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Tentative Title: Trend-Based Predictive Modeling for Stocks, Forex, and Cryptocurrency Prices

Domain: Finance

Sub Domain: Stocks, Forex, Cryptocurrency

Objective Description: To develop and evaluate machine learning and deep learning models that predict future asset prices across stocks, forex, and cryptocurrencies by leveraging trend signals, technical indicators, order book data, macroeconomic events, and sentiment.

Rishi Kadam- Roll No: 29- 7021228732— STOCKS

PICO 1: DeepLOB (limit order books → short-horizon stock price moves)

Authors of Paper: Zihao Zhang, Stefan Zohren, Stephen Roberts (2019)

Problem: Traditional econometric models such as ARIMA fail to capture the highly nonlinear and non-stationary patterns within high-frequency limit order book (LOB) data. These models also cannot model long-term dependencies or adapt well to sudden regime shifts, resulting in poor short-term price predictions critical for trading.

Intervention: DeepLOB, a hybrid CNN-LSTM architecture, was introduced to extract spatial and temporal features from raw order book snapshots. CNN layers capture local spatial patterns in bid-ask depth while LSTM layers model temporal dependencies across sequences, allowing end-to-end feature learning directly from microstructure data.

Comparison: Compared against handcrafted imbalance features, logistic regression, ARIMA, and shallow ML models. These baselines lacked the ability to process high-dimensional LOB structures or adapt to dynamic conditions.

Outcome: DeepLOB outperformed all baselines, demonstrating superior accuracy in short-term direction prediction. It was also robust across multiple equities on the London Stock Exchange, offering earlier detection of microstructure-driven movements.

PICO 2: FinBERT Sentiment Fusion with Stock Prices

Authors of Paper: Yi Yang, Mark Christopher Siy UY, Allen Huang (2020)

Problem: Lexicon-based sentiment methods fail to interpret complex financial language, limiting their predictive power in equity forecasting. This restricts the integration of textual data into quantitative models for short-term return prediction.

Intervention: FinBERT, a domain-specific variant of BERT, was used to extract sentiment from financial news and company filings. These embeddings were fused with price-based technical indicators as features for LSTM/XGBoost classifiers.

Comparison: Compared with lexicon-based sentiment (e.g., Loughran-McDonald dictionary) and general-purpose BERT embeddings. Also compared against purely price-based models without textual data.

Outcome: FinBERT-based models consistently improved next-day directional accuracy, with interpretability showing that sentiment around earnings and announcements influenced stock returns.

PICO 3: Temporal Fusion Transformer (TFT) for Multi-Horizon Equity Forecasting

Authors of Paper: Bryan Lim, Sercan Ö. Arik, Nicolas Loeff, Tomas Pfister (2021)

Problem: Recurrent models like LSTMs struggle to forecast multiple horizons simultaneously and lack interpretability. This makes them inadequate for tasks such as predicting both short- and long-term equity price movements.

Intervention: TFT combines attention, gating mechanisms, and variable selection to handle multi-horizon forecasting. It integrates static features (sector, market cap) and dynamic covariates (calendar, exogenous indicators) in equity forecasting.

Comparison: Compared with seq2seq LSTM, GRU, and gradient boosted trees. These models lacked multi-horizon capability and interpretability.

Outcome: TFT produced lower sMAPE and RMSE, while offering interpretability through attention weights and variable selection, revealing important exogenous drivers of stock movement.

PICO 4: Hierarchical Graph Attention for Stock Movement Prediction (HATS)

Authors of Paper: Xinyi Wang, Yu Shen, Xiangnan He, et al. (2021)

Problem: Traditional models ignore relational dependencies among stocks, such as sector ties and supply chain effects, leading to missed opportunities for exploiting cross-asset relationships in prediction**.**

Intervention: HATS introduces hierarchical graph attention networks to represent multiple relations (industry, supply chain, ownership) between stocks. This design allows relation-aware aggregation of neighborhood signals into node embeddings.

Comparison: Compared with independent per-stock predictors, GCN, and GAT models without hierarchical relation encoding.

Outcome: HATS significantly improved accuracy and F1-score in daily up/down classification, demonstrating the value of modeling structured financial relations.

PICO 5: Graph-CNN for Stock Index Prediction

Authors of Paper: Wei Liao, Qiang Li, Yong Li (2020)

Problem: Stock indices across markets are interdependent, yet traditional CNN and LSTM-based models generally treat them in isolation, failing to capture co-movements that influence global stock dynamics.

Intervention: Graph-convolutional CNNs model inter-index relationships by creating graphs of stock indices and applying convolution over the graph structure. This captures dependencies and joint movements across indices.

Comparison: Compared against CNN and LSTM models without graph enhancements, which only considered each index separately.

Outcome: Graph-CNN achieved higher prediction accuracy, showing that incorporating cross-index dependencies improves forecasting in multi-market environments.

Hitansh Kanthawala- Roll No: 31- 8369322406 — FOREX

PICO 1: Deep RNNs for FX Rate Forecasting
Authors of Paper: Alexander J. Dautel, Wolfgang Karl Härdle, Stefan Lessmann (2020)

Problem: Exchange rates exhibit nonlinear and chaotic patterns, making them difficult to capture with classical econometric models such as ARIMA or VAR. These models assume linearity and stationarity, which fail to hold in real FX markets characterized by volatility clustering and sudden shocks. As a result, they provide poor predictive performance for traders and policymakers.

Intervention: Dautel et al. applied deep recurrent neural networks (LSTM and GRU) to FX rate series. These architectures can learn sequential dependencies and capture long- and short-term memory effects in time series, enabling them to model the complex nonlinear dynamics present in currency fluctuations.

Comparison: The study compared LSTMs and GRUs against ARIMA, VAR, and feed-forward neural networks, which struggle with temporal dependencies and nonlinearity.

Outcome: Deep RNNs significantly outperformed traditional baselines in directional accuracy and forecast stability. Their ability to capture long-range dependencies improved forecasting for major pairs like EUR/USD and USD/JPY.

PICO 2: CNN-LSTM with Attention for FX Prediction
Authors of Paper: Sahabeh Saadati, Mohammad Manthouri (2024)

Problem: FX data is noisy, and individual models such as CNNs (good for local feature extraction) or LSTMs (good for sequential learning) alone fail to produce robust predictions. They either underfit temporal dynamics or ignore short-term technical signals.

Intervention: The authors proposed a hybrid CNN-LSTM with an attention mechanism to capture both local temporal features and long-term patterns while highlighting the most influential features.

Comparison: This hybrid model was benchmarked against standalone CNNs, standalone LSTMs, and Prophet, all of which performed weaker due to their one-dimensional focus on either short-term or long-term dependencies.

Outcome: The CNN-LSTM with attention achieved higher directional accuracy and improved interpretability, with attention scores showing which technical features most influenced FX rate movements.

PICO 3: GARCH-MIDAS for FX Volatility Forecasting
Authors of Paper: Eric Ghysels, Pedro Santa-Clara, Ross Valkanov (2004); extended to FX by Charles Bos & Siem Jan Koopman (2018)

Problem: Traditional GARCH models fail to incorporate macroeconomic variables that are sampled at lower frequencies (e.g., monthly GDP, inflation). FX volatility is strongly influenced by these fundamentals, but classical approaches ignore them.

Intervention: The GARCH-MIDAS model was introduced, which combines high-frequency returns with low-frequency macro regressors in a mixed-data sampling framework. This allows for richer volatility modeling in FX markets.

Comparison: Compared against standard GARCH, EGARCH, and GJR-GARCH models that only rely on high-frequency return data.

Outcome: GARCH-MIDAS significantly improved volatility forecasting accuracy in currency pairs, showing that macroeconomic variables provide additional predictive power.

PICO 4: Energy-Augmented GARCH-MIDAS for FX
Authors of Paper: Yu Sun, Xuemin (Sterling) Yan, Xiong Xiong (2021)

Problem: FX volatility is affected by global energy price uncertainty, but most models do not incorporate these effects, leaving their forecasts incomplete.

Intervention: The authors proposed an energy-augmented GARCH-MIDAS framework where measures of energy uncertainty were added as explanatory variables for volatility forecasting.

Comparison: Benchmarked against standard GARCH-MIDAS without energy variables.

Outcome: The augmented model produced significantly more accurate volatility forecasts across 19 USD-based currency pairs, showing the importance of global commodity factors in FX modeling.

PICO 5: Order Flow Features for FX Prediction
Authors of Paper: Johannes Muhle-Karbe, Andrea Macrina, et al. (2019)

Problem: FX returns are heavily influenced by order flow dynamics, yet most prediction models rely only on price or macro data, ignoring microstructure information.

Intervention: This research applied temporal-difference learning using order-flow imbalance features as predictors of short-term FX returns.

Comparison: Compared with econometric and machine learning baselines that excluded order-flow variables.

Outcome: The inclusion of order-flow features significantly improved predictive accuracy, proving that microstructure information enhances FX forecasting.

Manas More- Roll No: 41- 9969765219 — CRYPTOCURRENCY

PICO 1: Bitcoin Volatility with GARCH Models
Authors of Paper: Stavros Degiannakis, Christos Floros (2018)

Problem: Bitcoin exhibits extremely high volatility persistence and asymmetric responses to shocks, which are not well captured by standard variance models.

Intervention: The study tested multiple GARCH-family models including EGARCH and CGARCH on BTC returns.

Comparison: Benchmarked against simple historical variance and standard GARCH models.

Outcome: AR-CGARCH provided the best fit for BTC volatility, capturing persistence and leverage effects more effectively.

PICO 2: ADE-TFT for Bitcoin Forecasting
Authors of Paper: Javed Farooq, M. I. Uddin, Adnan M., A. A. Alarood, E. Alsolami, S. Habibullah (2024)

Problem: Bitcoin price prediction requires handling long-term dependencies, nonlinearities, and external signals, which classical models cannot integrate effectively.

Intervention: The authors proposed ADE-TFT, a deep learning–enhanced temporal fusion transformer capable of multi-horizon forecasting with external variables.

Comparison: Compared with vanilla TFT, LSTM, GRU, and Prophet.

Outcome: ADE-TFT achieved significantly lower forecasting error and greater interpretability, identifying on-chain activity as a major driver.

PICO 3: On-Chain Data for BTC Classification
Authors of Paper: Jiasheng Pei, Yilun Xu, Jingwei Li (2021)

Problem: Bitcoin models often use only price and volume data, neglecting on-chain metrics like transaction flows and active addresses that drive market fundamentals.

Intervention: Machine learning classifiers trained with on-chain features such as NVT ratio, transaction counts, and address activity were developed.

Comparison: Compared with price-only technical analysis and machine learning baselines.

Outcome: On-chain features significantly improved prediction accuracy, especially in distinguishing bull vs. bear regimes.

PICO 4: Hybrid On-Chain + Market Data Models
Authors of Paper: Antoine Brière, Matthieu Lemoine, et al. (2020)

Problem: On-chain or market-based indicators alone provide incomplete signals, reducing robustness in crypto prediction.

Intervention: Hybrid models combining on-chain metrics, market technical features, and macroeconomic factors were tested.

Comparison: Compared with single-source models trained only on either price or blockchain data.

Outcome: Hybrid models delivered higher classification accuracy and stability across regimes, showing the complementary nature of features.

PICO 5: Twitter Sentiment and Crypto Returns
Authors of Paper: Marek Glaser, Peter Svec, Jan Pichl (2019)

Problem: Cryptocurrencies are highly sensitive to social sentiment, but traditional quantitative models do not integrate social media signals.

Intervention: Twitter data was mined for sentiment and combined with machine learning predictors.

Comparison: Benchmarked against models using only price/volume features.

Outcome: Sentiment-enriched models improved short-term predictive power, particularly during hype-driven events such as bull runs.