

# Quantum ML for Drug Toxicity Prediction

Accelerating safer drug discovery with quantum-powered toxicity prediction

QVC + QSVM on 6-qubit circuits (ZZFeatureMap + TwoLocal)

Advanced preprocessing, class rebalancing, and rigorous evaluation

Designed for early risk detection and portfolio decision support

From data to decision: trustworthy ADMET insights

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	0	0.5	0.6	0.8	0.9	1.0
$U[V]$	0	0.5	0.6	0.8	0.9	1.0
$C_1$	0	0.5	0.6	0.8	0.9	1.0
$J[mA]$	0	0	4	44	115	125
$J[mA]$	0	0.4	0.6	0.8	0.9	1.0
$J[mA]$	0	-0.4	-0.76	-1.12	-1.5	-1.7
$U[V]$	0	-1	-2	-3	-4	-5
$J[mA]$	0	1.5	2.8	4.2	0.5	7.1
$U[V]$	0	1	2	3	4	5

# The Problem: Drug Toxicity Is the #1 R&D Failure

**90%** overall clinical failure rate; toxicity is a leading cause of attrition (preclinical to Phase I)

**\$2.6B** average cost to bring a drug to market; **10-12 years** timeline

Late-stage toxicity discoveries cause costly trial terminations and portfolio delays

Complex, non-linear biological interactions are hard to capture with classical models alone

Imbalanced and noisy datasets reduce signal detection in early screening

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# The Solution: Quantum Machine Learning for

- End-to-end QML pipeline leveraging **QVC** (Variational Classifier) and **QSVM** (Quantum SVM)

- Rich quantum feature embeddings + fidelity-based kernels for complex interaction capture

- Balanced training via **BorderlineSMOTE** to address minority toxic class

- NISQ-ready** design: dimensionality reduction to **6 qubits** while preserving variance

- Transparent model selection and reporting for regulatory-friendly evidence

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# Technology Stack

- Quantum:** Qiskit 1.2.4, AerSimulator, Sampler; **ZZFeatureMap** (reps=3), **TwoLocal** ansatz
  - ML & Data:** scikit-learn (PCA, feature selection, metrics), imbalanced-learn (BorderlineSMOTE)
  - Optimization:** COBYLA (stable for noisy landscapes), Optuna-ready for HPO
  - Engineering:** Python/Colab, reproducible artifacts (models, preprocessing, results .pkl/.csv)
  - Governance:** Deterministic splits, stratified sampling, robust scaling, exportable reports
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# Key Features

**Advanced preprocessing:** Variance thresholding, correlation filtering, mutual information, and feature importance

**Class imbalance handling:** BorderlineSMOTE for improved minority class detection and balancing

**Quantum-ready scaling:** RobustScaler + MinMax to  $[0, 2\pi]$  range for optimal quantum circuit initialization

**Dimensionality reduction:** PCA to 6 components (qubits) with variance tracking for NISQ compatibility

**Comprehensive evaluation:** Accuracy, Precision, Recall, F1, MCC metrics + confusion matrix analysis

**Model persistence:** Saved pipelines and artifacts for seamless deployment and reproducibility

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# Model Architecture: Quantum Circuits

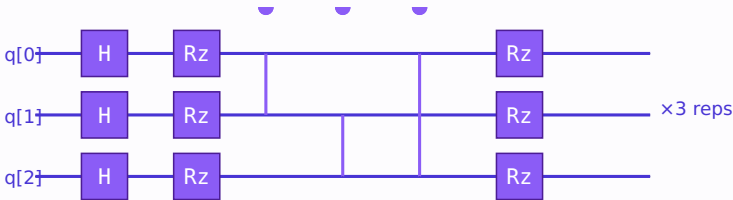
## Data-to-Circuit Flow

- Selected features (**20 features** after importance ranking)
- Robust scaling + MinMax normalization (**0 to  $2\pi$**  range)
- Class balancing with BorderlineSMOTE (**minority class augmentation**)
- Dimensionality reduction with PCA (**6 components = 6 qubits**)
- Quantum circuits (encoding data into quantum states)

## Quantum Algorithms

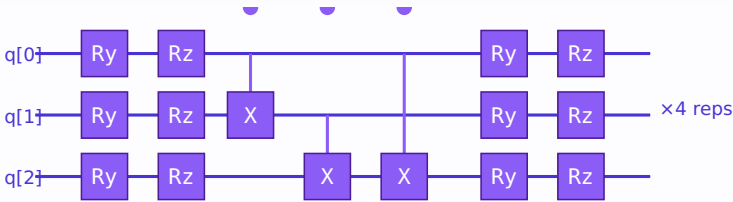
QVC  
ZZFeatureMap → TwoLocal ansatz → COBYLA optimizer  
QSVM  
FidelityQuantumKernel with ZZFeatureMap → margin maximization

## Feature Map (ZZFeatureMap, reps=3)



ZZFeatureMap with full entanglement

## TwoLocal Ansatz (ry/rz + cx, reps=4)



TwoLocal ansatz with rotation + entangling layers

## Fidelity Kernel (QSVM)

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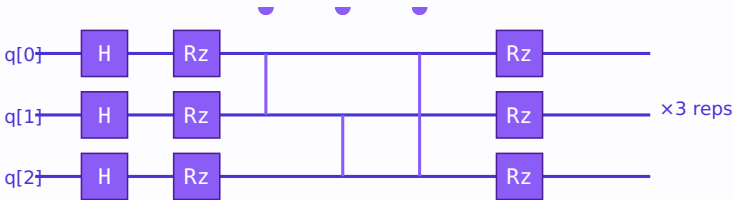
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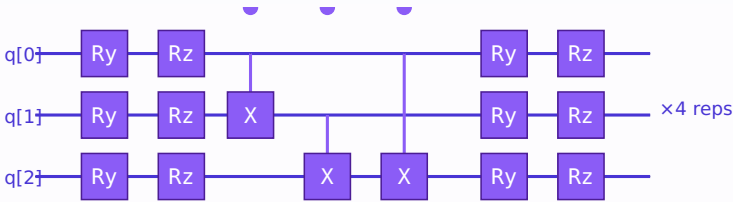
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# Results & Performance

## Model Comparison Metrics

Key Performance Highlights:

Best Model: QSVM (MCC: 0.734)

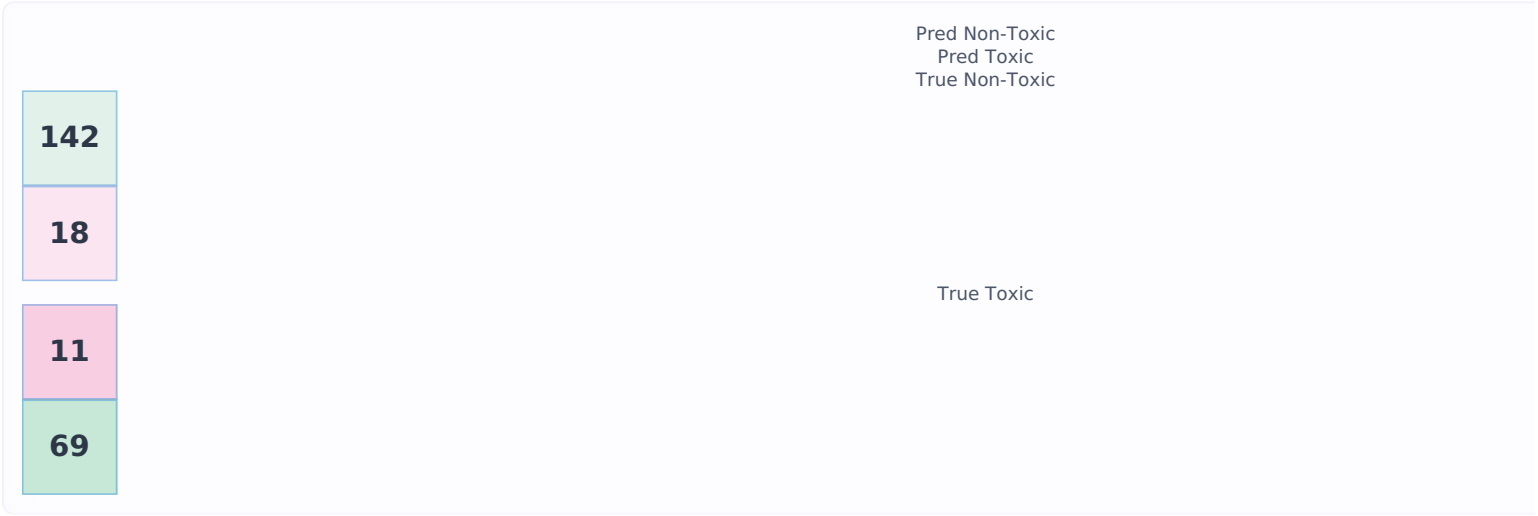
Highest Precision: QSVM (0.841)

Best F1-Score: QSVM (0.852)

MCC is prioritized for class-imbalanced toxicity datasets, as it balances true positive/negative rates.

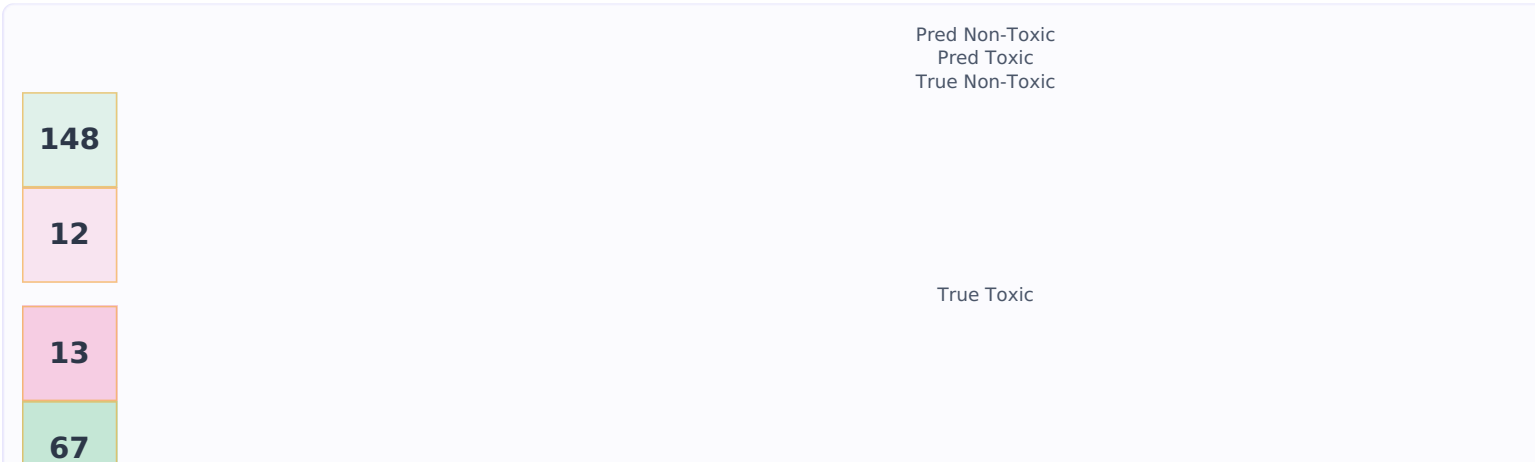
## Confusion Matrices (Test Set)

QVC Confusion Matrix



Accuracy: 0.879

QSVM Confusion Matrix





# Competitive Advantage

Quantum feature maps capture **high-order interactions** beyond many classical kernels

Expressive yet **parameter-efficient** circuits reduce overfitting on small datasets

**Fidelity-based kernels** provide powerful similarity measures for complex manifolds

Hybrid training (QVC) balances expressivity and **optimization stability**

**NISQ-aligned** design now; hardware acceleration path as quantum devices mature

Complements classical baselines; **ensemble-ready** for best-of-both worlds

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# Applications in Drug Discovery

**Early toxicity screening** for large compound libraries - rapidly identify and filter out toxic candidates in drug discovery pipeline

**Lead optimization:** flag off-target risks and cardiotoxicity concerns (e.g., hERG inhibition) during lead optimization

**ADMET profiling augmentation** to improve success probability - complement traditional assays with AI-powered predictions

**De-risking IND packages** with transparent metrics and comprehensive reports for regulatory submissions

**Drug repurposing:** reassess legacy compounds with improved toxicity prediction to identify new therapeutic applications

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# Impact & ROI

**Time:** compress toxicology signal-finding from months to weeks via prioritized screening

**Cost:** reduce late-stage attrition; shift failure left—millions saved per asset

**Portfolio:** improve hit triage, elevate likelihood of technical success (LoTS)

**Operations:** scalable simulations today; future hardware speed-ups

**KPI examples:** ↓ time-to-insight, ↓ cost-per-screen, ↑ precision in toxic class

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# Team & Technical Expertise

**Quantum ML Scientist:** Qiskit circuits, VQC/QSVM design, quantum kernel methods

**Computational Chemist/ADMET Lead:** domain features, assay integration, interpretability

**Data Engineer/MLOps:** pipelines, model versioning, secure data workflows

**Pharma Advisor:** translational strategy, regulatory alignment

**Partners & Ecosystem:** quantum hardware providers; academic collaborators

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# Next Steps & Call to Action

## Engagement Options:

- 4-6 week pilot** on your historical assays (confidential, secure)
- POC integration** with your cheminformatics stack (RDKit/ELN/LIMS)
- Joint research** or co-development for indication-specific toxicity

## Asks:

- Data access for benchmarking, feedback from tox and DMPK teams
- Investment/partnership to scale models and evaluate on proprietary datasets

## Contact & Timeline:

### Week 1:

Data onboarding & validation

### Weeks

2-3:

Model adaptation & benchmarking

### Weeks

4-6:

Results review, decision, and scale plan

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