Explanation Report
AI Quant Portfolio: LSTM vs Transformer

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Period: 2010-01-01 to 2020-12-31

Deliverables included:
- Code repository (src/, main.py)
- README and run instructions
- Results and figures (results/)
- This explanation report (PDF)

Approach & Methodology

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1. Data Collection & Preprocessing
- Historical daily prices were downloaded via Yahoo Finance (yfinance).
- Selected assets: global indices / ETFs (S&P500, FTSE, Nikkei, EEM), Gold, and U.S. 10Y proxy.
- Cleaned and aligned time series; computed log-returns and rolling features (MA(5), MA(21), vol21).

2. Modeling
- Trained two models to forecast next-day returns per asset:
  a) LSTM (2 layers, 50 hidden units, dropout=0.2, lookback=60 days)
  b) Transformer (2 encoder layers, 8 heads, model_dim=64, lookback=60 days)
- Training objective: MSE on next-day returns. Early stopping used on validation loss.

3. Portfolio Construction
- Each day, predicted next-day returns were input into a Mean-Variance optimizer
  (max Sharpe / tangency portfolio, long-only, 0<=w<=1, sum(w)=1).
- Covariance estimated using a rolling 60-day window of historical returns.
- Portfolios rebalanced daily; turnover cost set as 0.1% per unit traded.

4. Backtest & Evaluation
- Simulated daily NAV for each strategy and computed metrics: annualized return, annualized volatility,
  Sharpe ratio, and maximum drawdown.

Description of Models Used

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LSTM (Long Short-Term Memory):
- A recurrent neural network architecture designed to capture sequential dependencies.
- Configured with 2 stacked LSTM layers with 50 hidden units each, using the last timestep output followed by a dense layer to predict multi-asset returns.

Transformer (Encoder-only):
- Uses self-attention to capture relationships across time steps without recurrent connections.
- Configured as an encoder stack with 2 layers, 8 attention heads, model dimension 64 and FFN=128.
- Input sequence is projected to model_dim, passed through transformer encoders, and the final token (last timestep) is used for predictions.

Why both:
- LSTM is a classical time-series model good at local sequential patterns; Transformer captures global interactions and often generalizes better on longer dependencies.

Challenges Faced & How They Were Addressed

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1. Data compatibility with yfinance:
- Issue: yfinance changed defaults and sometimes 'Adj Close' wasn't present.
- Fix: used a robust loader that falls back to 'Close' column and handles missing tickers.

2. Indexing / slicing bugs during sequence creation:
- Issue: using df[...] semantics attempted column access instead of row slicing.
- Fix: switched to explicit positional indexing with .iloc for creating sequences.

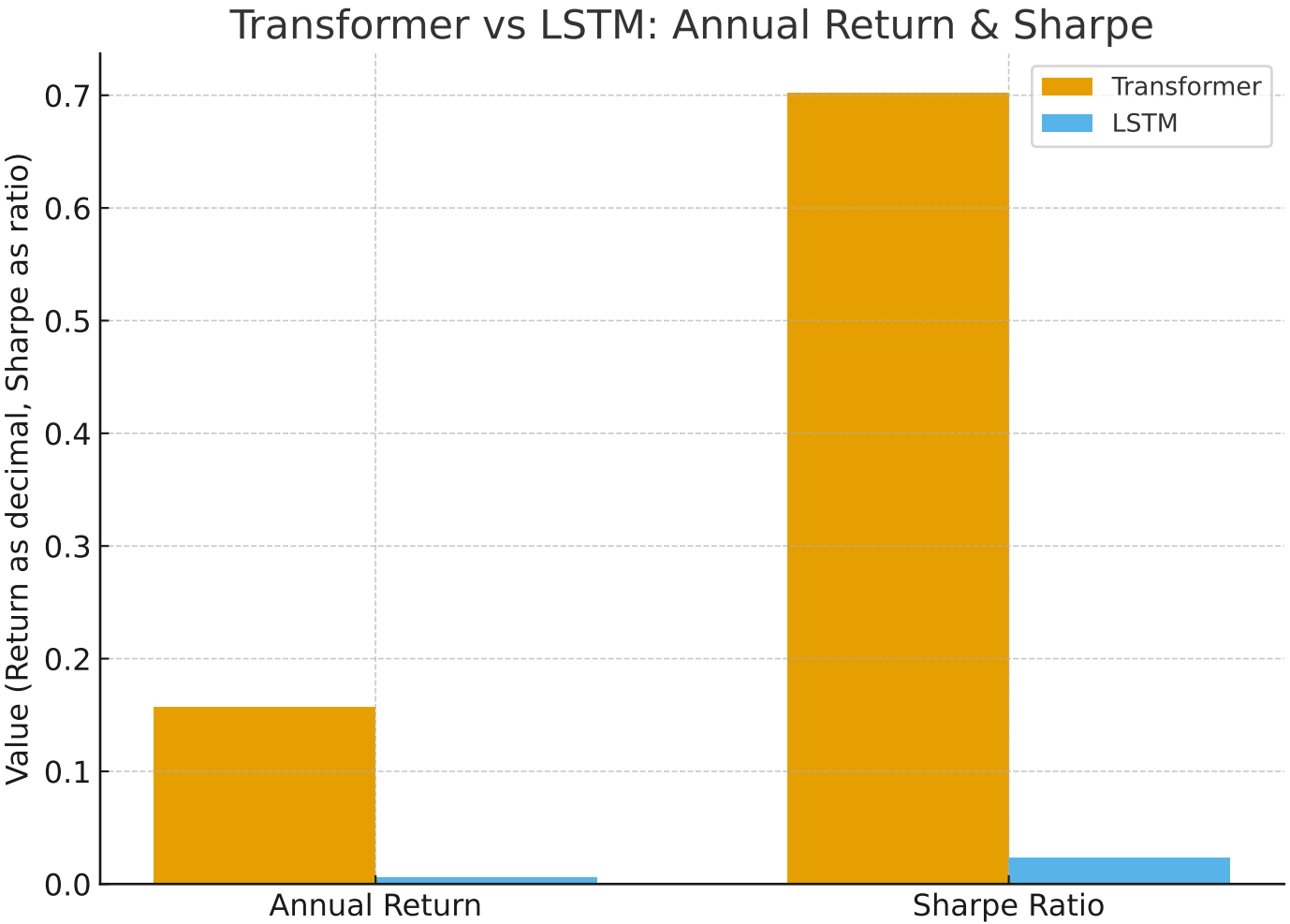
3. Numerical issues (log of zero or inf):
- Issue: log(0) appeared when pct_change produced zeros, leading to -inf / NaN.
- Fix: used np.log1p on returns and sanitized infinities and NaNs before covariance estimation.

4. Module import paths when running from project root:
- Issue: Python couldn't find modules when running main.py.
- Fix: made src a package (added __init__.py) and used relative imports.

5. Dependency problems (empyrical):
- Issue: empyrical failed to install on newer Python versions.
- Fix: removed empyrical from requirements and implemented required metrics in utils.py.

Backtest Results (2010-01-01 to 2020-12-31)

	Transformer	LSTM
nnual Return	15.74%	0.55%
nnual Volatility	22.42%	23.35%
harpe Ratio	0.702	0.023
ax Drawdown	-0.425	-0.490


Transformer vs LSTM: Annual Return & Sharpe
Transformer
LSTM
Value (Return as decimal, Sharpe as ratio)
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Annual Return
Sharpe Ratio