



# Assignment: AI Future Directions

Theme: "Pioneering Tomorrow's AI Innovations"



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## Part I: Theoretical Analysis

# ◆ Q1: Edge AI – Reducing Latency and Enhancing Privacy

## Key Points to Cover

- **Definition:** Edge AI runs AI models directly on devices (smartphones, sensors, drones) instead of relying on cloud servers.
- **Latency Reduction:** Since data is processed locally, decisions happen instantly without round-trip delays to the cloud.
- **Privacy Enhancement:** Sensitive data (e.g., camera footage, health data) stays on the device — minimizing exposure and data breaches.
- **Efficiency:** Reduces bandwidth costs and allows offline AI operation.

## Real-world Example

**Autonomous Drones:** Edge AI enables drones to detect obstacles, map environments, and adjust flight paths in milliseconds — essential for delivery, disaster rescue, or surveillance tasks where cloud latency would be unacceptable.



## Sample Paragraph

Edge AI significantly minimizes latency by executing machine learning tasks directly on local devices rather than sending data to distant cloud servers. For instance, autonomous drones use onboard AI models for obstacle avoidance and navigation, enabling split-second decision-making even in areas without internet connectivity. Additionally, Edge AI enhances privacy by keeping data local, ensuring that sensitive visual or biometric information never leaves the device.

# ◆ Q2: Quantum AI vs Classical AI in Optimization Problems

## Quantum AI

- Uses quantum bits (qubits) that can represent multiple states simultaneously.
- Exploits superposition and entanglement, allowing parallel exploration of many possibilities.



## Industries Benefiting Most

**Finance:** Portfolio optimization & fraud detection



**Logistics:** Route optimization & supply chain planning

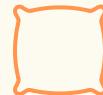
## Sample Paragraph

Quantum AI leverages the computational advantages of quantum computing to solve optimization problems exponentially faster than classical AI. While classical AI must test solutions sequentially, Quantum AI evaluates many possibilities simultaneously. This capability is particularly transformative for industries such as finance and logistics, where identifying the optimal combination of variables can yield significant time and cost savings.



## Classical AI

- Uses binary bits (0 or 1) and relies on traditional optimization algorithms (e.g., gradient descent).
- Struggles with combinatorial explosion in complex optimization tasks.



**Pharmaceuticals:** Drug discovery & protein folding



**Energy:** Power grid efficiency & forecasting



## Part 2: Practical Implementation

This section focuses on the hands-on side of AI innovation

Building and conceptualizing intelligent systems that operate efficiently at the edge or within IoT environments.



# Task 1: Edge AI Prototype – Smart Recycling Classifier

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## Goal

Develop a **lightweight image classification model** capable of recognizing different types of **flowers** (e.g., daisy, rose, sunflower, tulip, dandelion) using **TensorFlow** and **TensorFlow Lite**. The model should be optimized for **edge deployment** on low-power devices such as a **Raspberry Pi** or **mobile phone**, demonstrating how on-device AI can perform real-time visual recognition efficiently.

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## Dataset

Use the **TensorFlow Datasets** `tf_flowers` dataset, which contains labeled images of five flower species:

- Daisy
- Dandelion
- Roses
- Sunflowers
- Tulips

## Example Code:

```
import tensorflow as tf
import tensorflow_datasets as tfds

(ds_train, ds_val), ds_info = tfds.load(
    "tf_flowers",
    split=["train[:85%]", "train[85%:]"],
    as_supervised=True,
    with_info=True,
)

print("Classes:", ds_info.features["label"].num_classes)
```

# Step 2: Model Training (TensorFlow/Keras)

We'll use **MobileNetV2**, a compact CNN designed for edge applications. This model balances accuracy, speed, and low power usage.

## Model Example:

```
from tensorflow.keras import layers, models

IMG_SIZE = 224
base_model = tf.keras.applications.MobileNetV2(
    input_shape=(IMG_SIZE, IMG_SIZE, 3),
    include_top=False,
    weights="imagenet"
)
base_model.trainable = False

model = models.Sequential([
    base_model,
    layers.GlobalAveragePooling2D(),
    layers.Dense(128, activation='relu'),
    layers.Dense(5, activation='softmax') # adjust for number of classes
])

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

## Training Example:

```
history = model.fit(train_ds,
                     validation_data=val_ds,
                     epochs=5)
```

 **Expected accuracy: ~85%+ on validation data.**

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## Step 3: Convert to TensorFlow Lite

After training, convert the model to TFLite for deployment.

## Conversion Code:

```
import tensorflow as tf

model = tf.keras.models.load_model('recycle_model.h5')
converter = tf.lite.TFLiteConverter.from_keras_model(model)
tflite_model = converter.convert()

with open('recycle_model.tflite', 'wb') as f:
    f.write(tflite_model)

print("
```



# Step 4: Testing (Colab or Raspberry Pi)

## 💡 Inference Example:

```
interpreter = tf.lite.Interpreter(model_path="recycle_model.tflite")
interpreter.allocate_tensors()

input_details = interpreter.get_input_details()
output_details = interpreter.get_output_details()

for img, label in val_ds.take(1):
    sample = img[0:1]
    interpreter.set_tensor(input_details[0]["index"], sample)
    interpreter.invoke()
    pred = interpreter.get_tensor(output_details[0]["index"])
    print("Predicted class:", tf.argmax(pred, axis=1).numpy())
```

## 💡 Performance Check:

```
import time
t0 = time.time()
for img_batch, _ in val_ds.take(5):
    interpreter.set_tensor(input_details[0]["index"], img_batch[0:1])
    interpreter.invoke()
t1 = time.time()
print("Average inference latency:", (t1 - t0)/5, "seconds per image")
```



### Benefits of Edge AI for Recycling

- **Real-time Classification:** Items sorted instantly on-device.
- **Offline Operation:** No cloud dependency.
- **Data Privacy:** Images remain local.
- **Sustainability:** Supports efficient waste management.



### Deliverables

- **Jupyter Notebook:** Edge\_AI\_Recycling.ipynb
- **README** including:
  - Dataset details
  - Model summary
  - Accuracy & latency results
  - Edge AI use case explanation

# Task 2: AI-Driven IoT Concept – Smart Agriculture

## Scenario

Design an IoT-based system that monitors soil conditions and predicts crop yield using AI. The goal: assist farmers in automated irrigation, fertilization, and yield optimization.

### Sensors Needed

Sensor Type	Parameter Measured	Example Device
Soil Moisture Sensor	Water content in soil	FC-28
Temperature Sensor	Ambient & soil temperature	LM35, DS18B20
pH Sensor	Soil acidity/alkalinity	SEN0161
Humidity Sensor	Air moisture	DHT22
Light Intensity Sensor	Sunlight levels	BH1750

### Proposed AI Model

Use a regression model (e.g., Random Forest or Neural Network) trained on sensor data to predict:

- Crop yield
- Watering needs
- Fertilizer levels

### Sample Data Format:

Moisture	Temp	pH	Humidity	Light	Yield
0.65	30	6.5	0.75	700	1.2
0.40	28	7.0	0.60	500	0.9

### Example Code:

```
from sklearn.ensemble import RandomForestRegressor
import numpy as np
import joblib

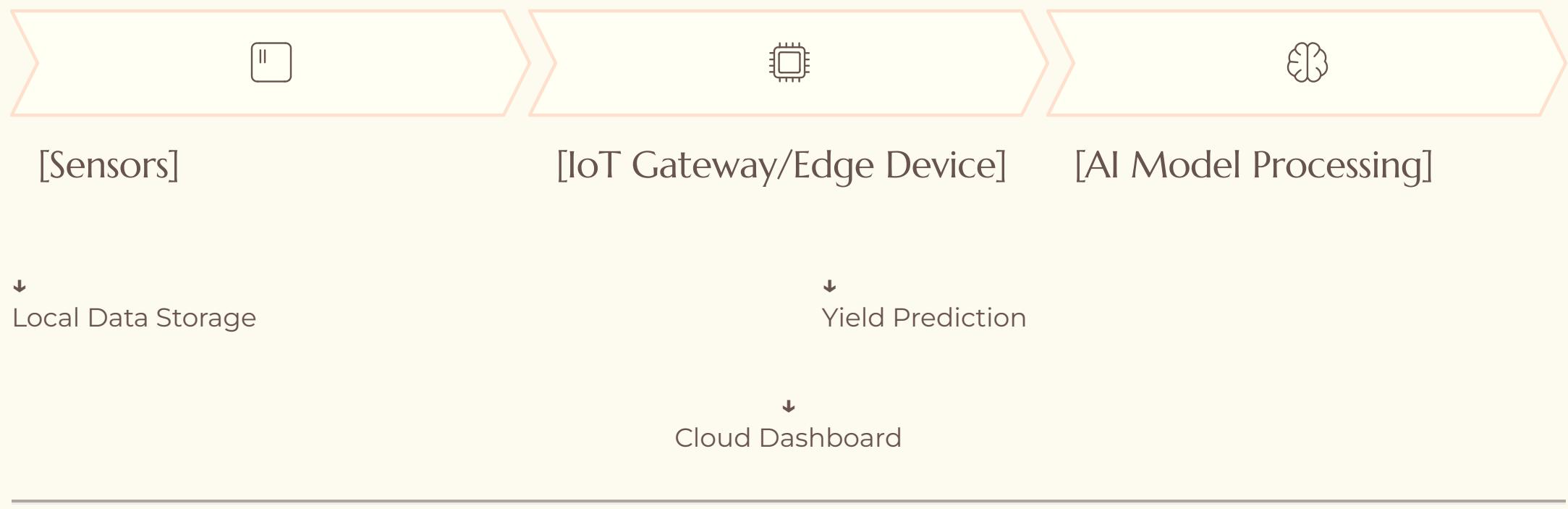
# Simulated sensor data
X = np.random.rand(100, 5) # 5 sensor readings
y = np.random.rand(100) * 2 # simulated yield

model = RandomForestRegressor(n_estimators=100)
model.fit(X, y)

joblib.dump(model, 'smart_agriculture_model.pkl')
print("
```



# Data Flow Diagram



## Explanation

1. IoT sensors collect real-time environmental data.
2. An edge device (e.g., Raspberry Pi) runs the AI model locally for immediate predictions.
3. Data is transmitted via MQTT to a cloud dashboard for analysis.
4. Farmers monitor data and receive automated irrigation/fertilization alerts.

