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# Adaptive Time-series Forecasting Framwork with Drift Detection & Deep Learning with XAI

## Automation Engineering Program

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## Introduction:

Thai Exhange Stocks are highly volatile, making static LSTM & Transformer models ineffective when concept drift changes market behavior over time. This often creates a profitability paradox, where low prediction error does not guarantee strong trading returns. To address this, the project introduces a drift-adaptive framework that combines drift detection with continual learning to improve both forecasting relevance & financial performance.

**Problem:**

Financial data is non-stationary (changes over time) and Models degrade due to Concept Drift.

**Objective:**

To develop **an adaptive & interpretable system** that maintains accuracy despite changing data patterns caused by concept drift.

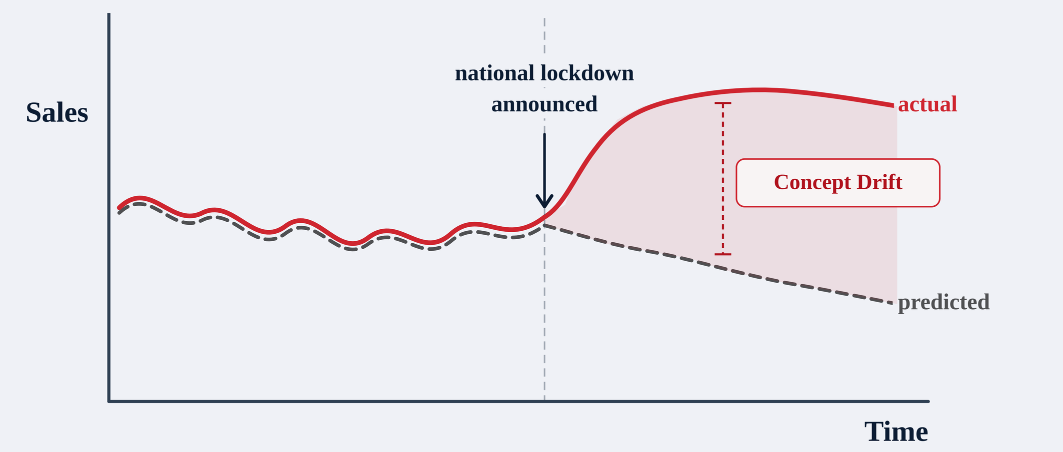


Fig.1 Concept Drift in Financial Time Series Prediction

## System Architecture:

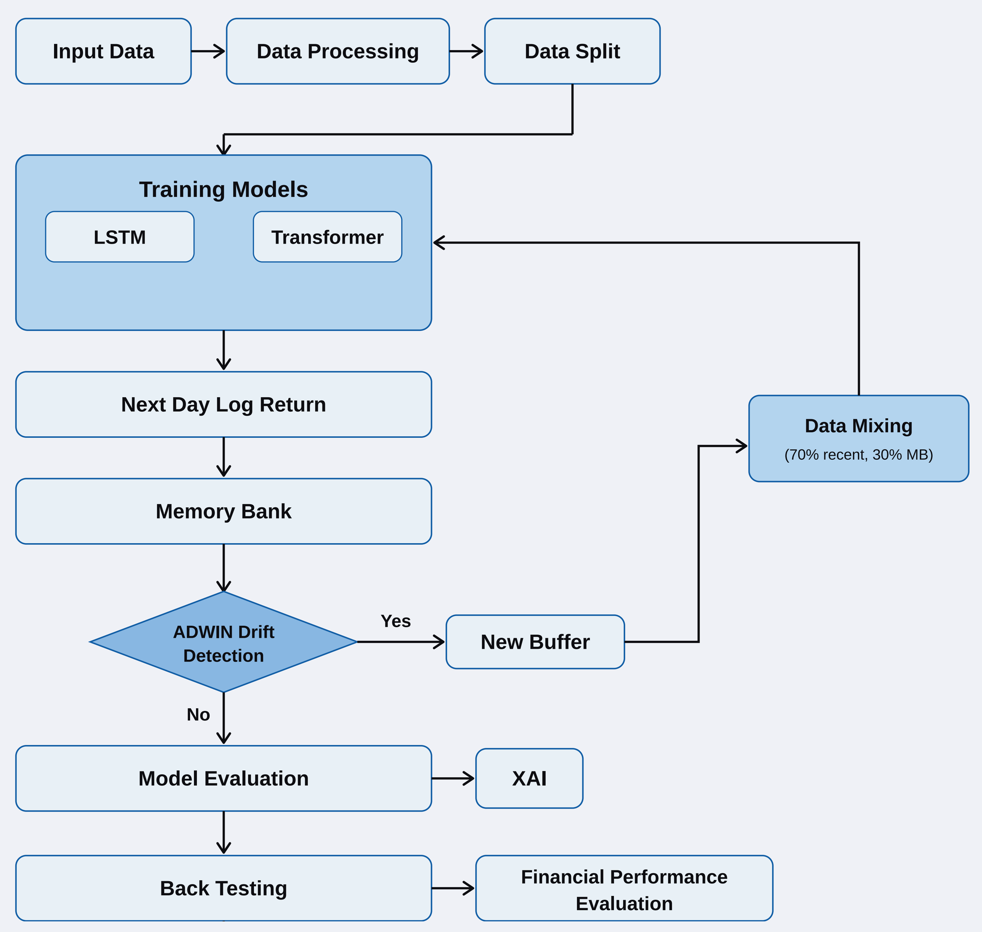


Fig.2 System Architecture

- Uses daily OHLCV, RSI, and MACD data from seven Thai banking stocks (2018–2025).
- LSTM & Transformer models predict next-day stock returns.
- ADWIN detects concept drift through prediction error changes.
- Experience Replay retrains models with 70% recent data & 30% historical memory.
- Performance is measured using MSE, Sharpe Ratio, & Maximum Drawdown.

## Experimental Setup:

- Four experiments compare static & adaptive LSTM & Transformer models.
- Baselines Exp 1 & 2 use no drift adaptation.
- Adaptive models use ADWIN + Experience Replay.
- All models predict next-day log returns on unseen data.
- Performance is evaluated using Sharpe Ratio & Expected Return to assess risk-adjusted financial performance.

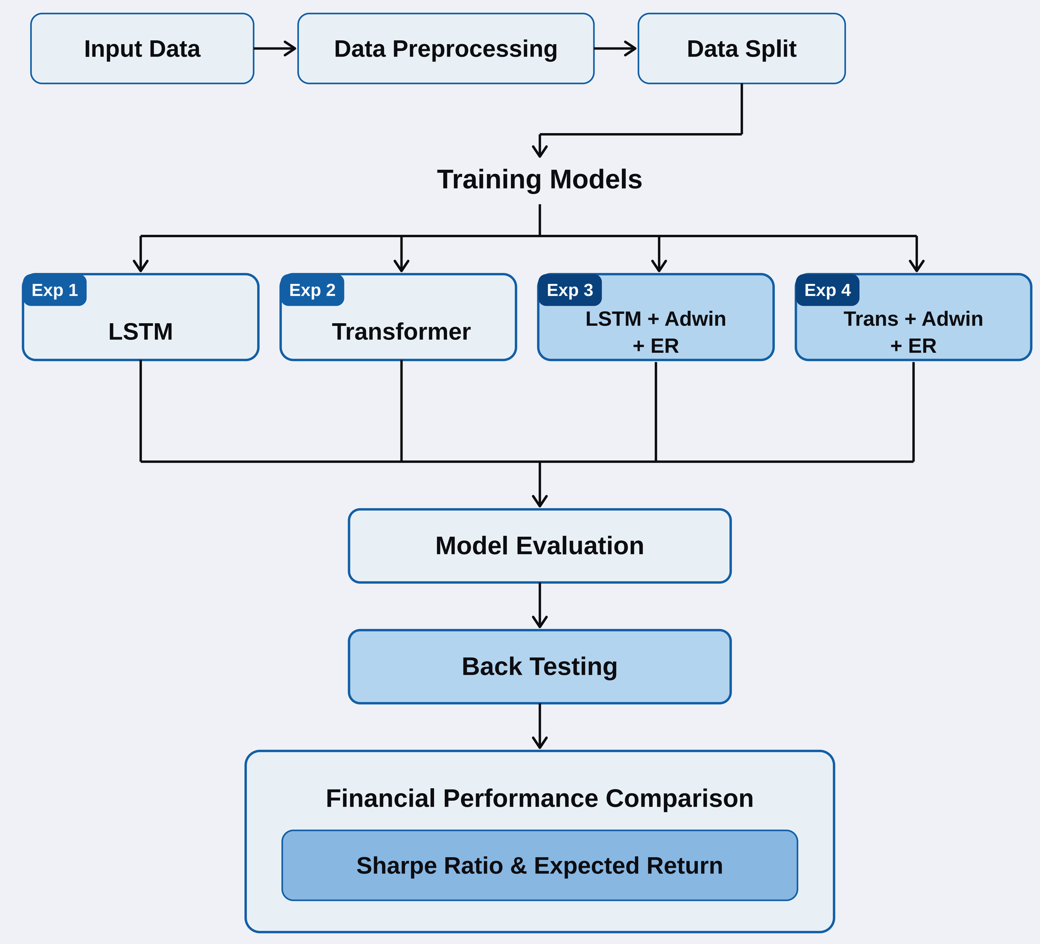


Fig.3 Experimental Setup

## Results & Discussion:

### MSE Comparison:

- Drift-Adaptive LSTM achieved the strongest overall financial performance with the highest Sharpe Ratio & Total Return.
- Static LSTM outperformed Static Transformer, but both baseline models declined under concept drift.
- ADWIN + Experience Replay improved both LSTM & Transformer models compared to static baselines.
- Results confirm that **drift adaptation enhances profitability & risk-adjusted returns** in dynamic financial markets.

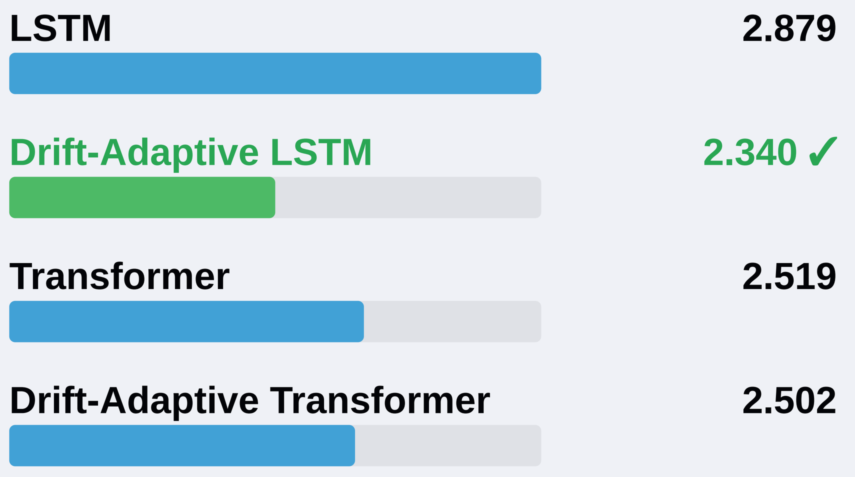


Fig.4 MSE Comparison

### Drift Events Detected:

- Drift frequency varied across stocks, showing that **concept drift impacts each banking stock differently.**
- High-drift stocks experienced more frequent market regime changes & required greater model adaptation.
- Low-drift stocks remained relatively stable, indicating fewer structural shifts over time.
- ADWIN effectively identified drift events, enabling targeted retraining only when significant changes occurred.

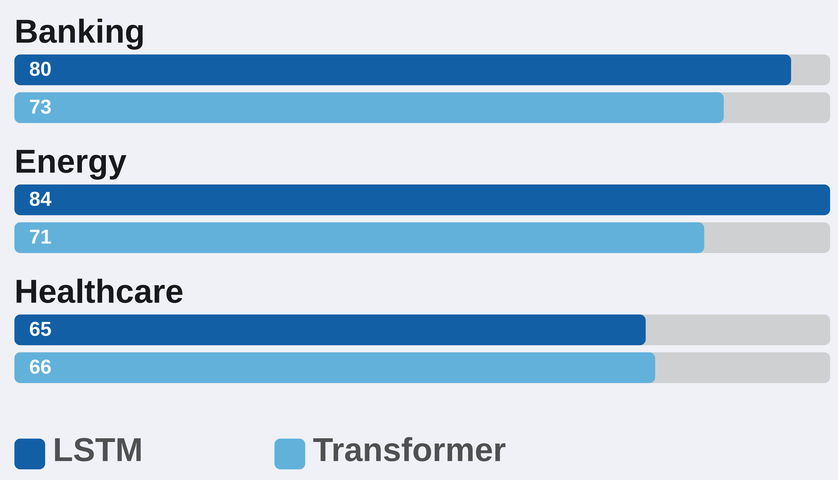


Fig.5 Drift Counts Across all three sectors

### Finanacial Performance:

- Drift-Adaptive LSTM achieved the highest Sharpe Ratio, indicating the strongest risk-adjusted profitability.
- Static LSTM outperformed Static Transformer, demonstrating stronger baseline financial stability.
- ADWIN + Experience Replay improved Sharpe Ratios for both architectures.
- Adaptive models provided more consistent profitability under changing market conditions.
- These results reinforce that **drift adaptation enhances long-term trading resilience** beyond static model performance.

| Model | Sharpe Ratio | Total Return % |
|---|---|---|
| LSTM | 0.438 | 11.14% |
| Drift-Adaptive LSTM | 0.470 | 14.89% |
| Transformer | 0.280 | 7.17% |
| Drift-Adaptive Transformer | 0.396 | 10.63% |

Table 1 Financial Performance Comparison

### Feature Importance (XAI):

- Technical indicators contributed differently across models, highlighting varied feature dependence in stock prediction.
- Price-based variables remained among the most influential features for forecasting next-day returns.
- RSI and MACD provided additional predictive value by capturing momentum & trend shifts.
- Feature importance analysis improved interpretability by identifying which inputs most influenced model decisions.

| Feature | LSTM | Transformer |
|---|---|---|
| Open | 0.000253 | 0.003597 |
| High | 0.000265 | 0.003275 |
| Low | 0.000261 | 0.002965 |
| Close | 0.000281 | 0.002303 |
| Volume | 0.001509 | 0.004936 |
| RSI | 0.000590 | 0.005109 |
| MACD | 0.001340 | 0.002336 |

Table 2 Feature Importance

## Conclusion:

**Conclusion:**

This study demonstrates that **Drift-adaptive models using ADWIN & Experience Replay outperform static LSTM & Transformer models** in non-stationary financial data. The approach improves both prediction reliability & risk-adjusted trading performance, with Drift-Adaptive LSTM achieving the best overall results.

**Future Work:**

Future work can explore advanced drift detection, hybrid models, & larger or higher-frequency datasets. Expanding to other sectors and global markets can improve generalizability. Integrating reinforcement learning & enhancing real-time deployment & explainability are also important directions.

## References:

Emeli Dral, ElenaSamuloya; Machine Learning Monitoring, Part 5: Why You Should Care About Data and Concept Drift, Nov 2020.