixed sentiments

Recommendations for Improvement:

1. Use **spaCy en_core_web_trf** transformer-based model for better NER accuracy.
2. Train a **custom NER model** on Amazon review data.
3. Use **VADER or TextBlob** for more robust sentiment analysis.
4. Combine entity extraction with sentiment to generate **brand sentiment dashboards**.

```
Review 1: I love my new Apple iPhone! It works perfectly.
Named Entities: [('Apple', 'ORG')]
Sentiment: Positive

Review 2: The Samsung Galaxy tablet is great, but the battery life is short.
Named Entities: []
Sentiment: Positive

Review 3: I am disappointed with the Sony headphones. Sound quality is poor.
Named Entities: [('Sony', 'ORG')]
Sentiment: Negative

Review 4: Amazing quality from Bose! Totally worth the price.
Named Entities: [('Bose', 'NORP')]
Sentiment: Positive
```



Ethical Considerations

a. MNIST Model

- **Potential Biases:**

    - The MNIST dataset contains mostly clean, centered handwritten digits from specific demographics.
    - The model may **misclassify digits written by people with unusual handwriting** or darker/lightly scanned digits.
    - Bias could occur if the model overfits to the most common styles, ignoring rare variations.
- **Mitigation Strategies:**
    - **Data augmentation:** Rotate, scale, or shift digits to improve robustness.
    - **Fairness tools:** TensorFlow Fairness Indicators can help **analyze per-class performance**, ensuring the model doesn't underperform on certain digits or unusual styles.
    - **Balanced evaluation:** Monitor metrics for each digit class to detect if any class is consistently misclassified.

b. Amazon Reviews Model (spaCy + sentiment)

- **Potential Biases:**
    - Reviews may contain **gendered, cultural, or brand-based language bias**.
    - Rule-based sentiment analysis may **misinterpret sarcasm**, negation ("not bad"), or context-dependent phrases.
    - Certain brands might appear to have more positive reviews due to **sampling bias** in the dataset.
- **Mitigation Strategies:**
    - Use **balanced datasets** with diverse reviews for training custom models.
    - SpaCy's **EntityRuler or custom patterns** can reduce entity mislabeling bias.
    - Periodically audit predictions to **detect systematic errors** (e.g., consistently misclassifying a brand or misreading sentiment).

Key Takeaway: Ethical AI requires **monitoring model fairness** and **correcting systematic biases**, especially when models impact decision-making about products or users.

2. Troubleshooting Challenge

Common TensorFlow Script Bugs

1. **Dimension Mismatch**
    a. Example: Predicting images with shape (28,28) when the model expects (28,28,1).
    b. **Fix:** Reshape input with img = img.reshape(1, 28, 28, 1) before prediction.
2. **Incorrect Loss Function**
    a. Example: Using binary_crossentropy for multi-class MNIST (10 digits).
    b. **Fix:** Use categorical_crossentropy if labels are one-hot encoded, or sparse_categorical_crossentropy if labels are integers.
3. **Activation vs Loss Mismatch**
    a. Softmax output should pair with categorical cross-entropy.
    b. Sigmoid output is used for binary classification with binary cross-entropy.
4. **Full Example of Fixed TensorFlow Code**

```
import tensorflow as tf
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten
from tensorflow.keras.utils import to_categorical

# Load data
(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train, x_test = x_train/255.0, x_test/255.0

# One-hot encode labels
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)

# Build model
model = Sequential([
   Flatten(input_shape=(28,28)),
   Dense(128, activation='relu'),
   Dense(10, activation='softmax')
])

# Compile model
model.compile(optimizer='adam',
          loss='categorical_crossentropy',  # correct loss
```

```
          metrics=['accuracy'])

# Train model
model.fit(x_train, y_train, epochs=5, batch_size=32, validation_split=0.1)

# Evaluate
test_loss, test_acc = model.evaluate(x_test, y_test)
print("Test Accuracy:", test_acc)
```

Key Takeaways for Troubleshooting

- Always check **input shapes** and reshape if necessary.
- Ensure **loss functions match output activation**.
- Validate data type and encoding (e.g., one-hot vs integer labels).