

Milestone 4

Model Training (ESN & Deep Baselines for Multi-Horizon Return Forecasting)

Group 3 – DS and AI Lab

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1 SCOPE

This milestone executes the training plan from M3: we train the proposed Echo State Network (ESN) and three deep baselines (LSTM, Transformer, Temporal ConvNet/TCN), alongside a linear Ridge lower bound. All models run in our leakage-safe, walk-forward pipeline (Train $\approx 10y = 2520$ days; Test $\approx 1y = 252$ days; Step = 252 days). We report preliminary results (fold 0, $h=1$ day) and document the training protocol, hyperparameter grids, and early findings.

2 TRAINING PROTOCOL

INPUTS. Per-fold standardized features $u_t \in \mathbb{R}^d$ (ret_1, ret_2, ret_5, vol_20, ma_10, ma_20, ma_gap, rsi_14, vol_z, dow); targets are forward log-returns y_{t+h} for $h \in \{1, 5, 20\}$.

WALK-FORWARD & SCALING. For each fold k : fit a *StandardScaler* on train features only, transform train/test, and save `train.csv`, `test.csv`, `scaler.json`. This prevents leakage of global moments.

MODEL-SPECIFIC TRAINING.

- **Ridge (lower bound):** minimize MSE with L2 penalty λ .
- **ESN (state-space):** roll the leaky reservoir

$$x_t = (1 - a)x_{t-1} + a \tanh(W_{\text{in}}[1; u_t] + Wx_{t-1}),$$

discard a washout w , then solve ridge closed-form for the readout: $W_{\text{out}} = (H^\top H + \alpha I)^{-1} H^\top Y$, with $H = [\mathbf{1} \ X]$.

- **LSTM/Transformer/TCN (deep baselines):** sequence-to-one regressors on left-padded windows of length L ; MSE loss, Adam optimizer. Validation = last 10% of the train window; best state by lowest val loss.

METRICS. On the test window: RMSE, MAE, R^2 , direction accuracy (sign agreement). We also compute a *toy* sign-based backtest (1 bp per-trade cost):

$$\text{position}_t = \text{sgn}(\hat{y}_t), \quad \text{pnl}_t = \text{position}_t \cdot y_t - \text{cost} \cdot |\Delta \text{position}_t|.$$

We summarize avg daily P&L, volatility, Sharpe (daily \rightarrow annualized by $\sqrt{252}$), hit ratio, and turnover. (This is diagnostic, not a trading claim.)

3 HYPERPARAMETER GRIDS

Small grids are used to keep runtime reasonable; they map one-to-one to `config/experiments.py`.

- **ESN:** $H \in \{400, 800\}$, spectral radius $\gamma \in \{0.85, 0.95\}$, leak $a \in \{0.3, 1.0\}$, ridge $\alpha \in \{0.3, 3.0\}$, density = 0.1, washout = 100, seed = 0.
- **LSTM:** $L \in \{32, 64\}$, hidden $\in \{128, 256\}$, layers $\in \{1, 2\}$, dropout $\in \{0.0, 0.1\}$, epochs = 15, batch = 128, lr = 10^{-3} .
- **Transformer:** $L \in \{32, 64\}$, $d_{\text{model}}=128$, heads = 4, layers = 2, feedforward = 256, dropout = 0.1, epochs = 15.
- **TCN:** $L \in \{32, 64\}$, channels $\in \{(64, 64), (64, 128)\}$, kernel = 3, dropout $\in \{0.0, 0.1\}$, epochs = 15.

4 PRELIMINARY RESULTS (FOLD 0, $h=1$ DAY)

Table 1 reports the first trained runs per model on fold 0. All models use the exact same features, scaling, and test window.

model	fold	horizon	RMSE	MAE	R^2	DirAcc	AvgPnL	Vol	Sharpe	Turnover
ridge	0	h1	0.008335	0.005989	-0.005	0.492	0.000077	0.008323	0.147	0.687
lstm	0	h1	0.009392	0.007025	-0.276	0.508	0.000208	0.008325	0.396	0.337
esn	0	h1	0.010098	0.007852	-0.475	0.528	0.000841	0.008278	1.612	0.853
transformer	0	h1	0.014366	0.011092	-1.986	0.480	-0.000127	0.008332	-0.242	0.456
tcn	0	h1	0.028566	0.019333	-10.807	0.552	0.000433	0.008313	0.826	0.631

Table 1: Preliminary test metrics (fold 0, $h=1$). Sharpe computed from the toy sign backtest (1 bp cost).

KEY FINDINGS (SO FAR).

- **Best forecaster by magnitude:** *Ridge* has the lowest RMSE/MAE (others yield $R^2 < 0$, i.e., not beating the mean on scale).
- **Best directional/trading signal:** *ESN* delivers the highest Sharpe (1.612) and the highest AvgPnL, with DirAcc > 0.52 .
- **TCN** achieves the highest DirAcc (≈ 0.552) but is poorly calibrated (very large RMSE/MAE); sign still produces Sharpe = 0.826.
- **LSTM** is mid-pack: DirAcc > 0.50 , moderate Sharpe.
- **Transformer** underperforms on this setup (likely undertrained/overparameterized for daily-noise scale).

5 DISCUSSION

WHY ESN HELPS ON DIRECTION. The nonlinear reservoir with controlled memory (γ, a) can capture regime-dependent sign cues even when absolute magnitudes are noisy. Although ESN’s RMSE trails Ridge, its *sign* accuracy and turnover profile yield the strongest toy Sharpe.

WHY RIDGE WINS ON RMSE. A linear readout on carefully standardized, low-variance features is hard to beat for scale in noisy daily returns. Linear bias often reduces variance and overfit.

ON TCN/TRANSFORMER. TCN’s causal dilations seem to learn directional motifs but over/under-scale predictions; calibration (or training on vol-normalized targets) should help. Transformers may require more data/regularization or shorter windows L to stabilize.

6 ERROR ANALYSIS (H=1, FOLD 0)

Residuals for the Ridge baseline are roughly centered and thin-tailed; ESN residuals show heavier tails yet improved sign. Autocorrelation of ESN residuals beyond small lags is weak, suggesting limited temporal structure remains once the sign is extracted. (Figures produced by `src/viz/plots.py`: residual histograms, ACF, true-vs-pred scatter, and last- N time series.)

7 ABLATIONS & NEXT STEPS

PLANNED SWEEPS. Expand grids per model, and evaluate across *all* folds and horizons:

- **ESN:** sweep H , γ , a , α , washout; try seed-averaged ensembles of reservoirs.
- **Targets:** train on volatility-normalized returns $y/\hat{\sigma}$ to improve magnitude calibration; compare to direction-only training.
- **Features:** add cross-asset exogenous inputs (e.g., VIX for SPY) and market-regime indicators; test robustness.
- **Calibration:** post-hoc scaling of predictions (isotonic/Platt on val) to address TCN/Transformer magnitude errors without harming sign.
- **Statistics:** aggregate metrics over folds and conduct Diebold–Mariano tests vs. Ridge for RMSE and sign loss.

8 REPRODUCIBILITY & ARTIFACTS

- **Code.** Modularized under `src/models/*`, `src/train/runner.py`, `src/viz/plots.py`; experiments use unique IDs via parameter slugs.
- **Data.** `data/raw/` (Yahoo), `data/processed/` (features), `data/splits/` (per-fold scaled CSVs + scalers).
- **Experiments.** `data/experiments/model/exp_id/fold.k/{preds,metrics}`; summaries stored per experiment.

9 CONCLUSIONS

On the first trained fold, **Ridge** remains the *magnitude* benchmark, while the proposed **ESN** is the strongest *directional* model by risk-adjusted returns. These patterns are consistent with expectations for noisy daily horizons. Milestone 5 will expand to all folds/horizons, refine grids, and include statistical significance and calibration analyses.

Ethics/Disclaimer. Academic project; not financial advice. Backtests here are simplified diagnostics and do not constitute tradable strategies.