Thesis Proposal - Improving Equity Volatility Forecasts for Emerging Markets: A Comparative Study of AI and Econometric Approaches Using South African Data

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Abstract

Testing whether modern AI methods can predict stock market swings in South Africa—driven by issues like power cuts and mining reliance—better than older models.

1. Introduction

Predicting stock market volatility—how wildly prices swing—is crucial for investors and policymakers, especially in emerging markets like South Africa. The Johannesburg Stock Exchange (JSE) faces unique challenges: its economy relies heavily on gold and platinum exports, suffers frequent power blackouts (like Eskom's load-shedding), and grapples with political uncertainty. Traditional forecasting models, such as GARCH or HAR, are designed for stable markets and often miss these local, real-world risks. This raises a critical question: *Can machine learning (ML) models like LSTM and XGBoost predict JSE volatility more accurately by incorporating these South African-specific factors?*

To answer this, the study will analyze JSE data (e.g., Top 40 index) and test whether ML models outperform traditional methods when local drivers are included. The process starts with preparing high-frequency trading data, calculating volatility, and integrating SA-specific variables like commodity prices and load-shedding schedules. Models will be trained using time-series techniques to avoid overfitting, including hybrid approaches that combine traditional methods (e.g., HAR) with ML (e.g., LSTM) to balance structure and flexibility.

Accuracy will be tested using standard metrics like mean squared error (MSE) and real-world scenarios, such as predicting losses during power blackouts or political crises. A key focus is transparency: tools like SHAP values will explain why models make predictions—for example, revealing whether load-shedding matters more than gold prices during crises.

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Results could help South African investors hedge risks more effectively and guide policymakers in stabilizing markets during infrastructure or political shocks. By focusing on SA's unique challenges, this study aims to show whether modern ML tools can outperform traditional models in messy, real-world emerging markets—where global theories often fall short.

What follows is the thesis outline, followed by Research Design & Data Collection, then Model Selection & Training, then Evaluation Framework, and finally Hopeful Contributions

2. Thesis Structure:

- Introduction
  - SA's volatility challenges; ML vs. traditional debate (Gunnarsson, Isern, Kaloudis, Risstad, Vigdel & Westgaard, 2024; Wu, Cheng, Jankovic & Kolanovic, 2024)
- Literature Review
  - ML in volatility forecasting (Gunnarsson *et al.*, 2024; Horvath, Muguruza & Tomas, 2021), emerging market gaps (Zhang, Zhang, Cucuringu & Qian, 2023).
- Methodology
  - Data preprocessing (Petrozziello, Troiano, Serra, Jordanov, Storti, Tagliaferri & Rocca, 2022; Zhang *et al.*, 2023)
  - Model design (Gunnarsson *et al.*, 2024; Horvath *et al.*, 2021; Wu *et al.*, 2024)
  - Adaptive learning (Zeng & Klabjan, 2019).
- Results
  - Statistical/economic metrics
  - SHAP interpretation (Gunnarsson *et al.*, 2024; Wu, Jankovic, Kaplan & Lee, 2025)
- Discussion
  - ML flexibility in SA's context vs. developed markets (Gunnarsson *et al.*, 2024; Zhang *et al.*, 2023).

- Policy/investor implications (Wu *et al.*, 2025; Zeng & Klabjan, 2019).

- Conclusion
  - Synthesis of findings; future work (e.g., rough volatility with JSE options data).

3. Research Design & Data Collection

Data sources

- Core Data: JSE Top 40 high-frequency returns (15-minute intervals, adjusted for liquidity constraints per Gunnarsson *et al.* (2024) and Petrozziello *et al.* (2022).

- Exogenous Variables:
  - Commodity prices (platinum, gold) – Gunnarsson *et al.* (2024), Wu *et al.* (2024).
  - Eskom load-shedding schedules (categorical/time-series) – (Petrozziello *et al.*, 2022; Zhang *et al.*, 2023).
  - SA political risk index (text-based scores) – Gunnarsson *et al.* (2024). *(Realistically this may be hard to do but I can attempt)*

- Benchmarks: Realized Volatility (RV) using subsampled kernels (Petrozziello *et al.*, 2022; Zhang *et al.*, 2023) to mitigate microstructure noise.

Preprocessing:

- RV Calculation: Use 15-minute intervals (not 5-minute, aligning with Gunnarsson *et al.* (2024) liquidity caveat).

- Feature Engineering:
  - Lagged RV components (HAR-RV structure) – Gunnarsson *et al.* (2024), Petrozziello *et al.* (2022)

- Grid Representation: Convert RV and exogenous variables into time-strike matrices (Horvath *et al.*, 2021) but limit grid complexity to 3 channels (RV, commodities, load-shedding) to avoid overfitting.
- Diurnal adjustment and winsorization (Zhang *et al.* (2023)) for intraday returns.

4. Model Selection & Training

Models

1. Traditional:
   - GARCH(1,1), HAR-RV (Gunnarsson *et al.* (2024), Petrozziello *et al.* (2022)).
2. Machine Learning:
   - LSTM: Stacked architecture with dropout (Petrozziello *et al.* (2022)), attention mechanisms for SA factors (Wu *et al.* (2024); Wu *et al.* (2025)).
   - XGBoost: Feature importance analysis via SHAP (Gunnarsson *et al.* (2024)).
3. Hybrid: HAR-LSTM (HAR-RV inputs + LSTM layers) (Gunnarsson *et al.* (2024), Horvath *et al.* (2021)).
4. Adaptive Online Learning: Incremental LSTM/XGBoost updates (Zeng & Klabjan (2019)) for crisis responsiveness.

Training Protocol

- Time-Series CV: Rolling window validation (70% train, 30% test) (Petrozziello *et al.* (2022), Gunnarsson *et al.* (2024)).
- Dynamic Feature Management: Retain top 10 features via SHAP-driven FVS (Zeng & Klabjan (2019)).
- Hardware: GPU acceleration for LSTM (Horvath *et al.* (2021)) but avoid FPGA (*due to feasibility concerns*).

5. Evaluation Framework

Metrics:

- Statistical: MSE, QLIKE (Gunnarsson *et al.* (2024), Petrozziello *et al.* (2022), Zhang *et al.* (2023)).
- Economic: VaR, Expected Shortfall (Gunnarsson *et al.* (2024)), Sharpe/Sortino ratios (Wu *et al.* (2024); Wu *et al.* (2025)).
- Robustness:
  - Diebold-Mariano tests (Petrozziello *et al.* (2022)).
  - Regime-specific analysis (load-shedding stages, political crises) (Zhang *et al.* (2023), Wu *et al.* (2024)).

Interpretability:

- SHAP Values: Track evolving importance of SA factors (e.g., load-shedding's impact during crises) (Gunnarsson *et al.* (2024), Zeng & Klabjan (2019)).
- Crisis-Tagged Plots: Overlay volatility forecasts with load-shedding/political events (Gunnarsson *et al.* (2024), Zhang *et al.* (2023)).

6. Hopeful Contributions

1. Emerging Market Insights:
   - Demonstrate ML's superiority in capturing SA-specific drivers (commodities, load-shedding) vs. GARCH/HAR.
2. Practical Tools:
   - Crisis-response dashboards with SHAP-driven volatility forecasts for policymakers.

3. Methodological Advancements:

- Hybrid HAR-LSTM model optimized for thin liquidity.

References

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