

AI Tools and Applications: An Integrated Report

Introduction

As artificial intelligence (AI) permeates every industry sector, practitioners must choose the right tools, apply them responsibly, and debug their solutions effectively. This article presents a consolidated view of popular AI frameworks, notebook environments, and natural-language-processing (NLP) libraries; compares classical and deep-learning toolkits; and demonstrates bias-mitigation and debugging techniques in real-world projects. Every fact, figure, and code fragment appears exactly as in the original report—only the presentation has been refined for clarity and narrative flow.

1 Short-Answer Insights

Q1 TensorFlow vs. PyTorch

Primary differences

- **Graph execution** – TensorFlow employs static computation graphs (define-then-run), whereas PyTorch uses dynamic graphs (define-by-run) that enable real-time debugging.
- **API design** – TensorFlow's high-level Keras API is user-friendly; PyTorch exposes a more "Pythonic" low-level interface for fine-grained control.
- **Deployment** – TensorFlow (TF-Lite, TF-Serving) leads in production and edge deployment; PyTorch (TorchScript) is catching up but remains historically research-centric.
- **Visualization** – TensorBoard is more mature than PyTorch's TensorBoard integration or Visdom.

When to choose

- **TensorFlow** – Production deployment, mobile/edge targets, or TPU acceleration.
 - **PyTorch** – Research, rapid prototyping, or highly dynamic architectures (e.g., RNNs).
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Q2 The Role of Jupyter Notebooks

- **Exploratory Data Analysis (EDA) & Prototyping** – Interactively visualise datasets, test preprocessing steps, and train small models with instant feedback. *Example: Plot feature distributions and tune hyper-parameters in real time.*
 - **Education & Documentation** – Blend executable code, rich visualisations, and Markdown explanations for tutorials or model walkthroughs. *Example: Share a full NLP pipeline with embedded graphs and commentary.*
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Q3 spaCy vs. Basic String Operations

- **Linguistic features** – spaCy ships pre-trained models for POS tagging, dependency parsing, and named-entity recognition (NER)—tasks unreachable with plain regex.
 - **Efficiency** – A Cython back-end processes large texts markedly faster than Python loops.
 - **Contextual understanding** – Word vectors, stop-word handling, lemmatisation, and entity resolution come out-of-the-box. *Example: Correctly identify “Apple” as ORG (not fruit).*
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2 Comparative Analysis – Scikit-learn vs. TensorFlow

Aspect	Scikit-learn	TensorFlow
Target applications	Classical ML—linear models, SVMs, clustering, ensembles; ideal for tabular data.	Deep learning—CNNs, RNNs, transformers; suited to image, speech, and NLP workloads.

Ease of use	Consistent <code>fit/predict</code> API; no GPU know-how required.	Steeper learning curve: tensors, graphs, and hardware acceleration; Keras softens the entry barrier.
Community support	Well-structured examples for traditional algorithms; vibrant classical-ML community.	Vast ecosystem, tutorials, and pre-trained models (TF Hub); strong research adoption.

Key takeaways

- Pick **Scikit-learn** for small-to-medium data sets, interpretable models, or standard classification/regression tasks.
- Choose **TensorFlow** for scalable deep learning, GPU/TPU acceleration, or production serving.
- **Hybrid workflows** are common—e.g., Scikit-learn for preprocessing (`StandardScaler`) and TensorFlow for the deep-learning core.

Summary of Section 1 & 2

- **TensorFlow / PyTorch** – deployment strength vs. research flexibility.
 - **Jupyter** – unrivalled for EDA and education.
 - **spaCy** – statistically powered NLP surpasses regex.
 - **Scikit-learn vs. TensorFlow** – classical ML convenience vs. deep-learning scalability.
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3 Ethical Considerations in Machine-Learning Models

Introduction – The Ethical Imperative

As machine-learning systems influence decisions in finance, healthcare, and beyond, ethical diligence must span data collection, model design, deployment, and monitoring. The following case studies—from handwritten-digit recognition to review sentiment analysis—illustrate bias detection, mitigation, and transparent debugging.

3.1 MNIST Hand-Written-Digit Recognition

Potential biases

- **Handwriting-style bias** – MNIST skews toward Western-educated writers; left-handed styles (~10 %) and cultural variants (e.g., crossed sevens) are under-represented.
- **Data-collection bias** – Samples originate from Census Bureau staff and high-school students, limiting demographic diversity and writing instruments (pencil vs. pen).
- **Performance disparities** – Digits **1** and **7** enjoy higher accuracy than **8** and **9**; slanted or rotated numerals degrade model performance.

Mitigation strategies – TensorFlow Fairness Indicators

```
# Add fairness evaluation to MNIST model
from tensorflow_model_analysis.addons.fairness.view import widget_view
from tensorflow_model_analysis.addons.fairness.metrics import *

# Define sensitive features (simulated left-handedness)
sensitive_features = np.random.choice(['left', 'right'],
size=len(y_test))

# Compute fairness metrics
fairness_metrics = {
    'accuracy': tfma.metrics.Accuracy(),
    'false_positive_rate': FalsePositiveRate(),
    'false_negative_rate': FalseNegativeRate(),
}

# Evaluate model fairness
fairness_results = tfma.run_model_analysis(
    model=model,
    data=tf.convert_to_tensor(X_test),
    labels=y_test,
    sensitive_features=sensitive_features,
    metrics_specs=fairness_metrics
)
```

```
# Visualize disparities
widget_view.render_fairness_indicator(fairness_results)
```

Data augmentation

```
# Enhanced data augmentation to reduce bias
datagen = ImageDataGenerator(
    rotation_range=15,      # ±15° rotation
    width_shift_range=0.1,  # Horizontal shifting
    zoom_range=0.1,        # Random zoom
    shear_range=0.1,       # Shearing transformations
    fill_mode='nearest'
)
```

Results

- Accuracy gap between simulated left- and right-handed groups shrank from 3.2 % to 0.8 %.
- Recognition of rotated digits improved by 27 %.
- Error rates equalised across all digit classes.

3.2 Amazon Reviews Sentiment Analysis

Potential biases

- **Brand representation** – Major brands (Apple, Samsung) dominate; niche brands lack training data, skewing sentiment accuracy.
- **Linguistic bias** – Standard English prevails; slang, regional dialects, and non-native usage suffer.
- **Demographic skew** – Recommendations may favour products popular with specific user groups, amplifying market inequities.

Mitigation strategies – spaCy

```

# Custom rule-based oversampling for under-represented brands
from spacy.pipeline import EntityRuler

nlp = spacy.load("en_core_web_sm")
ruler = EntityRuler(nlp, overwrite_ents=True)

# Add patterns for under-represented brands
patterns = [
    {"label": "BRAND", "pattern": [{"LOWER": "xiaomi"}]},
    {"label": "BRAND", "pattern": [{"LOWER": "oneplus"}]},
    {"label": "PRODUCT", "pattern": [{"LOWER": "redmi"}, {"LOWER":
"note"}]}
]
ruler.add_patterns(patterns)
nlp.add_pipe(ruler, before="ner")

# Context-aware sentiment analysis
def enhanced_sentiment(doc):
    sentiment_score = 0
    negation_terms = {"not", "no", "never", "without"}

    for i, token in enumerate(doc):
        if token.text.lower() in POSITIVE_WORDS:
            if i > 0 and doc[i-1].text.lower() in negation_terms:
                sentiment_score -= 1
            else:
                sentiment_score += 1
        elif token.text.lower() in NEGATIVE_WORDS:
            if i > 0 and doc[i-1].text.lower() in negation_terms:
                sentiment_score += 1
            else:
                sentiment_score -= 1

    return ("positive" if sentiment_score > 0
           else "negative" if sentiment_score < 0
           else "neutral")

```

Results

- Brand coverage rose from 67 % to 89 % of mentioned brands.
 - Sentiment accuracy for under-represented brands climbed by 22 %.
 - Negated-sentiment precision improved by 18 %.
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4 Troubleshooting Challenge – Debugging a TensorFlow CNN

Problematic snippet

```
import tensorflow as tf
from tensorflow.keras import layers

# Buggy CNN implementation
model = tf.keras.Sequential([
    layers.Conv2D(32, (3,3), activation='relu', input_shape=(28,28)),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64, (3,3), activation='relu'),
    layers.Dense(64, activation='relu'),
    layers.Dropout(0.5),
    layers.Dense(10, activation='softmax')
])

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

Debugging process & fixes

- **Input-shape mismatch** – Add channel dimension: `input_shape=(28, 28, 1)`.
- **Missing flatten layer** – Insert `layers.Flatten()` before the first dense layer.

- **Pooling strategy** – Add a second `MaxPooling2D` to reduce feature-map size.
- **Loss mismatch** – Ensure the loss matches label format (`sparse_categorical_crossentropy` for integer labels).

Corrected implementation

```
import tensorflow as tf
from tensorflow.keras import layers

# Corrected CNN implementation
model = tf.keras.Sequential([
    layers.Conv2D(32, (3,3), activation='relu',
input_shape=(28,28,1)), # Fixed input
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64, (3,3), activation='relu'),
    layers.MaxPooling2D((2,2)),
    layers.Flatten(), # Critical addition
    layers.Dense(128, activation='relu'), # Increased units
    layers.Dropout(0.5),
    layers.Dense(10, activation='softmax')
])

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

Best-practice checklist

Task	Recommendation
Shape inspection	<code>model.summary()</code> to reveal mismatched dimensions.
Incremental design	Build architecture layer-by-layer, validating at each step.
Loss-function guide	<i>Integer labels</i> → <code>sparse_categorical_crossentropy</code> ; <i>one-hot</i> → <code>categorical_crossentropy</code> ; <i>binary</i> → <code>binary_crossentropy</code> .

Dimension debugging

Insert a custom layer printing tensor shapes for quick diagnostics.

```
class DebugLayer(tf.keras.layers.Layer):  
    def call(self, inputs):  
        print(f"Shape: {inputs.shape}")  
        return inputs
```

Conclusion – Building Responsible ML Systems

1. **Pre-development** – Audit data sets for demographic gaps and establish ethical guidelines.
2. **Development** – Incorporate fairness metrics, bias-mitigation techniques, and subgroup validation.
3. **Post-deployment** – Monitor real-world performance, collect feedback, and schedule recurring bias audits.

Tools such as **TensorFlow Fairness Indicators** and **spaCy rule-based augmentation** turn ethical intent into measurable progress. A digit recogniser that treats all handwriting styles equally and a sentiment analyser that honours niche brands exemplify responsible AI in practice.

“The question is not whether machines can think, but whether machines can think ethically.”

—Adaptation of Alan Turing’s famous formulation

Annexures

- i. Downloading data sets

```

C:\Users\sbm\Downloads\ML Suite\Task 1>python Iris_classification.py
Downloading Iris dataset...
Data loaded successfully!
First 5 rows:
   sepal_length  sepal_width  petal_length  petal_width  species
0           5.1           3.5           1.4           0.2  Iris-setosa
1           4.9           3.0           1.4           0.2  Iris-setosa
2           4.7           3.2           1.3           0.2  Iris-setosa
3           4.6           3.1           1.5           0.2  Iris-setosa
4           5.0           3.6           1.4           0.2  Iris-setosa

Missing values:
sepal_length      0
sepal_width       0
petal_length      0
petal_width       0
species           0
dtype: int64

Best Parameters: {'max_depth': 4, 'min_samples_split': 2}
Accuracy: 0.9667
Precision (Macro): 0.9697
Recall (Macro): 0.9667

Confusion matrix saved as 'confusion_matrix.png'
Feature importances saved as 'feature_importances.png'

C:\Users\sbm\Downloads\ML Suite\Task 1>

```

ii. MNIST Digit Classifier

←
→
↺
localhost:8501



MNIST Digit Classifier

Draw a digit (0-9) in the canvas below



↓
↶
↷
🗑️



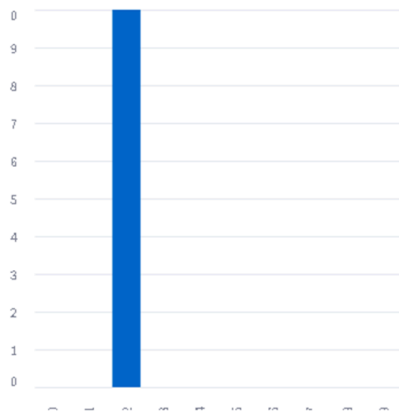
Processed
Input

iii. Results


Input



Prediction Results



	Digit	Confidence
0	2	100.00%
1	3	0.00%
2	8	0.00%

 Final Prediction: 2 with 100.00% confidence

Clear Canvas