Reflection on LSTM Model Deployment Risks and Monitoring

If deployed, my LSTM-based stock prediction model would face several critical risks. The most significant is regime change risk - sudden market shifts (like COVID-19 or the 2008 crisis) would render historical patterns useless. Overfitting risk is equally concerning, as the model might perform well backtested but fail with new data. Data quality risk could introduce garbage-in-garbage-out scenarios, while latency risk might cause delayed predictions in fast-moving markets.

For ongoing monitoring, I would implement four-layer surveillance:

Data Layer: Monitor feature distributions, missing data rates, and sudden statistical shifts in input data.
Model Layer: Track prediction drift, accuracy metrics degradation, and feature importance changes.
System Layer: Watch latency, throughput, error rates, and resource utilization.
Business Layer: Monitor P&L impact, win rates, Sharpe ratio, and maximum drawdowns.

Ownership would follow a shared model. Data scientists own model retraining and validation, ML engineers handle system performance and deployment, while quant traders own business metrics and trading decisions. Handoffs would occur through automated alert systems - when data layer anomalies exceed thresholds, engineers are notified; when model performance degrades, data scientists trigger retraining; when business metrics deteriorate, traders receive immediate alerts to adjust strategies. This ensures continuous feedback loops while maintaining clear accountability boundaries.