QUANTUM BRAINATHON

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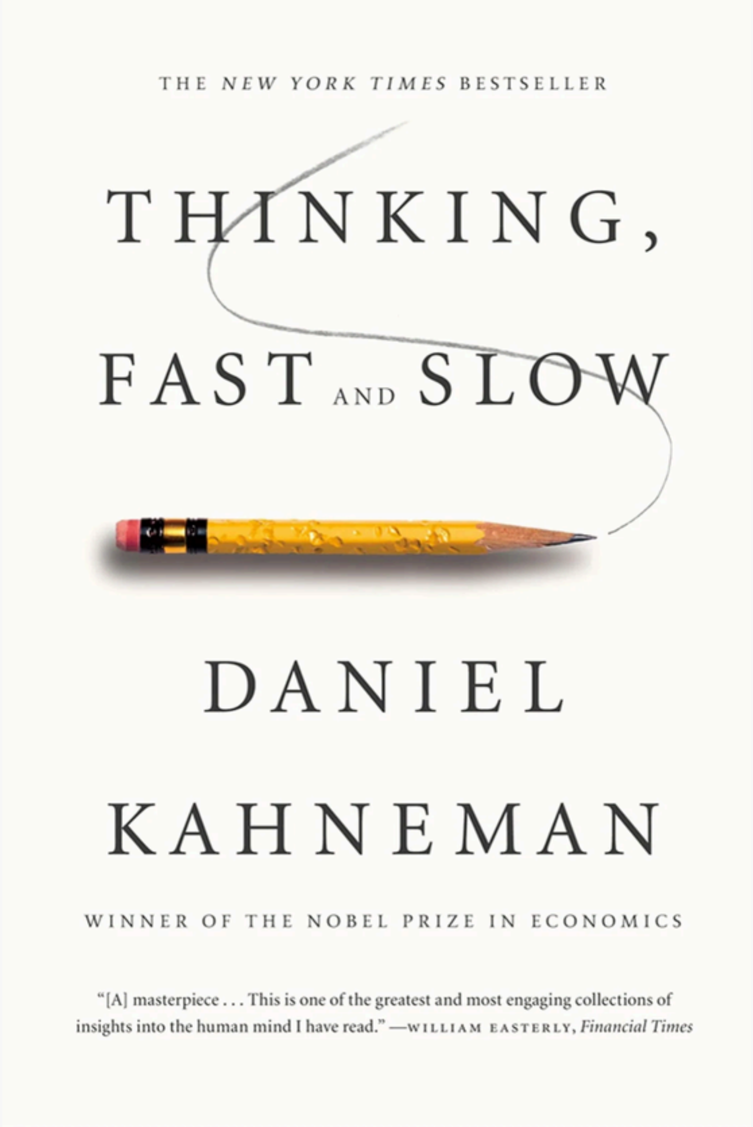
INTRODUCTION

Thinking, Fast and Slow
~David Kahneman

Kahneman described System 1 as fast, intuitive, and automatic, while System 2 is slow, analytical, and effortful.

EEG analysis can help study these cognitive processes, and QML may enhance insights into decision-making and neural activity.



OBJECTIVES

1. Data Preprocessing
2. Feature Extraction
3. Designing a quantum circuit
4. Applying suitable QML techniques
5. Results Visualisation

DATA PREPROCESSING

- Scale data to fit quantum circuit requirements.
- Applying Bandpass Filter to clean EEG signals.
- Use PCA to reduce feature space for limited qubits.

```
def apply_bandpass_filter(self, data, lowcut=1.0, highcut=40.0, order=5):
    nyquist = 0.5 * self.sampling_rate
    low = lowcut / nyquist
    high = highcut / nyquist
    b, a = signal.butter(order, [low, high], btype='band')
    return signal.filtfilt(b, a, data, axis=0)
```

FEATURE EXTRACTION

- Extract spectral band powers (e.g., delta, theta, alpha, beta, gamma).
- Compute connectivity measures between EEG channels.
- Capture key brain activity patterns to distinguish cognitive states effectively.

```python
class FeatureExtractor:
    def __init__(self):
        self.frequency_bands = {
            'delta': (0.5, 4), 'theta': (4, 8), 'alpha': (8, 13),
            'beta': (13, 30), 'gamma': (30, 45)
        }
        self.sampling_rate = 250
```

QUANTUM CIRCUIT

n_qubits = 6

- 6 qubits provide $2^6 = 64$ dimensions, which is sufficient for reduced EEG features.
- Balances computational cost and problem complexity.
- Matches the resource constraints of quantum simulators/hardware while retaining expressiveness.

```
def create_quantum_feature_map(n_qubits):
    return ZZFeatureMap(n_qubits, reps=1, entanglement='linear')

def create_variational_circuit(n_qubits):
    return RealAmplitudes(n_qubits, reps=2, entanglement='full')
✓ 0.0s
```

QUANTUM CIRCUIT

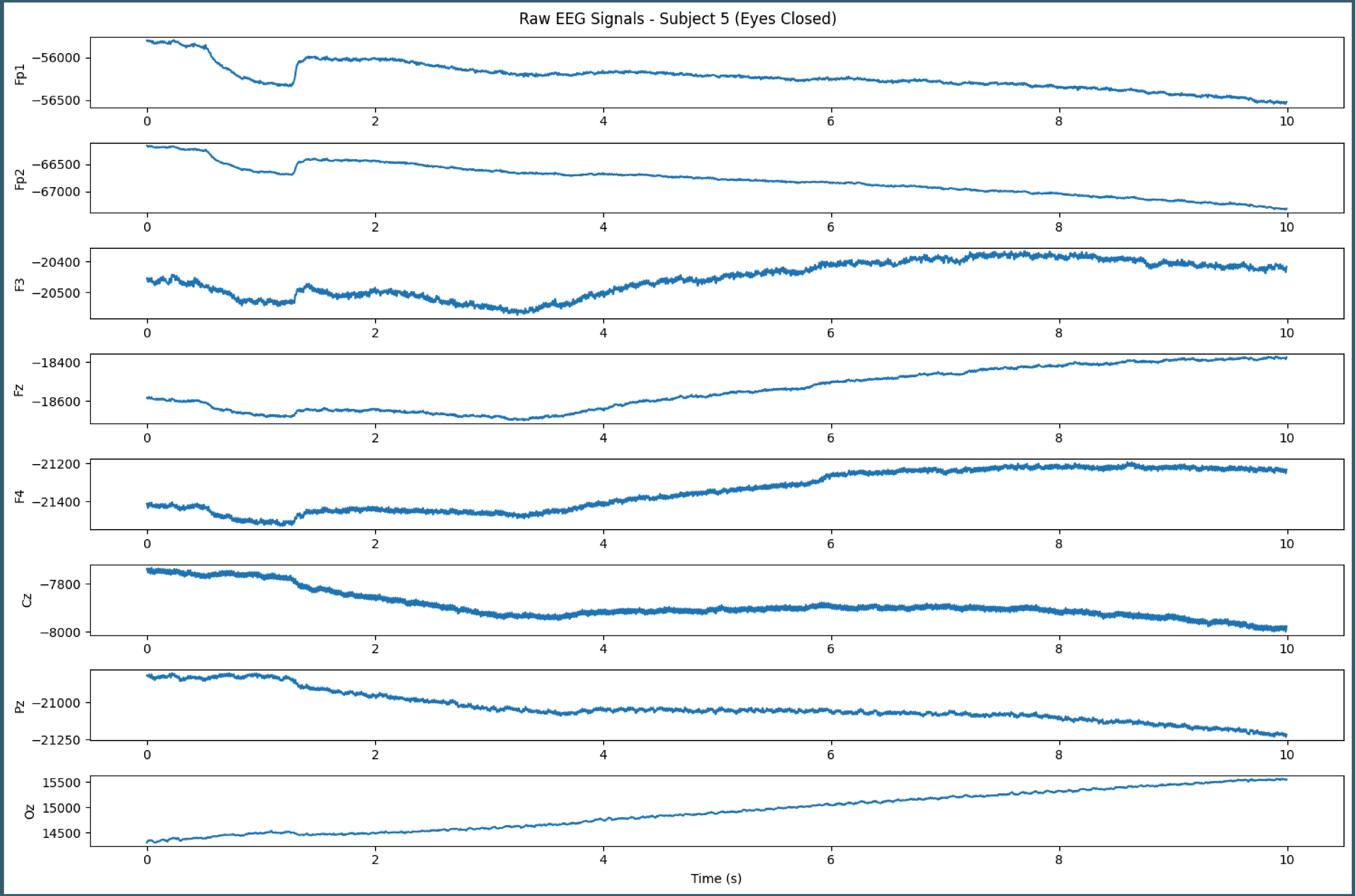
Design:

- Encoding: ZZFeatureMap to map classical EEG features into quantum states.
- Processing: RealAmplitudes variational form for trainable classification.

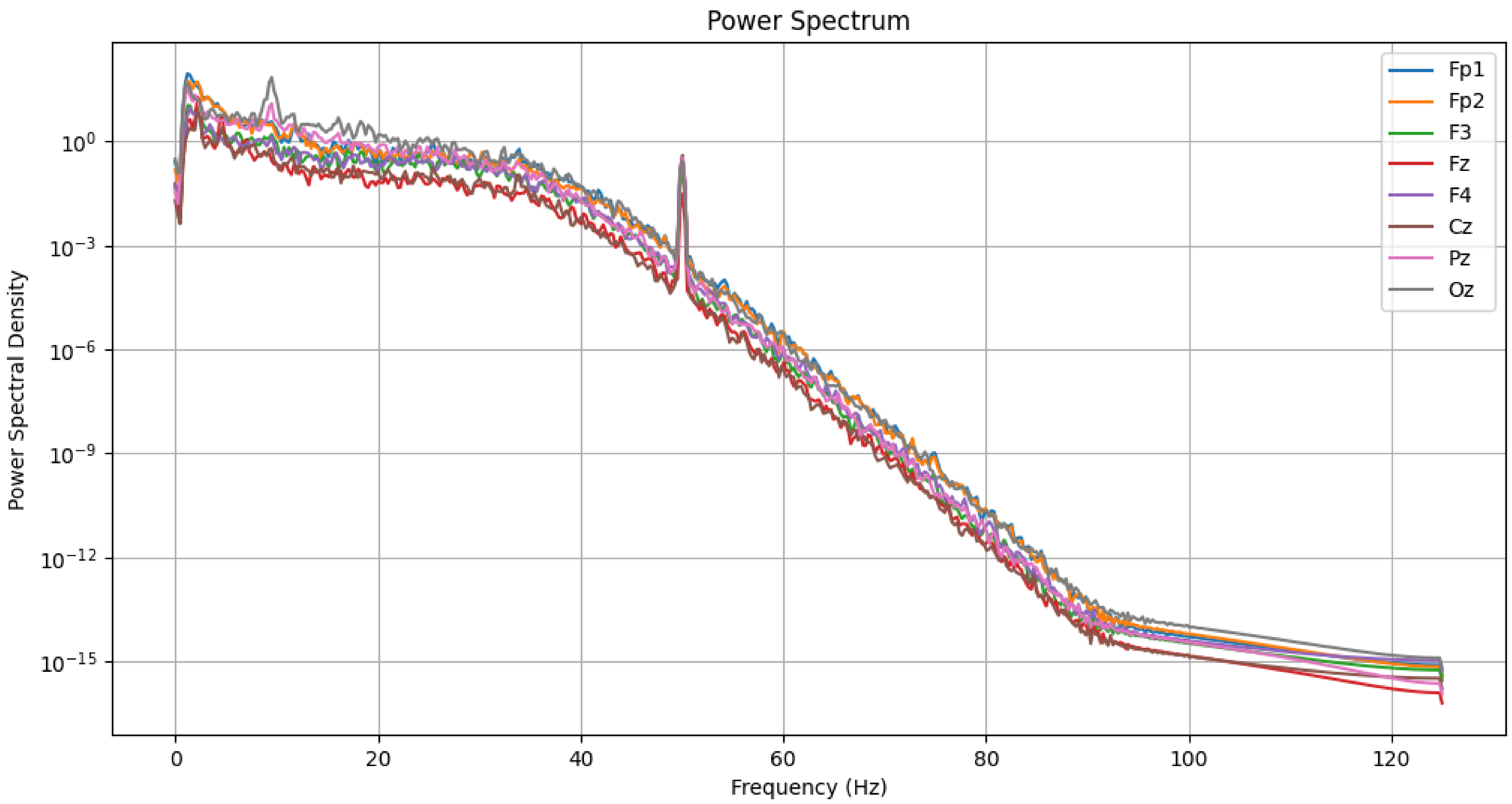
Advantage:

- Quantum Circuits leverage quantum gates for parallel computation and optimization.
- Quantum parallelism may outperform classical methods for specific tasks.

DATA VISUALIZATION



DATA VISUALIZATION



MODEL SELECTION

Variational Quantum Classifier (VQC)

- Advantages: Leverages quantum computing for potential speedups on specific problems; ideal for exploring quantum advantages in EEG classification.
- Challenges: Limited by qubit count (e.g., 6 qubits), noisy simulations, and longer training times (e.g., ~1.5 min/subject).
- Suitability: Best for research into quantum machine learning or when quantum hardware improves significantly.

MODEL SELECTION

Gradient Boosting (GB):

- Advantages: Robust, interpretable classical method; handles structured data well with moderate training time.
- Challenges: Slower than XGBoost, less optimized for high-dimensional data compared to modern gradient boosters.
- Suitability: Suitable for small-to-medium datasets with clear feature importance needs.

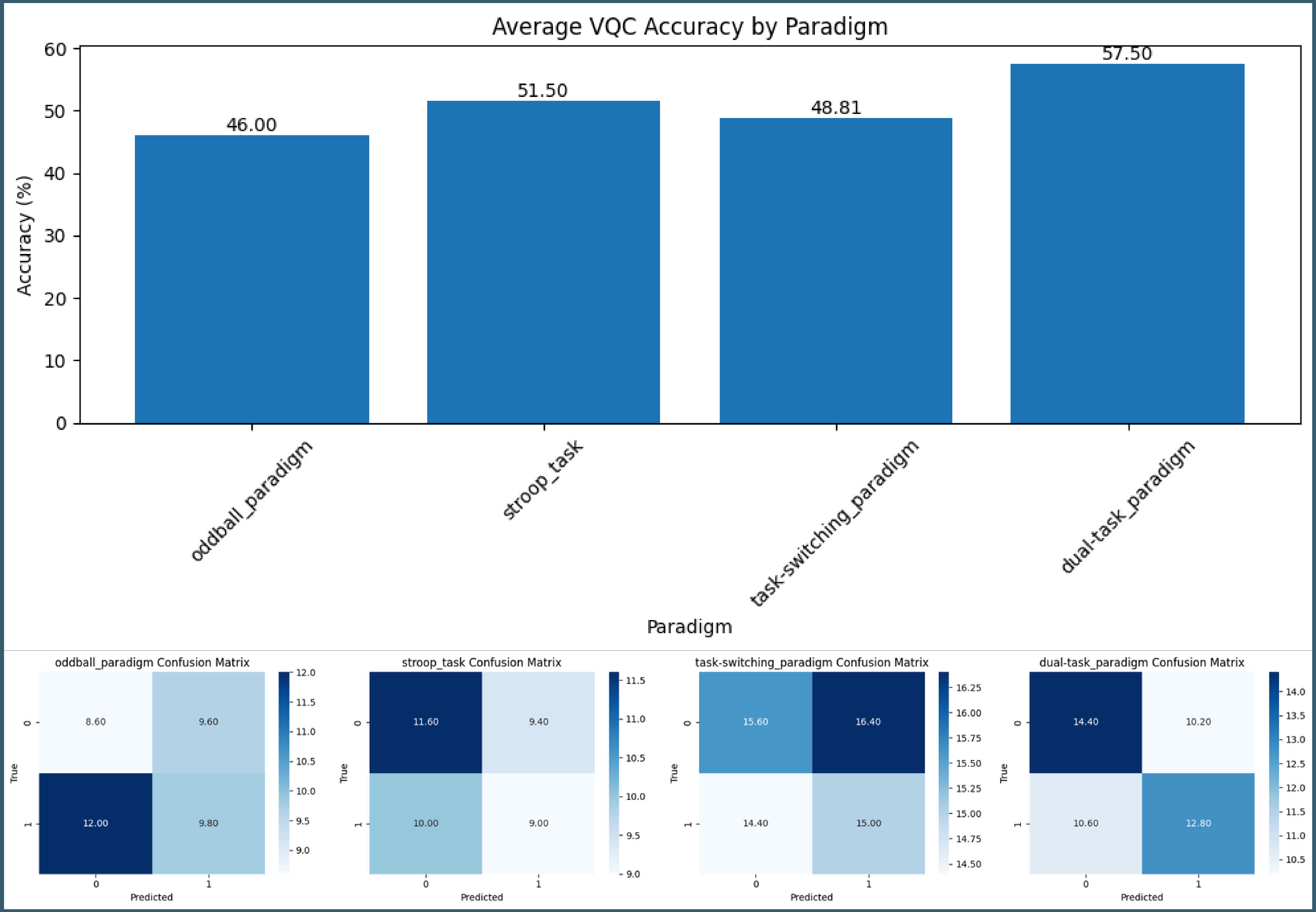
MODEL SELECTION

Extreme Gradient Boosting (XGBoost)

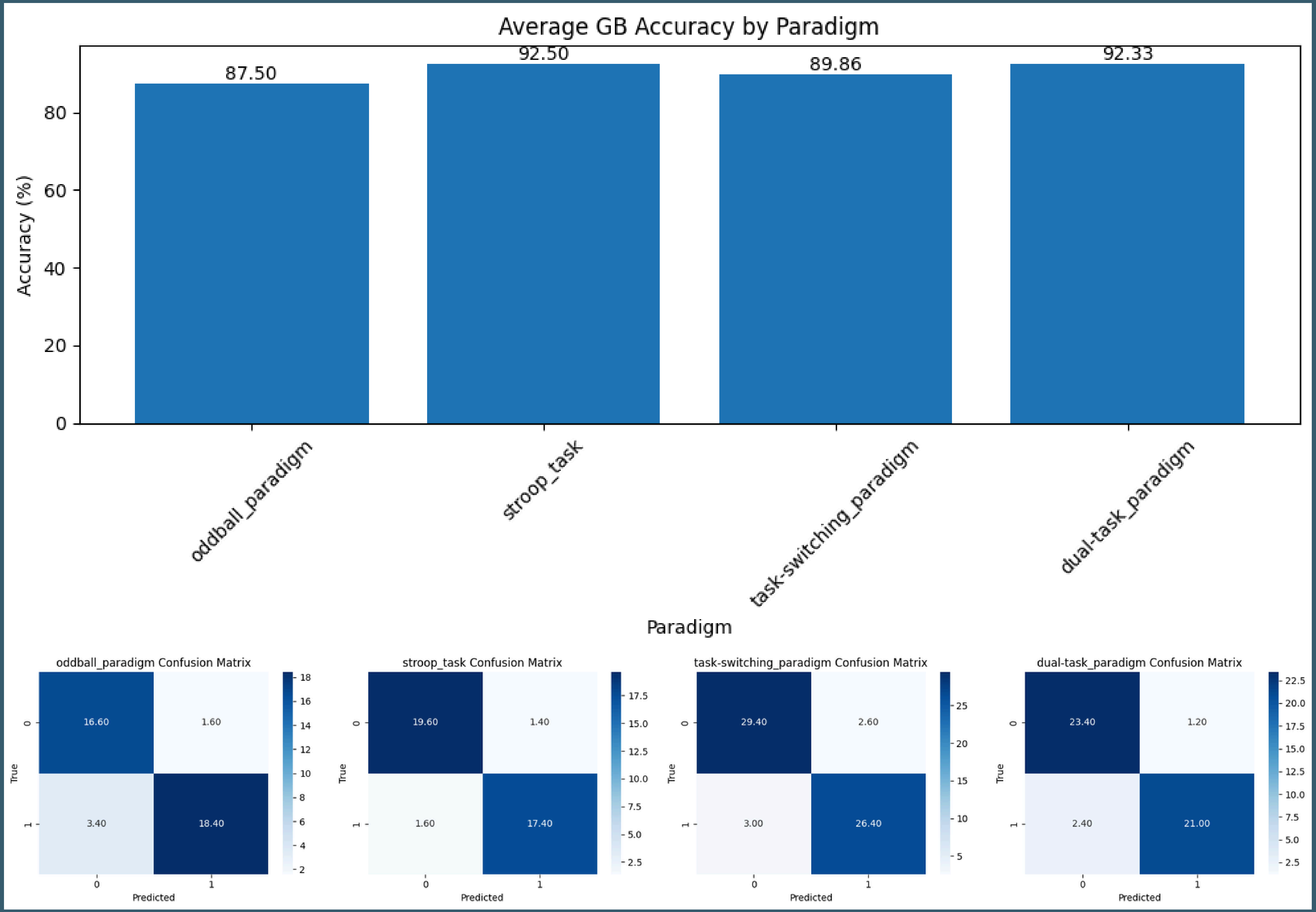
- Advantages: Fast, scalable, and highly accurate; excels with imbalanced data and high-dimensional features.
- Challenges: Requires tuning for optimal performance; less interpretable than GB.
- Suitability: Preferred for real-world applications requiring high accuracy and efficiency.

RESULTS ANALYSIS

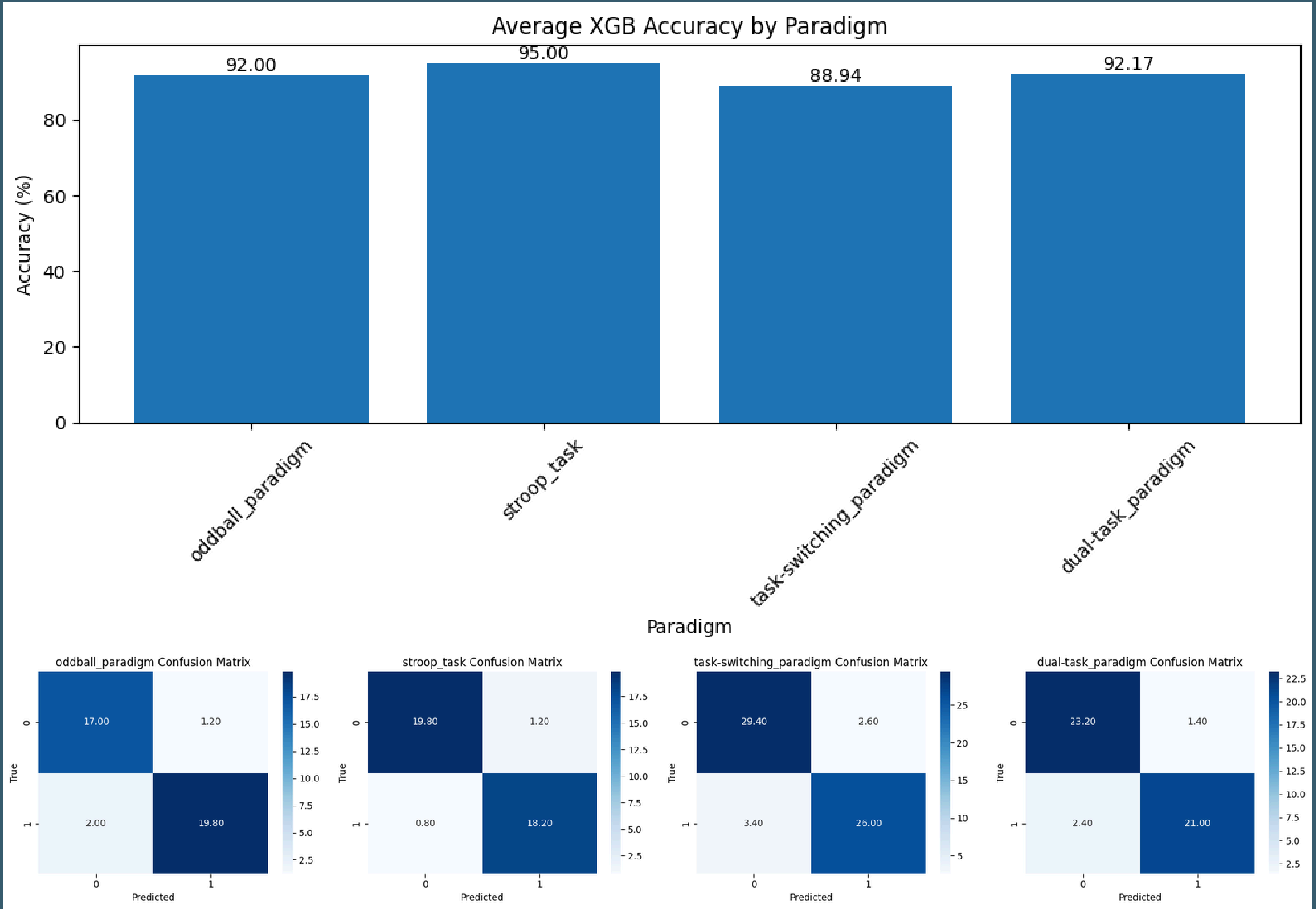
VARIATIONAL QUANTUM CLASSIFIER



GRADIENT BOOSTING CLASSIFIER



XGBOOST CLASSIFIER



Accuracy Results

```
Paradigm oddball_paradigm Average VQC Accuracy: 46.00%
Paradigm oddball_paradigm Average GB Accuracy: 87.50%
Paradigm oddball_paradigm Average XGB Accuracy: 92.00%
```

```
Paradigm stroop_task Average VQC Accuracy: 51.50%
Paradigm stroop_task Average GB Accuracy: 92.50%
Paradigm stroop_task Average XGB Accuracy: 95.00%
```

```
Paradigm task-switching_paradigm Average VQC Accuracy: 48.81%
Paradigm task-switching_paradigm Average GB Accuracy: 89.86%
Paradigm task-switching_paradigm Average XGB Accuracy: 88.94%
```

```
Paradigm dual-task_paradigm Average VQC Accuracy: 57.50%
Paradigm dual-task_paradigm Average GB Accuracy: 92.33%
Paradigm dual-task_paradigm Average XGB Accuracy: 92.17%
```

Accuracy Results

--- XGBoost Classification Report for Subject 3, Paradigm: oddball_paradigm ---

	precision	recall	f1-score	support
0	0.95	1.00	0.98	21
1	1.00	0.95	0.97	19
accuracy			0.97	40
macro avg	0.98	0.97	0.97	40
weighted avg	0.98	0.97	0.97	40

--- XGBoost Classification Report for Subject 2, Paradigm: stroop_task ---

	precision	recall	f1-score	support
0	0.95	0.91	0.93	22
1	0.89	0.94	0.92	18
accuracy			0.93	40
macro avg	0.92	0.93	0.92	40
weighted avg	0.93	0.93	0.93	40

Accuracy Results

--- XGBoost Classification Report for Subject 1, Paradigm: task-switching_paradigm ---

	precision	recall	f1-score	support
0	0.92	0.95	0.93	59
1	0.95	0.92	0.94	63
accuracy			0.93	122
macro avg	0.93	0.93	0.93	122
weighted avg	0.93	0.93	0.93	122

--- XGBoost Classification Report for Subject 5, Paradigm: dual-task_paradigm ---

	precision	recall	f1-score	support
0	0.94	0.91	0.92	33
1	0.89	0.93	0.91	27
accuracy			0.92	60
macro avg	0.92	0.92	0.92	60
weighted avg	0.92	0.92	0.92	60

All the classification techniques: VQC, GB, XGB performed on 5 subjects each for all the given paradigms

```
if __name__ == "__main__":
    main()
```

[19] ✓ 42m 15.3s

CONCLUSION

Accuracy

- Achieved 90–97.5% accuracy in EEG classification (vs. 40–52.5% for VQC, 82.5–92.5% for GB), as shown in results.
- XGB handles imbalanced data effectively with robust regularization and gradient optimization.

Efficiency

- Faster training and prediction times than GB and VQC, leveraging parallel processing and optimized algorithms.
- Outperforms VQC (limited by quantum noise and qubit constraints) and GB (less optimized for large datasets).

CONCLUSION

Scalability

- Scales well with high-dimensional EEG features and large datasets, unlike VQC's qubit limitations.
- Supports GPU acceleration for further speed gains, reducing runtime significantly.

Robustness

- Manages noise and outliers in EEG data better than VQC (prone to simulation noise) and GB (less adaptive to complex patterns).
- Proven in real-world applications, making it ideal for brain-computer interfaces or diagnostics.

FUTURE IMPROVEMENTS

- Increasing qubit count as quantum hardware improves, capturing more complex patterns.
- Experimenting with deeper quantum circuits (e.g. more layers in ZZFeatureMap/RealAmplitudes) for better expressivity.
- Combining QML with deep learning (e.g. LSTMs/CNNs) for superior performance on temporal EEG data.

THANK YOU