XEON

Quantum Error Mitigation

TEAM 8

AQC

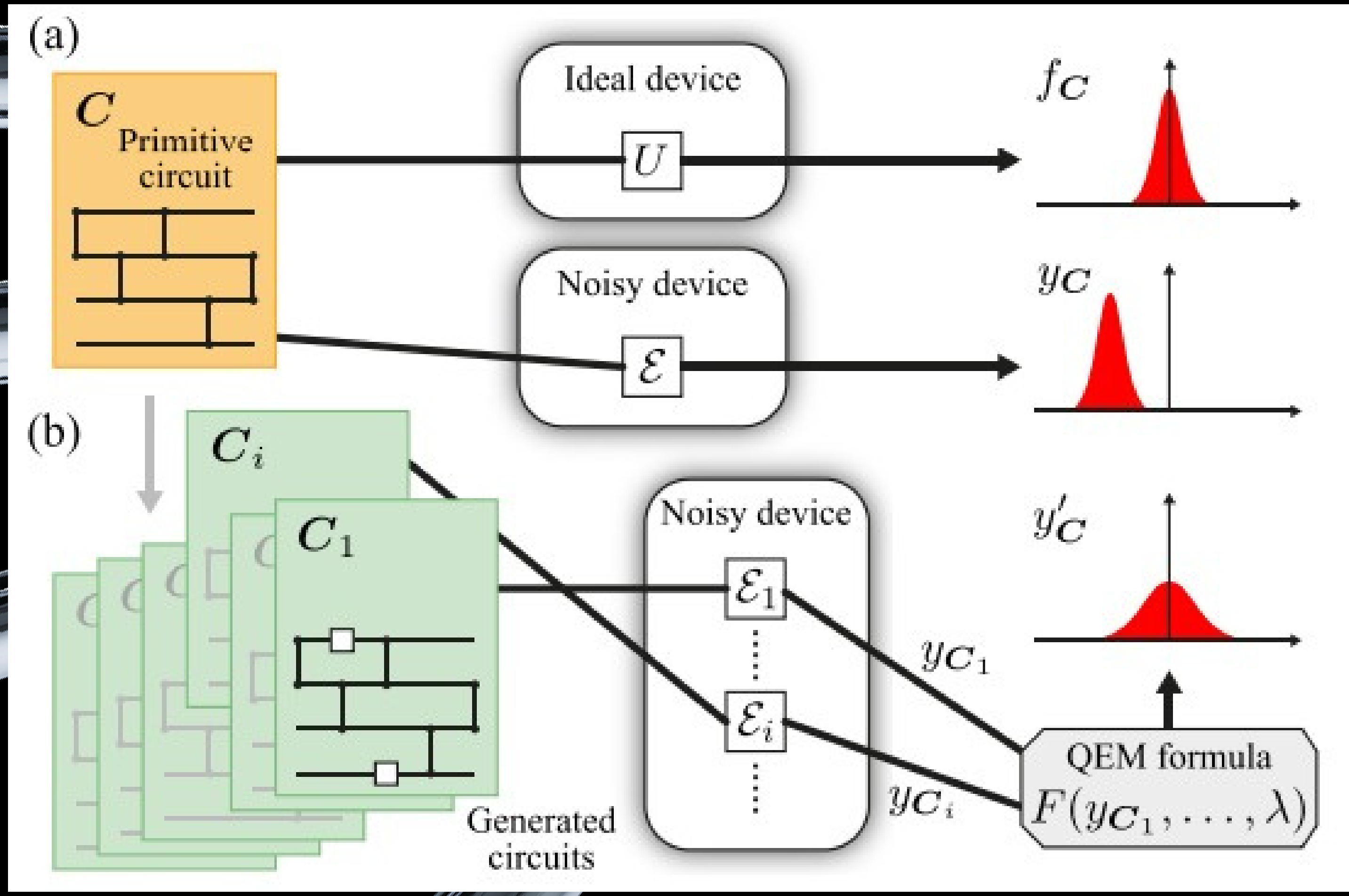
Druge-resistant TB affects 2.5 Million people Africa

TRADITIONAL SIMULATION TAKES 15 YEARS

SIMULATE DISEASE PROTIENS ACCURALTY IN MONTHS

CREDIT: THE NUMBERS AND STATISTICS BY WHO 2023,2024

QUANTUM NOISE



THE CHALLENGE

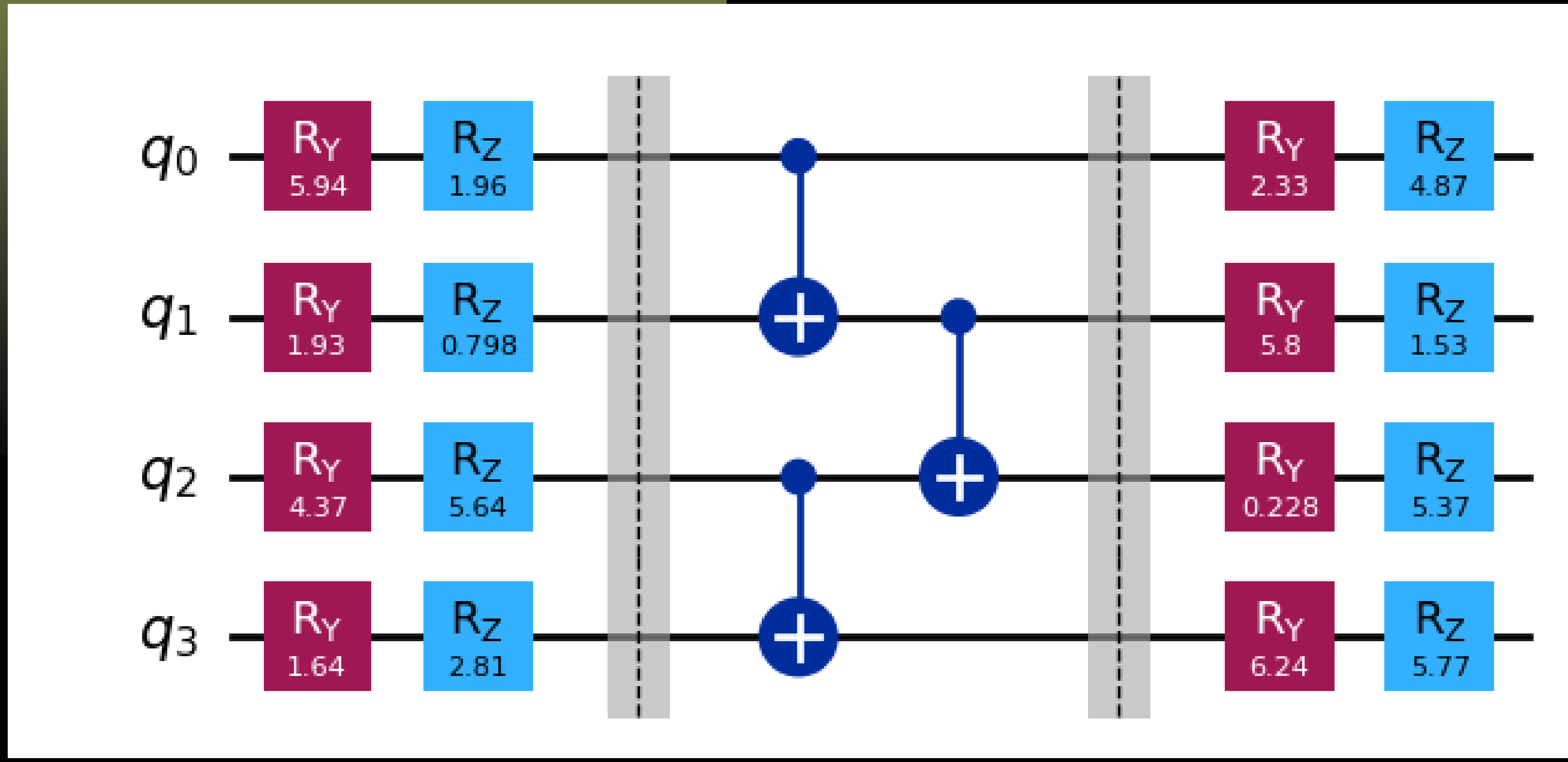
QUBITS ARE HIGHLY SENSITIVE TO DECOHERENCE AND CONTROL IMPERFECTIONS.

THE IMPACT

NOISY MEASUREMENTS BIAS EXPECTATION VALUES AND ALGORITHM PERFORMANCE DEGRADES RAPIDLY WITH DEPTH.

CREDIT: ERROR STATISTICS AND SCALABILITY OF QUANTUM ERROR MITIGATION FORMULAS (NPJ QUANTUM INFORMATION, 2023)

DATASET GENERATION



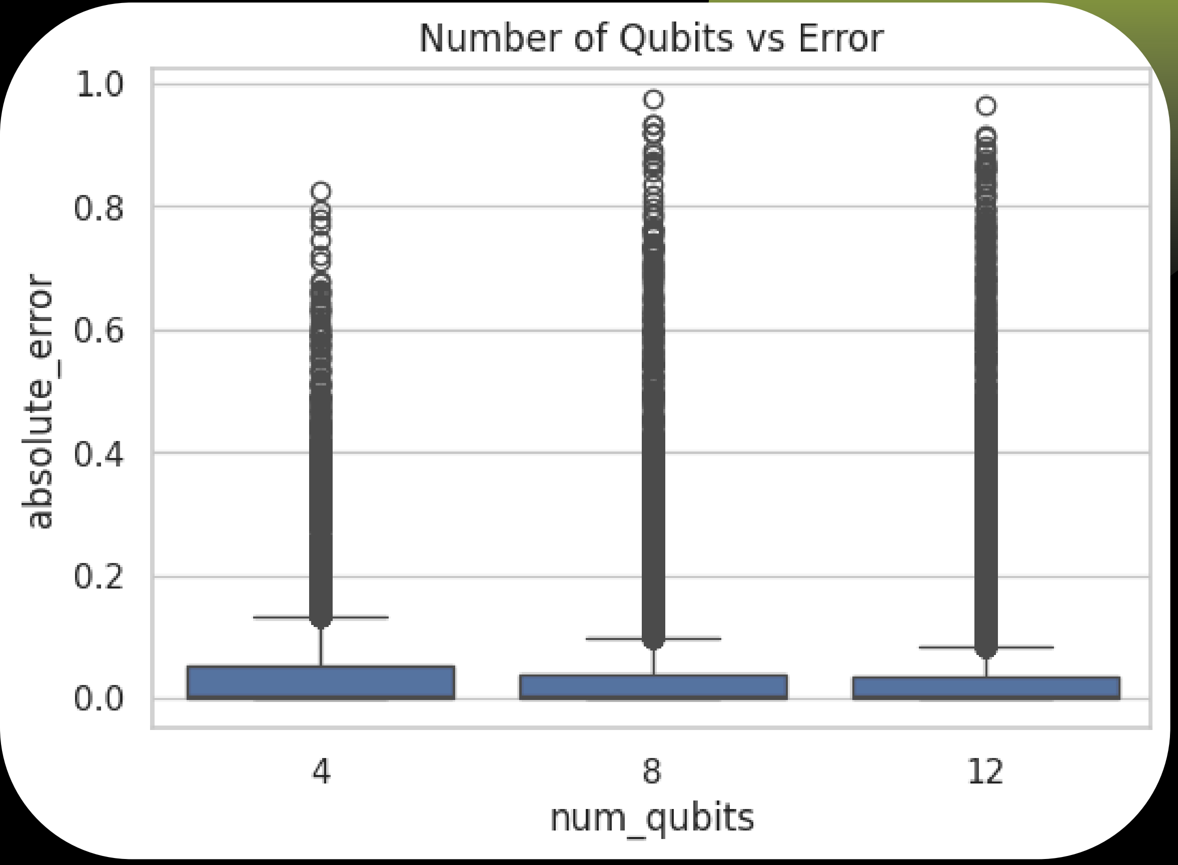
- EfficientSU2 ansatz creates hardware-efficient quantum circuits
- Three entanglement patterns: linear, full, pairwise
- Depth circuit multipliers: 1, 2, 3 repetitions
- Ideal simulations compute noise-free expectation values
- Three noise models: depolarizing, Amplitude damping, readout
- Multiple error rates: 0.001, 0.01, 0.1

DATASET STRUCTURE AND FEATURES

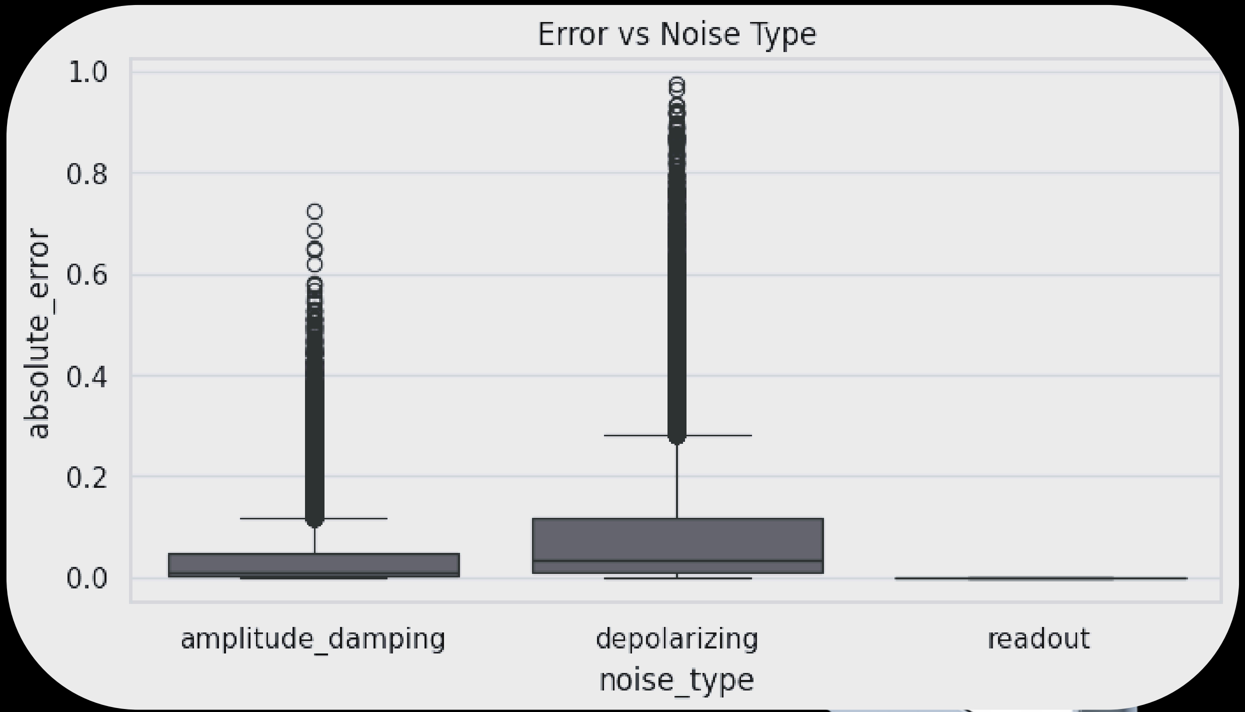
- Multi-scale systems: 4, 8, 12 qubits
- 900+ samples per qubit configuration generated
- Total 3k+ training samples across systems
- Paired data: noisy measurements, ideal targets
- Features: qubits, depth, entanglement, noise, error
- CSV format enables easy ML model training
- Combined dataset merges all qubit counts

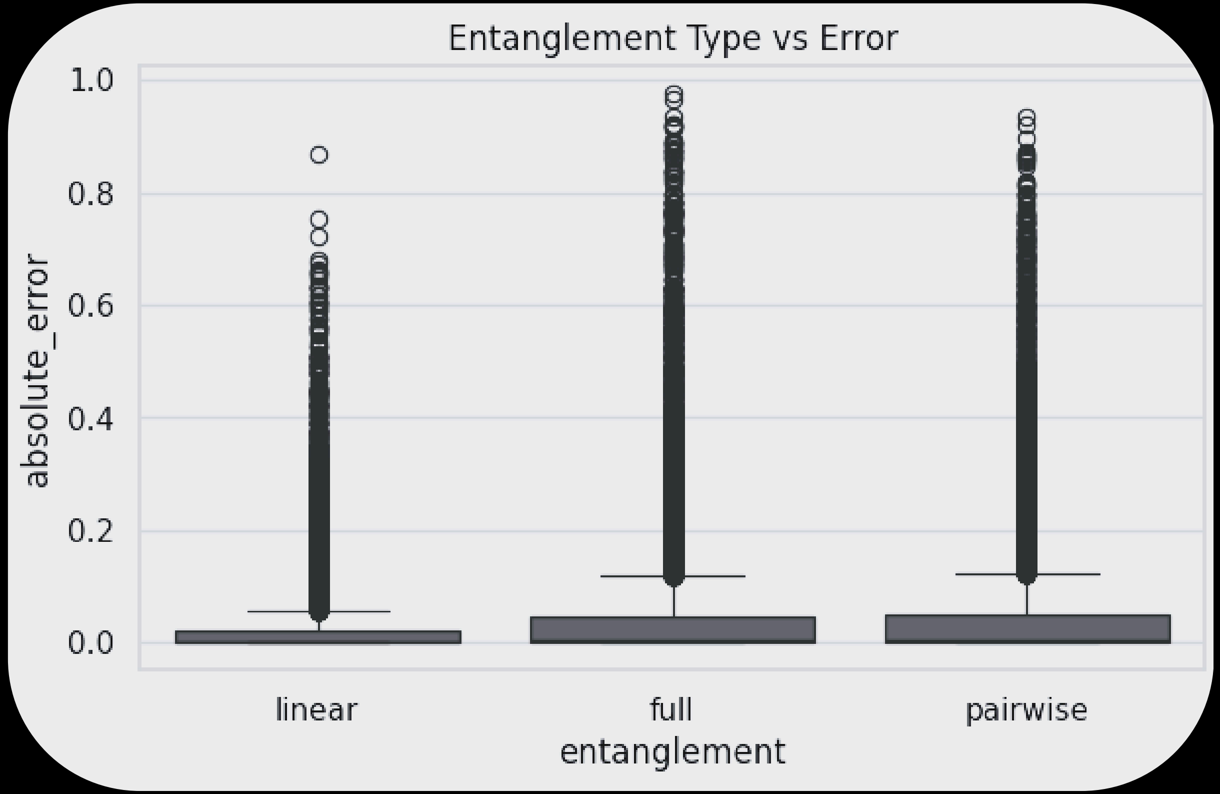
	n_qubits	rep	depth	entanglement	noise_type	error_rate	X_noisy	X_ideal
0	4	1	7	linear	depolarizing	0.100	-0.079067	-0.108459
1	4	1	7	linear	depolarizing	0.010	-0.283841	-0.292529
2	4	1	7	linear	depolarizing	0.001	0.295649	0.296538
3	4	1	7	linear	amplitude_damping	0.100	-0.027949	-0.027949
4	4	1	7	linear	amplitude_damping	0.010	0.002946	0.002946

DATA ANALYSIS

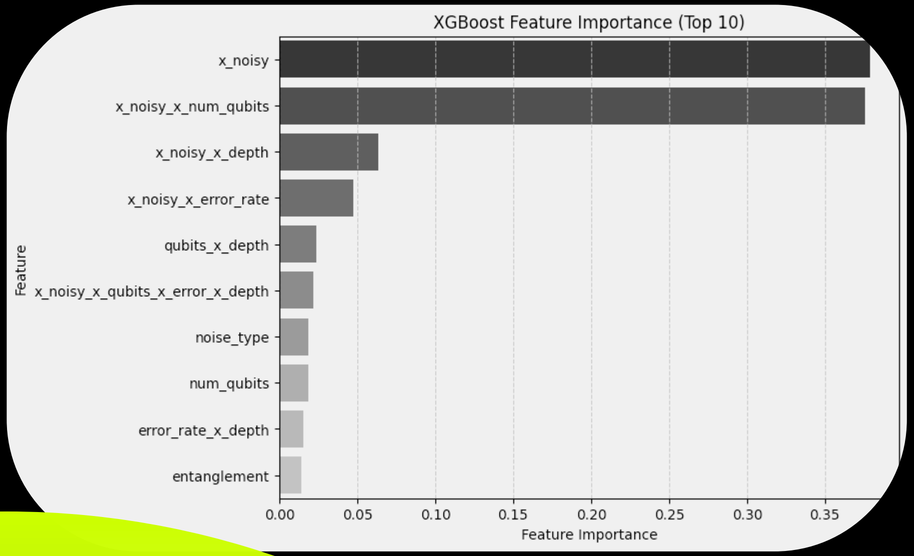


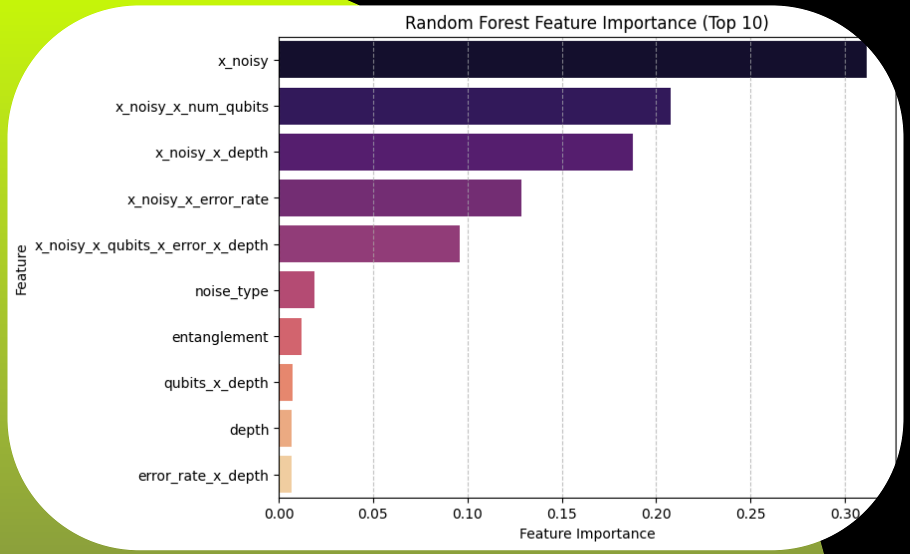
entanglement	absolute_error
full	0.052169
linear	0.030923
pairwise	0.057483

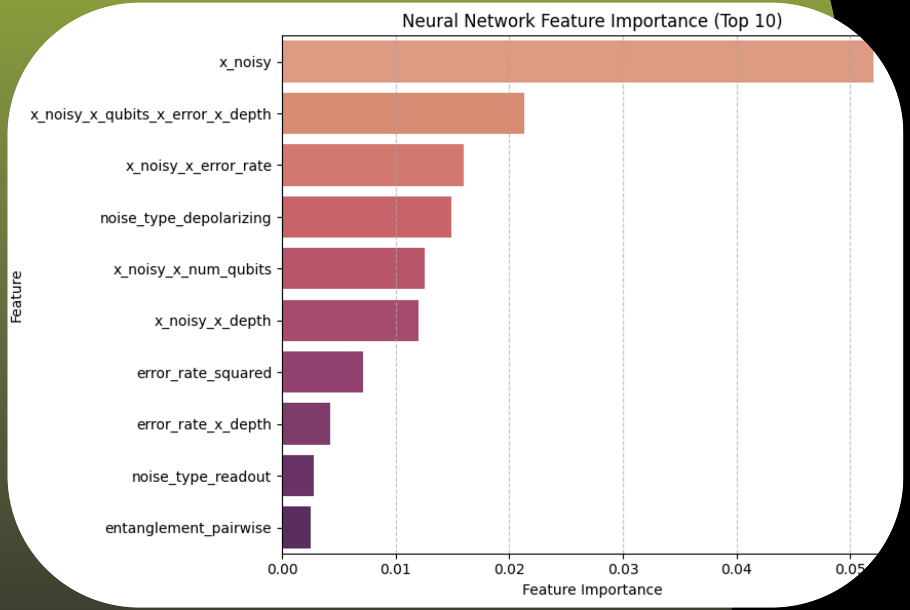


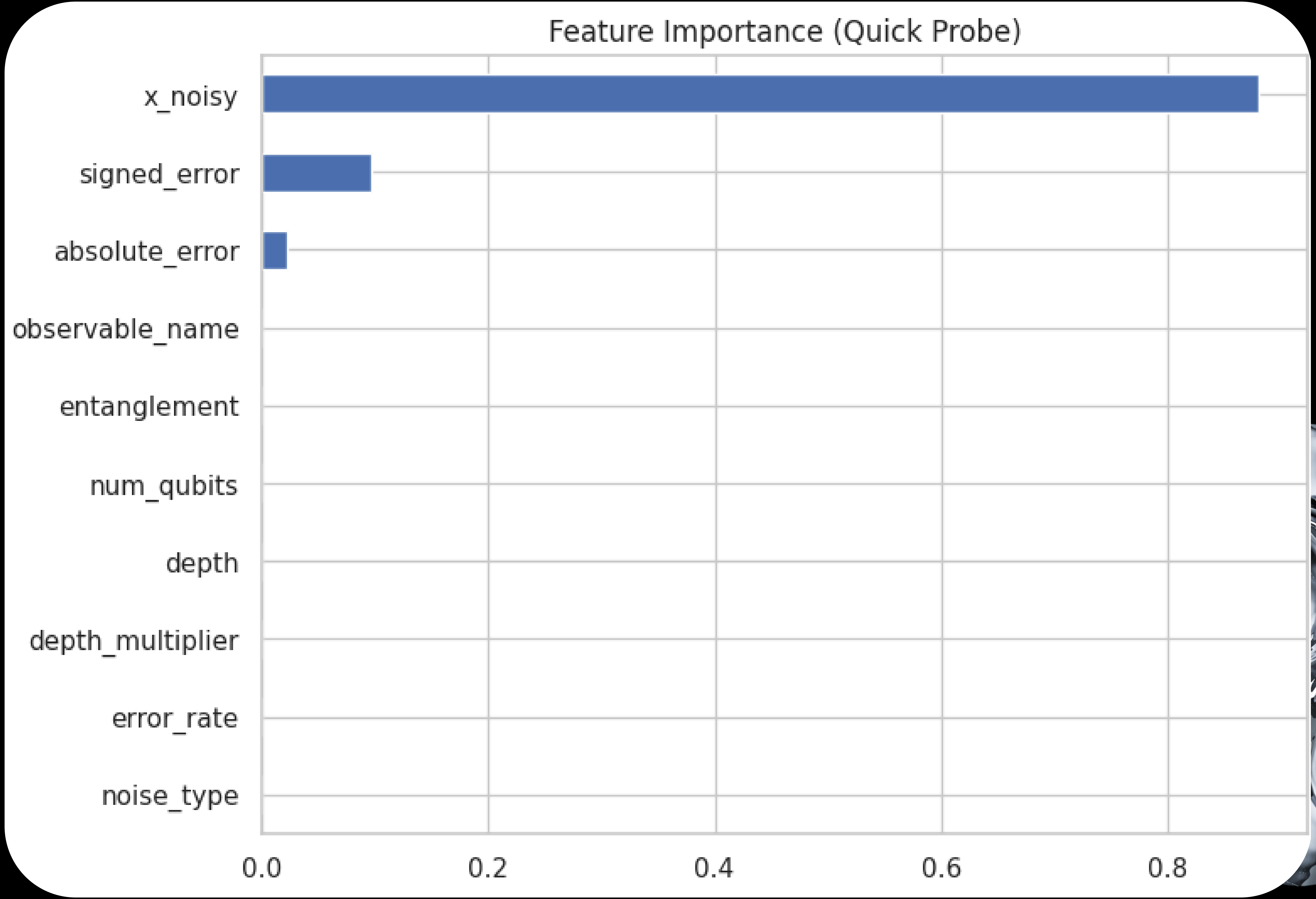


FEATURE IMPROTANCE & FEATURE ENGENEERING









QEM MODEL: DATA-DRIVEN MITIGATION ARCHITECTURE

Core Idea:

- **Data-Driven: Learns to correct noisy (x_noisy) to ideal (x_ideal) quantum measurements.**
- **Stacking Ensemble: Combines diverse base models for robust mitigation.**

Architecture:

- **Base Models (GPU-Accelerated):**
    - **XGBoost: Powerful gradient boosting.**
    - **Neural Network (PyTorch): Custom deep learning with LSTM, Batch Norm, Dropout for complex feature interactions.**
    - **Random Forest: Ensemble of decision trees for robustness.**

Meta-Learner:

- **Ridge Regression: Optimally weights base model predictions for the final mitigated output.**

- Features: x_noisy, error_rate, depth, num_qubits, noise_type, entanglement, observable_name, plus engineered interaction terms.
- Target: x_ideal (ideal, noiseless measurement).

Experimental Design:

- Data Split: Training (60%), Validation (20%), Test (20%) for robust evaluation.
  - Train (base models): 21,870 samples
  - Validation (meta-learner): 7,290 samples
  - Test (final eval): 7,290 samples

Comparison Groups:

- No Mitigation (Baseline): Raw x_noisy as prediction.
- Individual Base QEM Models: XGBoost, Neural Network, Random Forest.

```
# Prepare X and y
X = df[num_features + cat_features]
y = df["x_ideal"]

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

# Further split train into train and validation for stacking
X_train_base, X_val_base, y_train_base, y_val_base = train_test_split(
    X_train, y_train, test_size=0.25, random_state=42
)

print(f"\nBase train size: {len(X_train_base)}")
print(f"Validation size: {len(X_val_base)}")
print(f"Test size: {len(X_test)}")
```

BENCHMARKING SETUP: COMPREHENSIVE COMPARISON

```
Base train size: 21870
Validation size: 7290
Test size: 7290
```

EVALUATION METRICS: QUANTIFYING PERFORMANCE

Primary Metrics:

- Mean Absolute Error (MAE): Average absolute prediction error (lower is better).
- Root Mean Squared Error (RMSE): Measures magnitude of errors, penalizes large errors more.
- R-squared (R^2): Proportion of variance explained by the model (higher is better).

Improvement Quantification:

- Improvement (%) over Baseline: ((Baseline MAE - Model MAE) / Baseline MAE) * 100.
- Mitigation Factor: Baseline MAE / Model MAE (how many times error is reduced).

Generalization to Unseen Circuits:

- All final metrics reported on a completely unseen Test Set (20% of data).
- Ensures reliable performance estimate for new quantum circuits and noise conditions.

```python
# 1. Retrieve the Baseline MAE
baseline_mae = baseline_mae # This variable is already defined in the notebook

# 2. Retrieve the Stacked Ensemble MAE
stacked_ensemble_mae = results_df[results_df['Model'] == 'Stacked Ensemble']['MAE'].values[0]

# 3. Calculate the absolute improvement
absolute_improvement = baseline_mae - stacked_ensemble_mae

# 4. Calculate the percentage improvement
percentage_improvement = (absolute_improvement / baseline_mae) * 100

# 5. Print the results
print(f"\nBaseline MAE: {baseline_mae:.6f}")
print(f"Stacked Ensemble MAE: {stacked_ensemble_mae:.6f}")
print(f"Absolute Reduction in MAE: {absolute_improvement:.6f}")
print(f"Percentage Improvement over Baseline: {percentage_improvement:.2f}%")
```

```
================================================================================
CLARIFYING MODEL PERFORMANCE IMPROVEMENT
================================================================================

Baseline MAE: 0.046858
Stacked Ensemble MAE: 0.030826
Absolute Reduction in MAE: 0.016032
Percentage Improvement over Baseline: 34.21%
```

RESULTS: STACKED ENSEMBLE PERFORMANCE SUMMARY

Mitigated vs Unmitigated Performance:

- Baseline (No Mitigation) MAE: 0.046858
- Stacked Ensemble MAE: 0.030826
- Absolute MAE Reduction: 0.016032
- Percentage Improvement: 34.21%

Detailed Performance Comparison (Test Set):

```
================================================================================
CALCULATING MITIGATION FACTORS
================================================================================

Updated Results DataFrame with Mitigation Factors:
```

	Model	MAE	RMSE	R^2	Improvement (%)	Training Time (s)	Mitigation Factor
0	Baseline (No Mitigation)	0.046858	0.112830	0.877145	0.000000	0.000000	1.000000
1	XGBoost	0.035601	0.072544	0.949214	24.023159	2.087147	1.316191
2	Neural Network	0.042761	0.080968	0.936734	8.744417	31.861636	1.095823
3	Random Forest	0.035196	0.073790	0.947454	24.887696	18.012011	1.331340
4	Stacked Ensemble	0.030826	0.066567	0.957237	34.213471	51.962981	1.52006

```
# Calculate Mitigation Factor for each model
results_df['Mitigation Factor'] = baseline_mae / results_df['MAE']

print("\nUpdated Results DataFrame with Mitigation Factors:")
display(results_df)
```

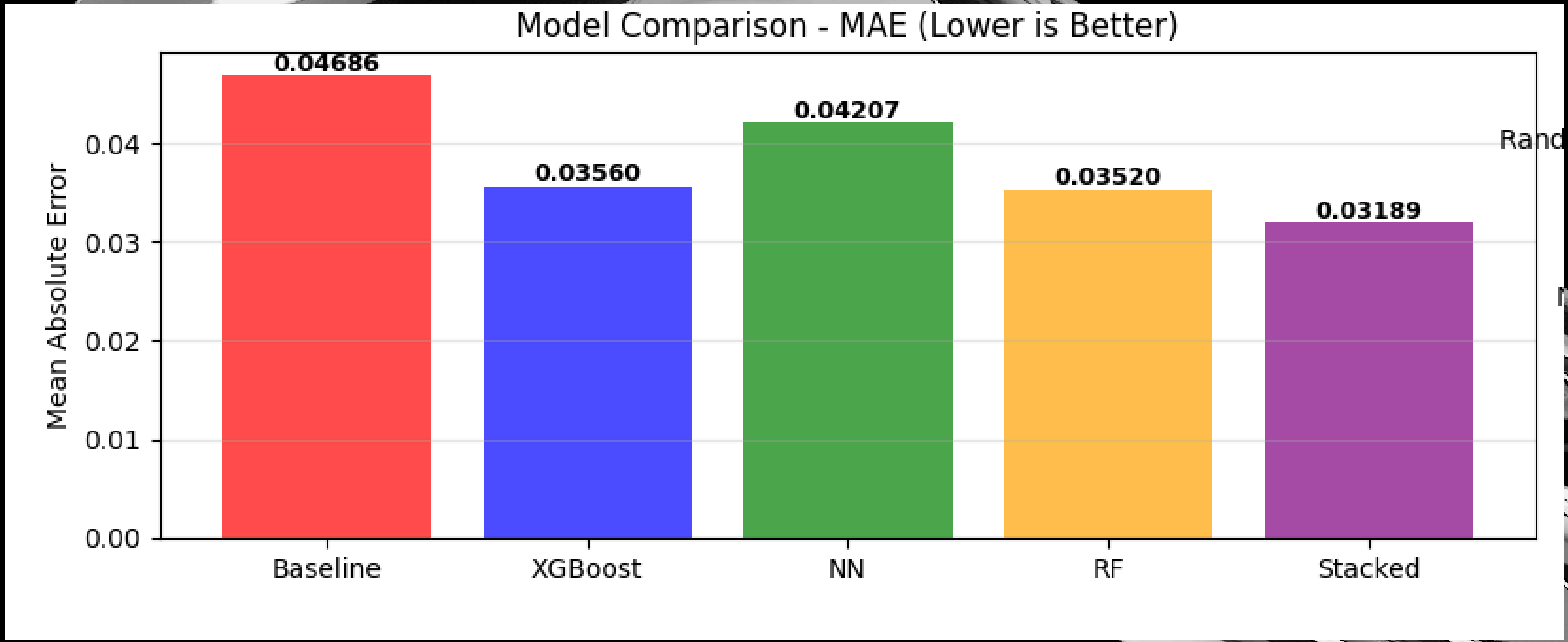
Key Findings:

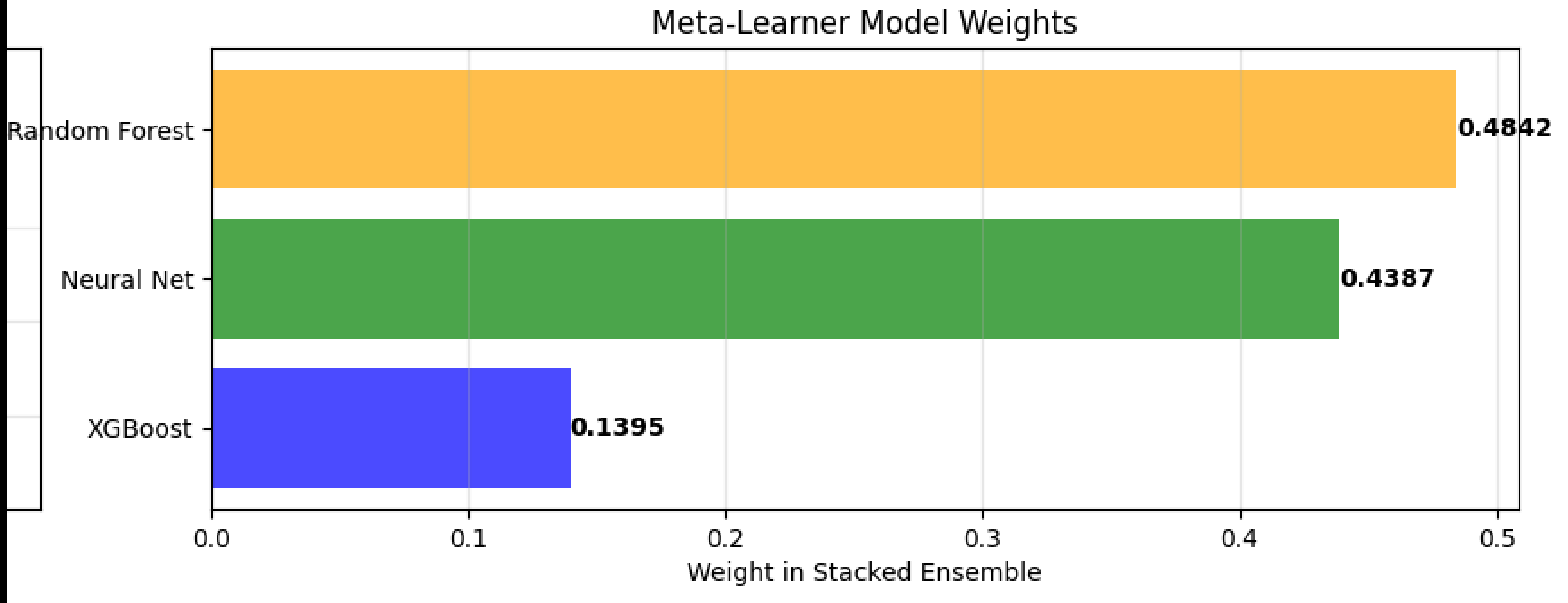
- Stacked Ensemble achieves lowest MAE and RMSE, signifying superior accuracy.
- Highest R^2 value, indicating best explanation of ideal outcomes.
- 34.21% improvement in MAE demonstrates significant error reduction.

QEM - STACKED ENSEMBL ANALYSIS

Model Robustness with Increasing Noise:

- The models are trained using error_rate as a feature, alongside x_noisy and various interaction terms (e.g., error_rate_x_depth, x_noisy_x_error_rate).
- This allows the models to implicitly learn relationships with different noise strengths present in the dataset.
- The strong generalization performance observed on the unseen test set suggests a good level of robustness across the range of noise conditions used in the quantum circuit simulations.





RESULTS: VISUALIZATIONS & META-LEARNER INSIGHT

RESULTS: MODEL ROBUSTNESS

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THANK YOU

what we are tackling is not merely a technical problem—it is a bridge between our most complex technologies and our most pressing human needs. We are not just correcting errors in qubits... we are restoring hope.

Mentor

Hamza Benkadour

TEAM MEMBERS:

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