Quantum Deepflow: A Quantum-Integrated Forecasting Platform for Strategic Decisions in Raw Material Procurement

Demo

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Introduction & Motivation

Challenges in Raw Material Forecasting

- Accurate demand and price forecasting is crucial for raw material procurement, especially in industries like steel manufacturing
- Commodity markets (*e.g.*, nickel, aluminum, gold) are highly volatile, driven by global economic and geopolitical factors
- Time-series data are often noisy, irregular, and nonlinear, which limits the reliability of traditional forecasting models
- Practical forecasting tools must remain interpretable, scalable, and responsive to sudden market shifts (many existing models fail to meet)

Quantum Machine Learning as a Solution [Cao et al., 2023; Chen et al., 2022]

- Quantum machine learning (QML) leverages superposition and entanglement to model complex patterns beyond classical reach
- Hybrid models like QLSTM replace LSTM gates with variational quantum circuits (VQCs) to enrich temporal modeling
- QML is particularly promising in settings with high uncertainty, limited data, and nonlinear patterns, which are common in industrial forecasting

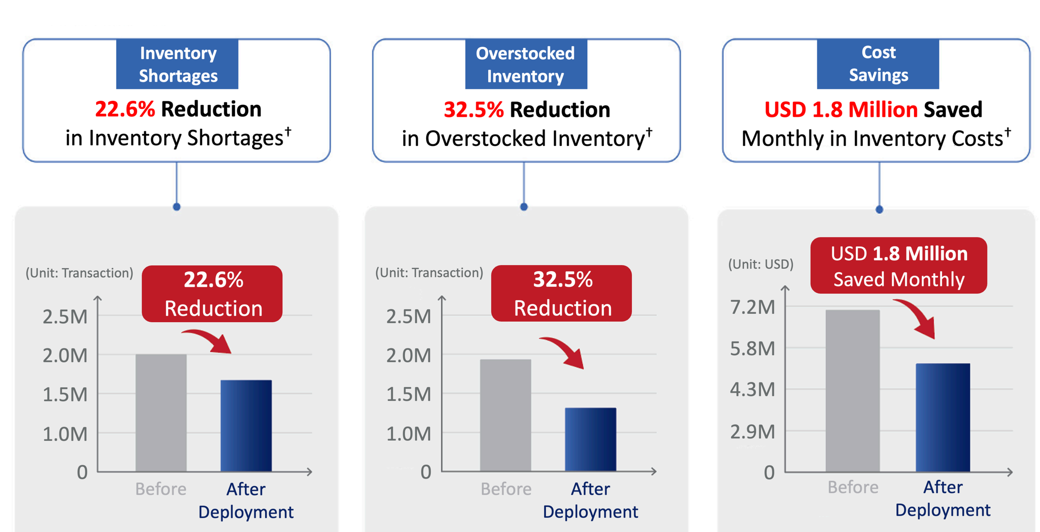
Deployment in Real Industry

- Quantum Deepflow was deployed at a Korean steel manufacturer to enhance procurement decisions in volatile markets
- It integrates an LSTM autoencoder, QLSTM, and AutoML-style workflow to deliver accurate, denoised forecasts via a visual interface

Demo & Contributions

Business Impact from Real Deployment

- Key operational outcomes (as of Nov. 2024):



† As of Nov. 2024

Key Contributions

- Hybrid quantum-classical architecture applied to real-world forecasting
- Accessible interface on complex models for business decision-making
- Validated through live industrial deployment and measurable KPIs

Future Directions

- Integration with real quantum hardware environments
- Expansion to multi-variate and multi-step forecasting pipelines

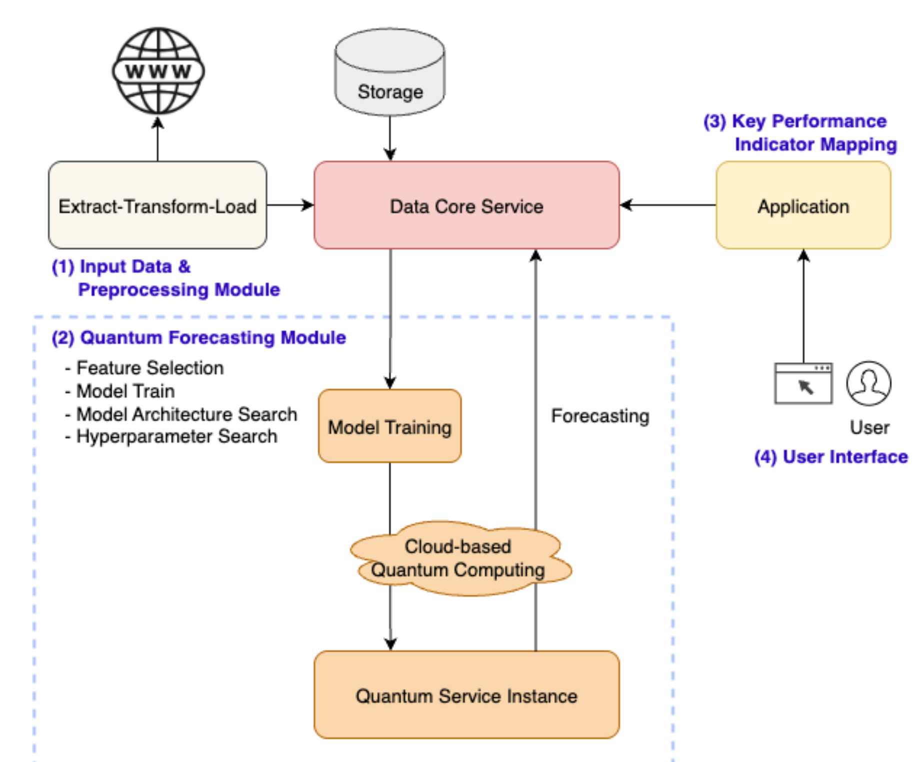
System Overview

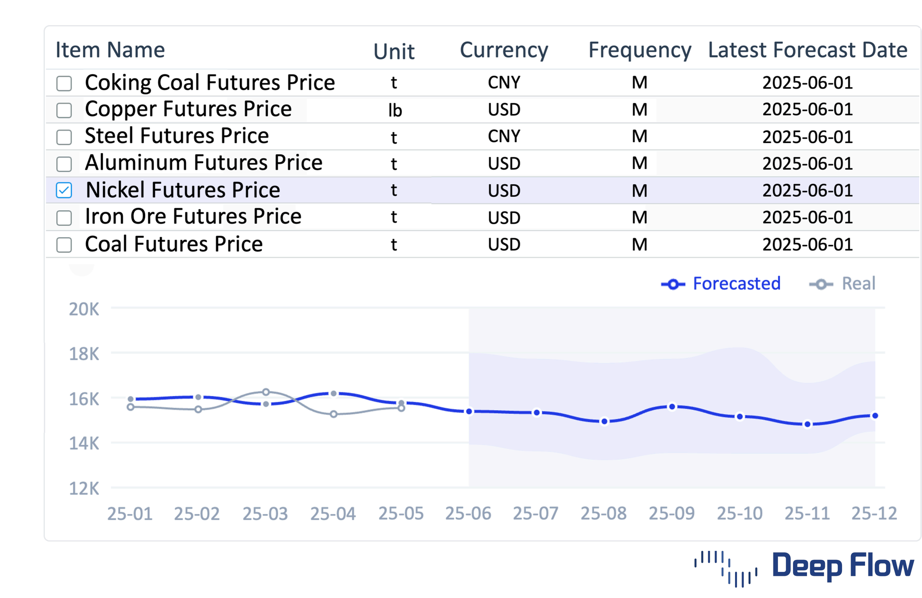
Backend: Forecasting Pipeline (AE-QLSTM)

- Autoencoder-based denoising: Raw multivariate time-series signals are first passed through an LSTM-based autoencoder to extract compact latent representations, denoted as $\mathbf{z}_t = \text{Encoder}(\mathbf{x}_{t-w:t})$, where $\mathbf{x}_{t-w:t}$ is a sliding window input
- Angle encoding for quantum circuit input: The latent vector $\mathbf{z}_t$ is transformed into rotation angles using a trigonometric encoding: $\phi(\mathbf{z}_t) = [\cos(z_t^{(1)}), \sin(z_t^{(1)}), \dots, \cos(z_t^{(d)}), \sin(z_t^{(d)})]$
- Quantum LSTM (QLSTM) Cell[Chen et al., 2022]: The encoded vector is concatenated with the previous hidden state and passed into Variational Quantum Circuits (VQCs) for each gate of the LSTM: $\mathbf{f}_t = \sigma(\text{VQC}_{\text{forget}}([\mathbf{h}_{t-1}; \phi(\mathbf{z}_t)]))$ $\tilde{\mathbf{c}}_t = \tanh(\text{VQC}_{\text{update}}([\mathbf{h}_{t-1}; \phi(\mathbf{z}_t)]))$ $\mathbf{i}_t = \sigma(\text{VQC}_{\text{input}}([\mathbf{h}_{t-1}; \phi(\mathbf{z}_t)]))$ $\mathbf{o}_t = \sigma(\text{VQC}_{\text{output}}([\mathbf{h}_{t-1}; \phi(\mathbf{z}_t)]))$
- Prediction output: The final hidden state is mapped to a forecast via: $\hat{y}_{t+1} = \text{MLP}(\mathbf{h}_t)$

Frontend: Visual Interface

- The platform provides a frontend dashboard that connects model outputs to business-relevant insights, including:
  - Forecast curves and uncertainty bands
  - Key performance indicators (KPI) mapping (*e.g.*, expected stockouts, cost estimates)
  - Custom query interface for inventory planning





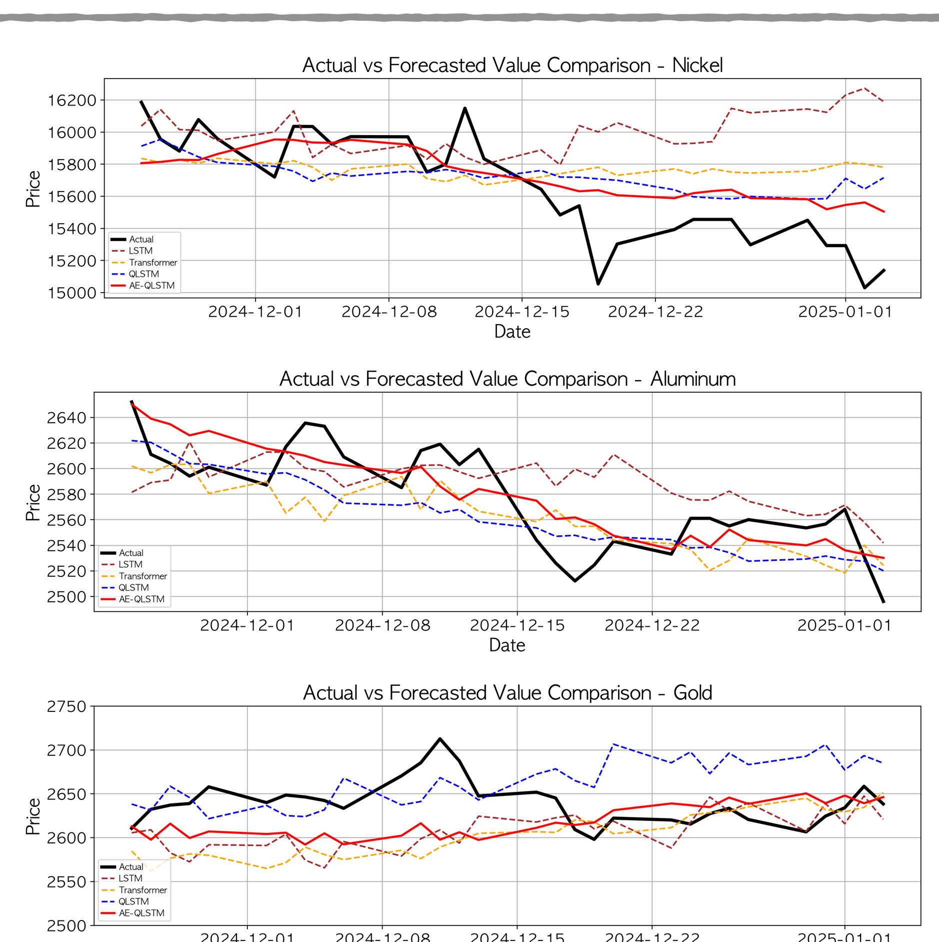
Results & Analysis

Interface Design

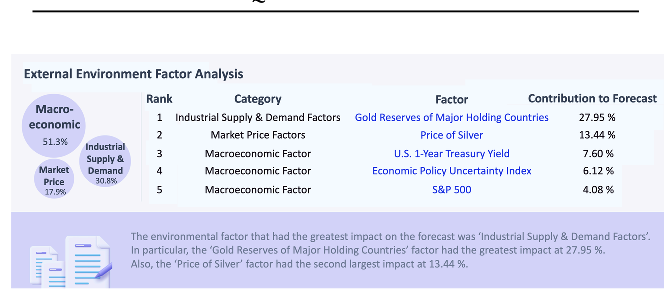
- Graphical UI allows data upload, forecast trigger, and KPI dashboard view
- Real-time inference with clear mapping to procurement decisions
- A procurement planner uploads commodity data and receives
  - Forecast values (1-4 weeks ahead)
  - Associated KPI risk scores (*e.g.*, cost deviation, volatility zone classification)
  - Automated decision-support prompts for inventory control

Performance Evaluation: a Case study with Nickel, Aluminum, Gold

- **Nickel price forecast**: AE-QLSTM records the lowest MAPE and volatility, indicating the effectiveness of autoencoding in denoising noisy data
  - AE-QLSTM shows superior responsiveness to local downward trends, with the overall trajectory with minimal lag
  - LSTM and Transformer consistently overestimate, with larger deviations and less sensitivity to short-term fluctuations
  - QLSTM performs better than classical baselines but exhibits variance during sharp price transitions
- **Aluminum price forecast**: AE-QLSTM outperforms others by combining trend fidelity with minimal volatility
  - AE-QLSTM accurately tracks turning points with a stable prediction profile, effectively smoothing out noise while retaining structure
  - Transformer fails to recognize sharp inflection zones, often lagging behind actual values
  - QLSTM captures local shifts more precisely than Transformer or LSTM, but exhibits less stable variance than AE-QLSTM
- **Gold price forecast**: AE-QLSTM yields the best performance in MAPE
  - In high-volatility regions, QLSTM and AE-QLSTM both outperform classical models, without large fluctuations
  - AE-QLSTM provides the smoothest and most interpretable trajectory, with fine-grained local dynamics
  - Vanilla LSTM and Transformer show irregular spikes and oscillations, especially in noisy regions



Raw Material	Model	MAPE (%)	MAE	R^2
Nickel (USD/ton)	LSTM	2.59	399.03	-1.391
	Transformer	1.85	287.71	0.024
	QLSTM	1.53	238.74	0.282
	AE-QLSTM	1.22	190.61	0.528
Aluminum (USD/ton)	LSTM	1.11	28.55	0.205
	Transformer	1.11	27.19	0.311
	QLSTM	0.91	23.52	0.504
	AE-QLSTM	0.71	18.35	0.693
Gold (USD/t.oz)	LSTM	1.44	38.23	-2.233
	Transformer	1.71	45.25	-3.272
	QLSTM	1.55	40.81	-2.206
	AE-QLSTM	1.31	34.82	-1.516



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