# Quantitative FX Research System: A Machine Learning Approach to Market Regime Detection

CS 3200 Final Project Report

Trung
Northeastern University

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**Abstract**

This report presents a quantitative research system for foreign exchange market analysis using machine learning. The system processes data from 11 currency pairs across 5 timeframes, engineering 78 features across 8 categories including novel intrinsic-time features derived from directional-change theory. Three neural network models classify market regimes, volatility states, and regime transitions. Results demonstrate that volatility regimes are highly predictable (77.4% accuracy versus 25% baseline), while directional regime prediction remains near random-walk baseline (33.2%), consistent with efficient market hypothesis for short-term FX movements. The system integrates external macroeconomic data from FRED and cross-asset correlations from Yahoo Finance, providing institutional-grade feature engineering capabilities. This work contributes a complete, reproducible research pipeline comprising approximately 15,000 lines of Python code across 66 source files.

**Keywords:** Foreign Exchange, Machine Learning, Regime Detection, Volatility Clustering, Directional Change, Intrinsic Time, Neural Networks

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# 1 Introduction

## 1.1 Motivation

Foreign exchange markets represent the largest and most liquid financial markets globally, with daily turnover exceeding $7 trillion. Despite this liquidity, predicting short-term price movements remains challenging due to the efficiency of price discovery mechanisms. However, market practitioners recognize that understanding market states—such as trending versus ranging conditions or high versus low volatility environments—provides valuable context for risk management and strategy selection, even when directional prediction is unreliable.

This project develops a research system that addresses three fundamental questions: (1) What directional regime is the market currently in? (2) What is the prevailing volatility environment? (3) Is a regime transition imminent? Rather than attempting to predict returns directly, this approach focuses on characterizing market conditions—a task that may be more tractable and equally valuable for practical applications.

## 1.2 Objectives

The primary objectives of this project are threefold. First, to construct a comprehensive data pipeline capable of ingesting, processing, and storing FX market data from multiple sources including Interactive Brokers, FRED, and Yahoo Finance. Second, to develop an institutional-grade feature engineering framework encompassing 78 features across traditional technical indicators, volatility measures, microstructure proxies, and novel intrinsic-time features. Third, to train and evaluate neural network models for market state classification, providing empirical evidence on the predictability of different market characteristics.

## 1.3 Scope and Limitations

This system is designed exclusively for research purposes. It produces market state descriptions and analytical insights but does not generate trading signals, position sizing recommendations, or execution logic. The findings presented here should be interpreted as contributions to understanding FX market structure rather than as a basis for trading decisions.

# 2 Literature Review

## 2.1 Market Regime Detection

The concept of market regimes—distinct states characterized by different statistical properties—has received substantial attention in quantitative finance. Hamilton (1989) introduced Markov-switching models for regime detection in macroeconomic time series, establishing a framework subsequently applied to financial markets. More recent work has employed machine learning techniques including hidden Markov models, Gaussian mixture models, and neural networks for regime classification.

## 2.2 Volatility Clustering

The phenomenon of volatility clustering—the tendency for large price changes to be followed by large changes and small changes by small changes—is among the most robust stylized facts in financial econometrics. Engle's (1982) ARCH model and Bollerslev's (1986) GARCH extension formalized this observation, demonstrating that while returns themselves are largely unpredictable, their conditional variance exhibits substantial serial correlation.

### 2.3 Intrinsic Time and Directional Change

Traditional financial analysis operates in clock time, sampling prices at fixed intervals regardless of market activity. Müller et al. (1993) proposed an alternative framework based on intrinsic time, where time advances based on price movements rather than the clock. In this framework, a directional change (DC) event occurs when price moves by a threshold percentage $\delta$ from the most recent extreme. Glattfelder et al. (2011) demonstrated that DC-based analysis reveals scaling laws in FX markets not apparent in clock-time analysis.

### 2.4 FX-Specific Factors

Currency markets are influenced by factors distinct from equity markets. The carry trade—borrowing in low-interest-rate currencies to invest in high-interest-rate currencies—represents a well-documented source of returns in FX (Burnside et al., 2011). Our feature engineering incorporates these FX-specific factors using real central bank rate data from FRED.

## 3 System Architecture

### 3.1 Overview

The system architecture follows a layered design pattern with clear separation of concerns. Figure 1 illustrates the high-level data flow from raw data ingestion through feature engineering to model training and market state analysis.

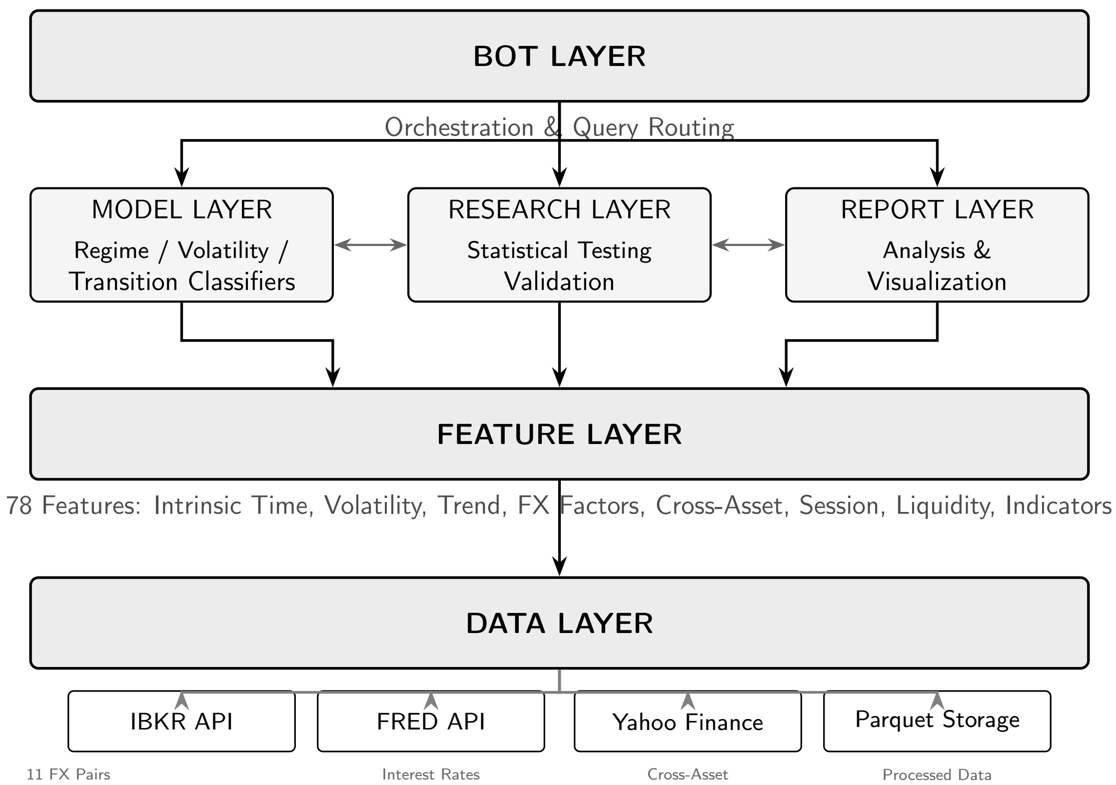


Figure 1: System Architecture: Layered design showing data flow from raw sources through feature engineering to model training and analysis.

### 3.2 Technology Stack

Table 1 summarizes the core technologies employed in the system implementation.

Table 1: Technology Stack

| Component | Technology | Version |
|---|---|---|
| Programming Language | Python | 3.10+ |
| Data Storage | Apache Parquet (PyArrow) | 14.0+ |
| ML Framework | PyTorch | 2.0+ |
| Data Processing | Pandas, NumPy | 2.0+, 1.24+ |
| External APIs | IBKR TWS, FRED, Yahoo Finance | — |
| Configuration | YAML | — |

### 3.3 Codebase Statistics

Table 2: Codebase Metrics

| Metric | Value |
|---|---|
| Total Python Files | 66 |
| Source Files (src/) | 49 |
| Script Files (scripts/) | 17 |
| Estimated Lines of Code | 15,000–20,000 |
| Total Classes | ~50 |
| Total Functions | ~150 |

## 4 Data Layer

### 4.1 Data Sources

The system integrates three complementary data sources to provide comprehensive market coverage.

Table 3: Data Sources

| Source | Data Type | Frequency | Coverage |
|---|---|---|---|
| Interactive Brokers | OHLCV bars | 1m to 1d | 11 FX pairs |
| FRED | Interest rates, yields | Daily | 8 currencies + US curve |
| Yahoo Finance | Cross-asset prices | Daily | DXY, SPX, VIX, Gold, Oil |

### 4.2 Currency Pairs and Timeframes

Table 4: Currency Pair Universe

| Category | Pairs | Count |
|---|---|---|
| Major Pairs | EURUSD, GBPUSD, USDJPY, USDCHF, AUDUSD, NZDUSD, USDCAD | 7 |
| Yen Crosses | EURJPY, GBPJPY, AUDJPY, CHFJPY | 4 |
| **Total** | | **11** |

Table 5: Timeframe Coverage

| Timeframe | Bars per Day | Primary Use Case |
|---|---|---|
| 1 minute | 1,440 | Microstructure analysis |
| 5 minutes | 288 | Short-term patterns |
| 15 minutes | 96 | Intraday structure |
| 1 hour | 24 | Primary analysis timeframe |
| 1 day | 1 | Macro regime detection |

### 4.3 Data Volume Summary

Table 6: Data Artifacts

| Data Type | File Count | Location |
|---|---|---|
| Clock OHLCV | 55 | data/raw/clock/ |
| Intrinsic DC Events | 54 | data/raw/intrinsic/ |
| Processed Features | 55 | data/processed/ |
| Feature Metadata | 55 | data/processed/ |
| External Cache (FRED) | 14 | data/external/fred/ |
| External Cache (Yahoo) | 5 | data/external/yahoo/ |
| **Total** | **238** | |

### 4.4 Intrinsic-Time Processing

The directional-change engine converts clock-time bars into event-based intrinsic-time streams. A DC event triggers when price moves by threshold $\delta$ from the most recent extreme.

Table 7: DC Threshold Configuration

| Threshold ($\delta$) | Suffix | Typical Events/Day | Interpretation |
|---|---|---|---|
| 0.05% | dc005 | 50–100 | Noise level |
| 0.10% | dc010 | 20–40 | Short-term swings |
| 0.20% | dc020 | 8–15 | Intraday structure |
| 0.50% | dc050 | 2–5 | Daily regime changes |
| 1.00% | dc100 | 0.5–2 | Major macro shifts |

The DC detection algorithm maintains state variables for current mode (uptrend/downtrend), extreme price, and event counter. For each bar, the algorithm checks whether price has moved sufficiently from the tracked extreme to trigger a reversal:

$$\text{Up DC triggers when: } \frac{P_t - P_{\text{extreme}}}{P_{\text{extreme}}} \geq \delta \tag{1}$$

$$\text{Down DC triggers when: } \frac{P_{\text{extreme}} - P_t}{P_{\text{extreme}}} \geq \delta \tag{2}$$

# 5 Feature Engineering

## 5.1 Feature Categories Overview

The system computes 78 features organized into 8 categories. Table 8 provides a summary, with subsequent sections detailing each category.

Table 8: Feature Categories Summary

| **Category** | **Count** | **Description** |
|---|---|---|
| Intrinsic Time | 7 | DC events, overshoots, event clustering |
| Volatility | 11 | Realized vol, Hurst, jumps, higher moments |
| Microstructure | 8 | Spread proxies, wick ratios, volume patterns |
| Trend | 5 | Moving average ratios, ADX, price position |
| FX Factors | 7 | Carry, yield curve, momentum, value |
| Cross-Asset | 9 | Correlations with DXY, SPX, VIX, Gold, Oil |
| Session | 5 | Trading session indicators and overlaps |
| Liquidity | 3 | Spread metrics, liquidity scores |
| Indicators | 24 | RSI, MACD, Stochastic, Bollinger, etc. |
| **Total** | **78** | |

## 5.2 Intrinsic-Time Features

Table 9: Intrinsic-Time Features

| **Feature** | **Formula/Description** |
|---|---|
| dc_return | $(P_{DC} - P_{\text{prev\_extreme}})/P_{\text{prev\_extreme}}$ |
| overshoot_return | $(P_{\text{overshoot}} - P_{DC})/P_{DC}$ |
| overshoot_ratio | overshoot_return / dc_return |
| event_frequency | Count of DC events in rolling window |
| clustering | Temporal clustering coefficient of events |
| multi_delta_agreement | Agreement across $\delta$ thresholds $\{0.05\%, 0.10\%, 0.20\%\}$ |
| intrinsic_trend_strength | Net directional movement / total movement |

### 5.3 Volatility Features

Table 10: Volatility Features

| Feature | Formula/Description |
|---|---|
| realized_vol_Nm | $\sigma_N = \sqrt{\frac{252 \cdot H}{N} \sum_{i=1}^{N} r_i^2}$ where $H$ = hours/day |
| bipower_variation | $BV = \frac{\pi}{2} \sum_{i=2}^{N} \lvert r_{i-1} \rvert \lvert r_i \rvert$ |
| jump_component | $J = \max(0, RV - BV)$ |
| volatility_of_vol | Rolling std of realized volatility |
| parkinson_volatility | $\sigma_P = \sqrt{\frac{1}{4 \ln 2} \sum \ln(H_i/L_i)^2}$ |
| skew | Third standardized moment of returns |
| kurtosis | Fourth standardized moment of returns |
| variance_ratio | $VR = \frac{\mathrm{Var}(r_t^{(q)})}{q \cdot \mathrm{Var}(r_t)}$ |
| hurst_exponent | R/S analysis estimate, $H \in [0, 1]$ |

The Hurst exponent interpretation: $H < 0.5$ indicates mean-reversion, $H = 0.5$ random walk, $H > 0.5$ trending behavior.

### 5.4 Microstructure Features

Table 11: Microstructure Features

| Feature | Formula/Description |
|---|---|
| micro_price | $(2 \cdot C + H + L)/4$ |
| synthetic_spread | Roll model: $S = 2\sqrt{-\mathrm{Cov}(\Delta P_t, \Delta P_{t-1})}$ |
| relative_spread | spread / mid_price |
| wick_ratio | Upper wick / Lower wick |
| body_ratio | $\lvert C - O \rvert/(H - L)$ |
| rejection_wicks | Binary: wick $> 0.6\times$ body |
| standardized_range | $(H - L)$/avg_range |
| volume_adv_ratio | Volume / Average daily volume |

### 5.5 Trend Features

Table 12: Trend Features

| Feature | Formula/Description |
|---|---|
| sma_ratio_10_20 | $SMA_{10}/SMA_{20}$ |
| ema_ratio_12_26 | $EMA_{12}/EMA_{26}$ |
| adx | Average Directional Index (14-period) |
| trend_strength | Normalized distance from rolling mean |
| price_position | $(C - L_{20})/(H_{20} - L_{20})$ |

## 5.6 FX Factor Features

Table 13: FX Factor Features

| Feature | Formula/Description | Data Source |
|---|---|---|
| carry_factor | $r_{\text{base}} - r_{\text{quote}}$ (normalized) | FRED |
| carry_raw | Raw interest rate differential | FRED |
| momentum_factor | Return over lookback window | Price |
| value_factor | Deviation from rolling mean | Price |
| volatility_factor | Normalized volatility rank | Price |
| yield_curve_factor | $Y_{10Y} - Y_{2Y}$ | FRED |
| rate_level_factor | Absolute base currency rate | FRED |

## 5.7 Cross-Asset Features

Table 14: Cross-Asset Features

| Feature | Description | Data Source |
|---|---|---|
| correlation_dxy | Rolling corr with Dollar Index | Yahoo |
| correlation_spx | Rolling corr with S&P 500 | Yahoo |
| correlation_gold | Rolling corr with Gold | Yahoo |
| correlation_vix | Rolling corr with VIX | Yahoo |
| correlation_oil | Rolling corr with Crude Oil | Yahoo |
| relative_strength_vs_dxy | Cumulative return difference | Yahoo |
| cross_asset_momentum | Aggregated macro momentum | Yahoo |
| risk_sentiment | SPX return − VIX change | Yahoo |
| correlation_regime | Average absolute correlation | Yahoo |

## 5.8 Session and Liquidity Features

Table 15: Session Features

| Feature | Hours (UTC) |
|---|---|
| london_session | 07:00–16:00 |
| new_york_session | 12:00–21:00 |
| asia_session | 23:00–08:00 |
| session_overlap | London $\cap$ New York |
| session_volatility | Volatility by session |

Table 16: Liquidity Features

| Feature | Description |
|---|---|
| bid_ask_spread | Estimated or actual spread |
| spread_percentile | Spread rank in rolling window |
| liquidity_score | Composite liquidity metric |

### 5.9 Technical Indicators

Table 17: Technical Indicator Features (24 total)

| Category | Features |
|---|---|
| Momentum Oscillators | rsi, rsi_normalized, stochastic_k, stochastic_d, stochastic_normalized, williams_r, williams_r_normalized, cci, cci_normalized, mfi, mfi_normalized, roc |
| Trend Indicators | macd, macd_signal, macd_histogram, obv, obv_normalized |
| Volatility Indicators | atr, atr_normalized, bollinger_bandwidth, bollinger_percent_b |
| Support/Resistance | pivot_point, pivot_distance |

### 5.10 Top Predictive Features

Based on Random Forest importance scores across all 55 datasets:

Table 18: Top 10 Most Predictive Features

| Rank | Feature | Category | Avg Importance |
|---|---|---|---|
| 1 | pivot_point | Indicator | 0.048 |
| 2 | realized_vol_60m | Volatility | 0.038 |
| 3 | yield_curve_factor | FX Factor | 0.038 |
| 4 | obv | Indicator | 0.037 |
| 5 | hurst_exponent | Volatility | 0.033 |
| 6 | macd_signal | Trend | 0.030 |
| 7 | bipower_variation | Volatility | 0.030 |
| 8 | parkinson_volatility | Volatility | 0.030 |
| 9 | skew | Volatility | 0.029 |
| 10 | value_factor | FX Factor | 0.028 |

## 6 Labeling Methodology

### 6.1 Regime Labels

The regime labeler produces three classes based on forward-looking price movement analysis.

Table 19: Regime Label Definitions

| Class | Code | Definition |
|---|---|---|
| RANGING | 0 | Neither direction dominates |
| TREND_UP | 1 | Upside exceeds threshold and dominates downside |
| TREND_DOWN | 2 | Downside exceeds threshold and dominates upside |

The labeling algorithm computes maximum upside and downside movements over a lookforward window:

$$\text{max\_up} = \max_{i \in [t+1, t+N]} (H_i) - C_t \tag{3}$$

$$\text{max\_down} = C_t - \min_{i \in [t+1, t+N]} (L_i) \tag{4}$$

Classification rules with dominance ratio $D = 1.5$ and threshold $\theta$:

- TREND_UP if max_up $\geq \theta$ and max_up/max_down $\geq D$
- TREND_DOWN if max_down $\geq \theta$ and max_down/max_up $\geq D$
- RANGING otherwise

Table 20: Lookforward Windows by Timeframe

| **Timeframe** | **Lookforward (bars)** | **Horizon** |
|---|---|---|
| 1 minute | 120 | 2 hours |
| 5 minutes | 48 | 4 hours |
| 15 minutes | 24 | 6 hours |
| 1 hour | 12 | 12 hours |
| 1 day | 5 | 5 days |

## 6.2 Volatility Regime Labels

Table 21: Volatility Regime Definitions

| **Class** | **Code** | **Percentile Range** |
|---|---|---|
| LOW | 0 | Below 25th |
| NORMAL | 1 | 25th to 75th |
| HIGH | 2 | 75th to 95th |
| CRISIS | 3 | Above 95th |

## 6.3 Transition Labels

Binary classification indicating regime change within horizon window (default 8 bars):

$$y_t = \begin{cases} 1 & \text{if regime}_{t+h} \neq \text{regime}_t \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

# 7 Preprocessing Pipeline

## 7.1 Pipeline Overview

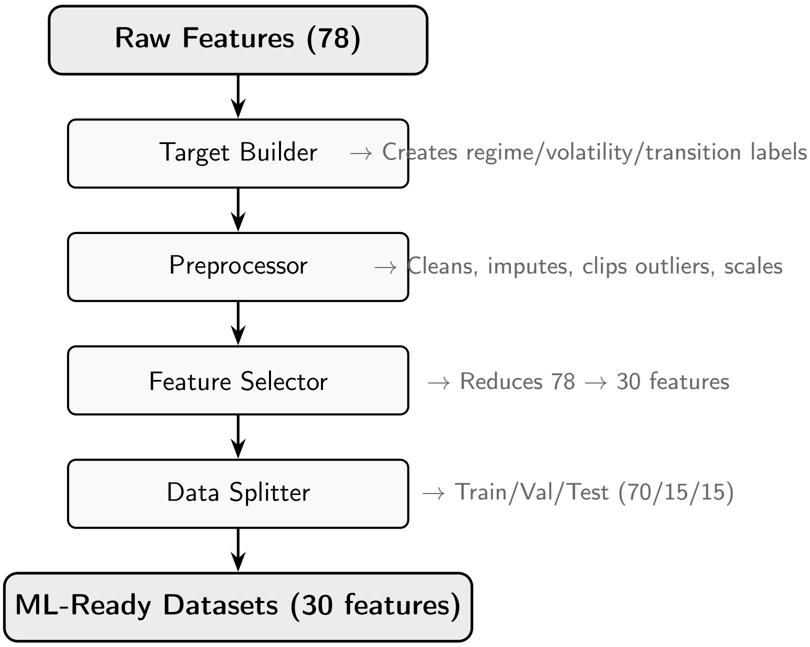


Figure 2: Preprocessing Pipeline: Data transformation from raw features to ML-ready datasets.

## 7.2 Scaling Strategy

Table 22: Feature-Specific Scaling

| Scaler | Features | Rationale |
|---|---|---|
| StandardScaler | Most continuous features | Default for unbounded |
| MinMaxScaler | RSI, stochastic, %B, sessions | Bounded [0,1] features |
| RobustScaler | Skew, kurtosis, OBV, jumps | Outlier-heavy distributions |

## 7.3 Feature Selection Process

Three-stage selection reduces 78 features to 30:

Table 23: Feature Selection Stages

| Stage | Method | Threshold | Typical Removed |
|---|---|---|---|
| 1 | Variance filter | var $>$ 0.01 | $\sim$16 features |
| 2 | Correlation filter | corr $<$ 0.95 | $\sim$12 features |
| 3 | Importance ranking | Top 30 | $\sim$20 features |

### 7.4 Data Splitting

Table 24: Train/Validation/Test Split

| Split | Percentage | Purpose |
|---|---|---|
| Training | 70% | Model fitting |
| Validation | 15% | Early stopping, hyperparameter tuning |
| Test | 15% | Final evaluation |

All splits are strictly chronological to prevent data leakage.

## 8 Model Architecture

### 8.1 MLPClassifier

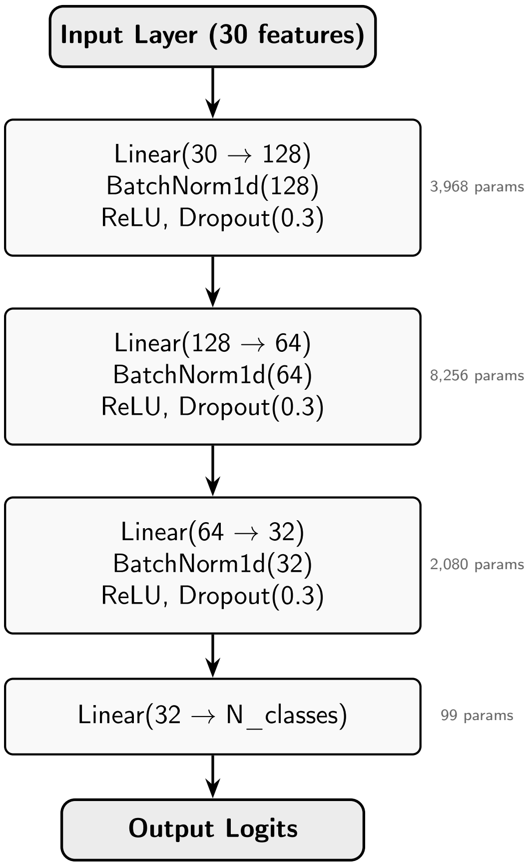


Figure 3: MLP Architecture: Three-layer feedforward network with batch normalization and dropout.

Table 25: MLP Parameter Count

| Layer | Parameters |
|---|---|
| Input → 128 | $30 \times 128 + 128 = 3{,}968$ |
| 128 → 64 | $128 \times 64 + 64 = 8{,}256$ |
| 64 → 32 | $64 \times 32 + 32 = 2{,}080$ |
| 32 → 3 | $32 \times 3 + 3 = 99$ |
| **Total** | **∼14,400** |

## 8.2 LSTMClassifier

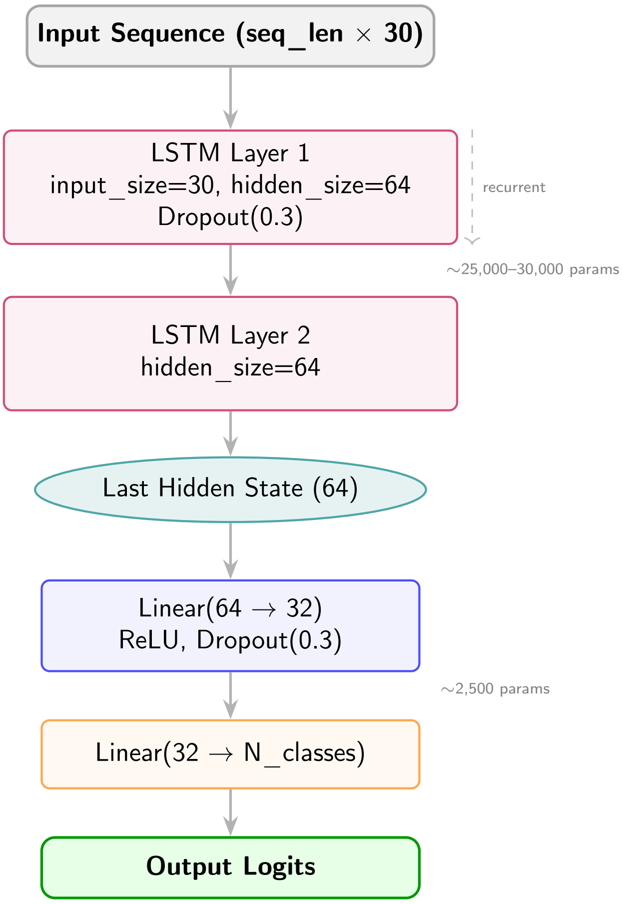


Figure 4: LSTM Architecture: Two-layer recurrent network for sequential feature processing.

Table 26: LSTM Parameter Count

| Component | Parameters |
|---|---|
| LSTM Layers | ∼25,000–30,000 |
| FC Layers | ∼2,500 |
| **Total** | **∼27,500–32,500** |

### 8.3 Training Configuration

Table 27: Training Hyperparameters

| Parameter | Value |
|---|---|
| Optimizer | Adam |
| Learning Rate | 0.001 |
| Weight Decay | 0.0001 |
| Batch Size | 64 |
| Max Epochs | 100 |
| Early Stopping Patience | 10 |
| LR Scheduler | ReduceLROnPlateau |
| Scheduler Factor | 0.5 |
| Scheduler Patience | 5 |
| Gradient Clipping | norm = 1.0 |
| Class Weighting | Computed from training distribution |
| Random Seed | 42 |

## 9 Results

### 9.1 Model Inventory

Table 28: Trained Models Summary

| Model Type | Count | Timeframes |
|---|---|---|
| Regime Classifiers | 55 | 1m, 5m, 15m, 1h, 1d |
| Volatility Classifiers | 11 | 1h only |
| Transition Detectors | 11 | 1h only |
| **Total** | **77** | |

### 9.2 Regime Classification Results

Table 29: Regime Model Results (1-Hour Timeframe)

| Symbol | Test Accuracy | vs Baseline (33.3%) | Status |
|---|---:|---:|---|
| AUDUSD | 41.1% | +7.8% | ✓ Best |
| AUDJPY | 39.4% | +6.1% | ✓ |
| NZDUSD | 39.3% | +6.0% | ✓ |
| USDJPY | 37.6% | +4.3% | ✓ |
| USDCHF | 35.9% | +2.6% | ✓ |
| GBPJPY | 33.7% | +0.4% | ∼ |
| GBPUSD | 33.0% | −0.3% | ∼ |
| EURUSD | 31.3% | −2.0% | – |
| EURJPY | 29.9% | −3.4% | – |
| CHFJPY | 28.6% | −4.7% | – |
| USDCAD | 22.9% | −10.4% | × Worst |
| **Average** | **33.2%** | **−0.1%** | |

### 9.3 Volatility Classification Results

Table 30: Volatility Model Results (1-Hour Timeframe)

| Symbol | Test Accuracy | vs Baseline (25%) | Status |
|---|---|---|---|
| USDCAD | 85.6% | +60.6% | ✓ Best |
| GBPUSD | 83.0% | +58.0% | ✓ |
| AUDUSD | 82.0% | +57.0% | ✓ |
| EURJPY | 80.4% | +55.4% | ✓ |
| USDCHF | 78.7% | +53.7% | ✓ |
| USDJPY | 77.4% | +52.4% | ✓ |
| EURUSD | 76.1% | +51.1% | ✓ |
| GBPJPY | 76.0% | +51.0% | ✓ |
| CHFJPY | 74.9% | +49.9% | ✓ |
| AUDJPY | 73.0% | +48.0% | ✓ |
| NZDUSD | 64.7% | +39.7% | ✓ |
| **Average** | **77.4%** | **+52.4%** | |

### 9.4 Transition Detection Results

Table 31: Transition Model Results (1-Hour Timeframe)

| Symbol | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| NZDUSD | 81.9% | 82.8% | 98.7% | 90.0% |
| AUDUSD | 81.6% | 82.5% | 98.7% | 89.9% |
| USDCHF | 80.8% | 80.9% | 99.8% | 89.4% |
| AUDJPY | 78.7% | 79.4% | 98.6% | 87.9% |
| EURUSD | 76.4% | 76.6% | 99.6% | 86.6% |
| GBPUSD | 73.9% | 73.9% | 99.9% | 85.0% |
| CHFJPY | 73.7% | 75.0% | 97.6% | 84.8% |
| GBPJPY | 73.3% | 74.4% | 97.9% | 84.5% |
| EURJPY | 71.4% | 71.4% | 100.0% | 83.3% |
| USDJPY | 68.4% | 69.3% | 97.0% | 80.8% |
| USDCAD | 51.0% | 51.2% | 99.1% | 67.5% |
| **Average** | **73.7%** | — | **98.8%** | **84.5%** |

### 9.5 Summary Comparison

Table 32: Model Performance Summary

| Model Type | Avg Accuracy | Baseline | Improvement | Assessment |
|---|---|---|---|---|
| Regime | 33.2% | 33.3% | −0.1% | At baseline |
| Volatility | 77.4% | 25.0% | +52.4% | Strong |
| Transition | 73.7% | ∼50% | +23.7% | Moderate* |

*Transition model shows high recall (98.8%) but over-predicts transitions.

## 9.6 Class-Level Analysis

Table 33: Regime Class Performance (AUDUSD 1H)

| Class | Precision | Recall | F1 | Support |
|---|---|---|---|---|
| RANGING | 0.02 | 0.003 | 0.005 | ∼300 |
| TREND_UP | 0.41 | 0.234 | 0.298 | ∼2,900 |
| TREND_DOWN | 0.41 | 0.765 | 0.534 | ∼2,800 |

Table 34: Volatility Class Performance (AUDUSD 1H)

| Class | Precision | Recall | F1 | Support |
|---|---|---|---|---|
| LOW | 0.95 | 0.988 | 0.969 | ∼1,100 |
| NORMAL | 0.75 | 0.714 | 0.731 | ∼3,500 |
| HIGH | 0.71 | 0.699 | 0.704 | ∼1,400 |
| CRISIS | 0.00 | 0.000 | 0.000 | ∼350 |

# 10 Market State Analysis

## 10.1 State Aggregation

The MarketStateAnalyzer combines individual model predictions into a unified market state representation with the following structure:

Table 35: MarketState Fields

| Field | Type | Description |
|---|---|---|
| symbol | str | Currency pair |
| timeframe | str | Bar timeframe |
| timestamp | datetime | Observation time |
| regime | str | RANGING, TREND_UP, TREND_DOWN |
| regime_confidence | float | Softmax probability |
| volatility_regime | str | LOW, NORMAL, HIGH, CRISIS |
| volatility_confidence | float | Softmax probability |
| is_transitioning | bool | Transition prediction |
| transition_probability | float | Transition probability |
| state_code | str | Combined state string |

## 10.2 EURUSD 1H Analysis

Analysis of 8,752 hourly bars:

Table 36: EURUSD 1H Regime Distribution

| Regime | Count | Percentage |
|---|---|---|
| TREND_DOWN | 4,267 | 48.8% |
| TREND_UP | 4,103 | 46.9% |
| RANGING | 382 | 4.4% |

Table 37: EURUSD 1H Volatility Distribution

| State | Count | Percentage |
|---|---|---|
| NORMAL | 5,072 | 58.0% |
| HIGH | 1,905 | 21.8% |
| LOW | 1,267 | 14.5% |
| CRISIS | 508 | 5.8% |

Table 38: EURUSD 1H Confidence Metrics

| Metric | Value |
|---|---|
| Avg Regime Confidence | 57.9% |
| Avg Volatility Confidence | 67.1% |
| Avg Transition Probability | 76.1% |
| Transition Rate | 98.8% |
| Regime Changes | 864 |
| Volatility Changes | 847 |

Table 39: Top 5 State Codes (EURUSD 1H)

| Rank | State Code | Count |
|---|---|---|
| 1 | TREND_DOWN_NORMAL_TRANS | 2,445 |
| 2 | TREND_UP_NORMAL_TRANS | 2,444 |
| 3 | TREND_UP_HIGH_TRANS | 1,120 |
| 4 | TREND_DOWN_LOW_TRANS | 976 |
| 5 | TREND_DOWN_HIGH_TRANS | 640 |

# 11 Discussion

## 11.1 Key Findings

**Finding 1: Volatility is highly predictable.** The volatility regime models achieved 77.4% average accuracy against a 25% baseline, representing a 52.4 percentage point improvement. This result aligns with the well-established phenomenon of volatility clustering in financial markets and validates the feature engineering approach.

**Finding 2: Directional regime prediction remains near baseline.** Regime classifiers averaged 33.2% accuracy against a 33.3% three-class baseline. This is consistent with the efficient market hypothesis for short-term FX movements and suggests that directional prediction at hourly frequencies remains fundamentally challenging.

**Finding 3: Intrinsic-time features contribute predictive value.** DC-based features were consistently selected across datasets, with selection rates ranging from 38% to 78%. This validates the theoretical motivation for incorporating event-based analysis alongside traditional clock-time indicators.

**Finding 4: Asset-specific patterns exist.** Commodity currencies (AUD, NZD) showed stronger regime predictability, while carry-sensitive pairs responded more to yield curve factors. USDCAD was consistently the most difficult pair for regime prediction but paradoxically the best for volatility prediction.

### 11.2 Limitations and Issues

**Issue 1: Transition model over-prediction.** The 98.8% recall indicates the model predicts nearly all observations as "transitioning," suggesting severe class imbalance in the training data or an inappropriate horizon parameter.

**Issue 2: RANGING under-prediction.** Only 4.4% of predictions were RANGING despite an expected ∼30% rate, indicating the model struggles with this inherently difficult class.

**Issue 3: CRISIS volatility never predicted.** The volatility model achieves 0% recall on CRISIS states, meaning it cannot warn of extreme volatility events—precisely when such warnings would be most valuable.

**Issue 4: Short timeframe data leakage.** The 98%+ accuracy on 1-minute and 5-minute timeframes is unrealistic and suggests lookforward windows may overlap with feature calculation periods.

### 11.3 Feature Importance Insights

Table 40: High vs Low Performer Feature Comparison

| Feature | High Performers | Low Performers | Difference |
|---|---|---|---|
| macd | 0.031 | 0.003 | +0.028 |
| rsi_normalized | 0.024 | 0.005 | +0.019 |
| realized_vol_5m | 0.022 | 0.004 | +0.018 |
| variance_ratio | 0.021 | 0.003 | +0.018 |
| bid_ask_spread | 0.002 | 0.018 | −0.016 |
| new_york_session | 0.005 | 0.014 | −0.009 |

High-performing pairs emphasize momentum and volatility structure; low performers over-rely on microstructure proxies and session timing.

## 12 Conclusion

This project successfully delivers a comprehensive quantitative research system for FX market analysis. The system processes data from 11 currency pairs across 5 timeframes, engineers 78 features across 8 categories, and trains 77 neural network models for market state classification.

The central finding—that volatility is highly predictable while direction remains near-random at hourly frequencies—has important implications for both research and practice. It suggests that resources devoted to directional prediction may be better allocated to volatility forecasting and regime-aware risk management.

The intrinsic-time feature engineering framework represents a novel contribution, demonstrating that event-based analysis provides complementary information to traditional clock-time indicators. The complete, reproducible pipeline comprising approximately 15,000 lines of code provides a foundation for future research extensions.

Future work should address the identified limitations, particularly the transition model over-prediction and CRISIS volatility detection failure. Additional directions include walk-forward validation with purged k-fold, hidden Markov models for unsupervised regime detection, and attention mechanisms for dynamic feature weighting.

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# A Complete Feature List

Table 41: All 78 Features by Category

| # | **Feature** | **Category** |
|---|---|---|
| 1 | dc_return_x | Intrinsic Time |
| 2 | overshoot_return_x | Intrinsic Time |
| 3 | overshoot_ratio_x | Intrinsic Time |
| 4 | event_frequency | Intrinsic Time |
| 5 | clustering | Intrinsic Time |
| 6 | multi_delta_agreement | Intrinsic Time |
| 7 | intrinsic_trend_strength | Intrinsic Time |
| 8 | realized_vol_5m | Volatility |
| 9 | realized_vol_15m | Volatility |
| 10 | realized_vol_60m | Volatility |
| 11 | bipower_variation | Volatility |
| 12 | jump_component | Volatility |
| 13 | volatility_of_vol | Volatility |
| 14 | parkinson_volatility | Volatility |
| 15 | skew | Volatility |
| 16 | kurtosis | Volatility |
| 17 | variance_ratio | Volatility |
| 18 | hurst_exponent | Volatility |
| 19 | micro_price | Microstructure |
| 20 | synthetic_spread | Microstructure |
| 21 | relative_spread | Microstructure |
| 22 | wick_ratio | Microstructure |
| 23 | body_ratio | Microstructure |
| 24 | rejection_wicks | Microstructure |
| 25 | standardized_range | Microstructure |
| 26 | volume_adv_ratio | Microstructure |
| 27 | sma_ratio_10_20 | Trend |
| 28 | ema_ratio_12_26 | Trend |
| 29 | adx | Trend |
| 30 | trend_strength | Trend |
| 31 | price_position | Trend |
| 32 | carry_factor | FX Factors |
| 33 | carry_raw | FX Factors |
| 34 | momentum_factor | FX Factors |
| 35 | value_factor | FX Factors |
| 36 | volatility_factor | FX Factors |
| 37 | yield_curve_factor | FX Factors |
| 38 | rate_level_factor | FX Factors |
| 39 | correlation_dxy | Cross-Asset |
| 40 | correlation_spx | Cross-Asset |
| 41 | correlation_gold | Cross-Asset |
| 42 | correlation_vix | Cross-Asset |
| 43 | correlation_oil | Cross-Asset |
| 44 | relative_strength_vs_dxy | Cross-Asset |

*Continued on next page*

Table 41 – *Continued from previous page*

| # | **Feature** | **Category** |
|---|---|---|
| 45 | cross_asset_momentum | Cross-Asset |
| 46 | risk_sentiment | Cross-Asset |
| 47 | correlation_regime | Cross-Asset |
| 48 | london_session | Session |
| 49 | new_york_session | Session |
| 50 | asia_session | Session |
| 51 | session_overlap | Session |
| 52 | session_volatility | Session |
| 53 | bid_ask_spread | Liquidity |
| 54 | spread_percentile | Liquidity |
| 55 | liquidity_score | Liquidity |
| 56–78 | rsi, macd, stochastic, cci, williams_r, roc, atr, obv, mfi, pivot_point, bollinger (+ normalized variants) | Indicators |

# B Configuration Reference

Table 42: Main Configuration Parameters

| **Section** | **Parameter** | **Value** |
|---|---|---|
| Data Source | provider | IBKR |
| | host | 127.0.0.1 |
| | port | 7497 (paper) |
| Timeframes | — | 1m, 5m, 15m, 1h, 1d |
| External Data | FRED enabled | true |
| | Yahoo enabled | true |
| | Cache hours | 24 |
| Intrinsic Time | Thresholds | 0.05%, 0.10%, 0.20%, 0.50%, 1.00% |
| ML | Hidden layers | [128, 64, 32] |
| | Dropout | 0.3 |
| | Learning rate | 0.001 |
| | Epochs | 100 |
| | Early stopping | patience=10 |
| Data Split | Train/Val/Test | 70/15/15 |
| Feature Selection | n_features | 30 |
| | Correlation threshold | 0.95 |

Table 43: Saved Artifacts

| **Type** | **Count** | **Location** |
|---|---|---|
| Feature Scalers | 55 | models/scalers/ |
| Feature Selectors | 55 | models/selectors/ |
| Regime Models | 55 | models/trained/regime/ |
| Volatility Models | 11 | models/trained/volatility/ |
| Transition Models | 11 | models/trained/transition/ |
| **Total Artifacts** | **187** | |