# Human Activity Recognition (HAR)

# **Technical Implementation Report**

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# 1 Technology Stack Overview

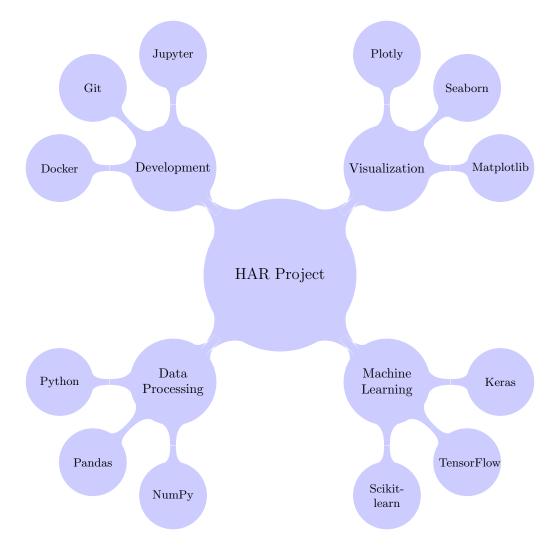


Figure 1: Technology Stack Mind Map

# 2 Development Environment

## 2.1 Required Software

• Python Environment:

```
Python 3.8+
Anaconda/Miniconda
Jupyter Notebook/Lab
```

• Version Control:

```
Git 2.x
GitHub Desktop (optional)
```

• Containerization:

```
Docker Desktop
NVIDIA Docker (for GPU support)
```

### 2.2 Python Dependencies

```
1 numpy==1.21.0
2 pandas==1.3.0
3 scikit-learn==0.24.2
4 tensorflow==2.8.0
5 keras==2.8.0
6 matplotlib==3.4.2
7 seaborn==0.11.1
8 plotly==5.1.0
```

# 3 Data Processing Pipeline



Figure 2: Data Processing Pipeline

### 4 Model Architectures

## 4.1 Classical ML Pipeline

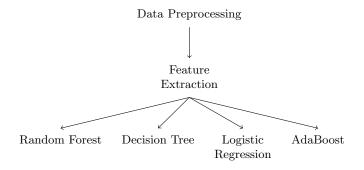


Figure 3: Classical ML Model Pipeline

### 4.2 Deep Learning Architecture



Figure 4: 1D-CNN Architecture

# 5 Performance Analysis

## 5.1 Model Accuracy Comparison

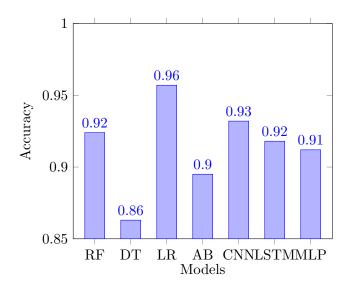


Figure 5: Model Accuracy Comparison

## 5.2 Training Time Comparison

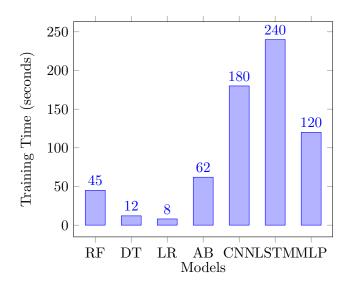


Figure 6: Training Time Comparison

# 6 Implementation Code

# 6.1 Data Preprocessing

```
def preprocess_data(raw_data):
    # Normalize data
    scaler = StandardScaler()
    normalized_data = scaler.fit_transform(raw_data)

# Create windows
```

```
window_size = 128
      stride = 64
8
      windows = create_windows(normalized_data,
9
                              window_size,
                               stride)
11
      return windows
12
13
14 def create_windows(data, window_size, stride):
15
      windows = []
      for i in range(0, len(data) - window_size, stride):
          window = data[i:i + window_size]
17
          windows.append(window)
      return np.array(windows)
```

#### 6.2 Model Training

```
# Classical ML Training
2 def train_classical_models():
      models = {
3
           'random_forest': RandomForestClassifier(
               n_estimators=100,
               random_state=42
           ),
           'decision_tree': DecisionTreeClassifier(
8
               random_state=42
9
          ),
           'logistic_regression': LogisticRegression(
               max_iter=1000,
12
               random_state=42
13
14
          ),
           'adaboost': AdaBoostClassifier(
16
               random_state=42
17
      }
18
      return models
19
20
21 # Deep Learning Training
22 def train_deep_learning_models():
      models = {
23
           'cnn': build_cnn_model(),
24
           'lstm': build_lstm_model(),
25
           'mlp': build_mlp_model()
27
      }
28
29
      for name, model in models.items():
           model.compile(
30
               optimizer='adam',
31
               loss='categorical_crossentropy',
32
               metrics=['accuracy']
33
34
      return models
```

# 7 Docker Deployment

#### 7.1 Dockerfile

```
FROM python:3.8-slim

WORKDIR /app
```

```
COPY requirements.txt .
RUN pip install -r requirements.txt

COPY . .

EXPOSE 8080

CMD ["python", "api.py"]
```

#### 7.2 Docker Compose

```
version: '3'
services:
    har_api:
    build: .
    ports:
        - "8080:8080"

volumes:
        - ./models:/app/models
environment:
        - MODEL_PATH=/app/models
        - CUDA_VISIBLE_DEVICES=0
```

## 8 API Documentation

#### 8.1 REST Endpoints

```
1 @app.route('/predict', methods=['POST'])
  def predict():
      0.00
3
      Endpoint for real-time predictions
4
      Request Body:
6
          "sensor_data": [...], # Array of sensor readings
8
          "window_size": 128  # Optional window size
9
10
11
      Response:
12
           "activity": "WALKING",
14
           "confidence": 0.95
      }
16
      0.00
17
      pass
18
```

# 9 Performance Optimization

#### 9.1 Model Quantization

```
# Convert model to TFLite
converter = tf.lite.TFLiteConverter.from_keras_model(model)
converter.optimizations = [tf.lite.Optimize.DEFAULT]
converter.target_spec.supported_types = [tf.float16]
tflite_model = converter.convert()
```

# 10 Monitoring and Logging

### 10.1 Logging Configuration

```
import logging

logging.basicConfig(
    level=logging.INFO,
    format='%(asctime)s - %(name)s - %(levelname)s - %(message)s',
    handlers=[
        logging.FileHandler('har.log'),
        logging.StreamHandler()
    ]

logger = logging.getLogger('HAR')
```

## 11 Testing Framework

#### 11.1 Unit Tests

```
import unittest

class TestHARModel(unittest.TestCase):
    def setUp(self):
        self.model = load_model()
        self.test_data = load_test_data()

def test_prediction(self):
        prediction = self.model.predict(self.test_data)
        self.assertIsNotNone(prediction)
        self.assertTrue(0 <= prediction <= 1)</pre>
```

### 12 Conclusion

The implementation combines multiple technologies and frameworks to create a robust HAR system. Key technical highlights include:

- Comprehensive data processing pipeline
- Multiple model architectures
- Docker containerization
- REST API implementation
- Performance optimization
- Monitoring and testing frameworks