



PARSHWANATH CHARITABLE TRUST'S

A.P. SHAH INSTITUTE OF TECHNOLOGY

Department of Computer Science and Engineering
Data Science



Semester: VII

Subject: AIFB

Academic Year: 2024-25

- Sharpe Ratio
- Max drawdown
- Win/Loss ratio
- Hit rate (classification accuracy)

(6) Walk Forward Analysis:

- Train the model on a rolling window (eg. last 2 years), test on the next month.
- Continue forward, updating the model periodically.

(7) Evaluation and Comparison:

Compare DNN strategy with .

- * Buy and hold model.
- * Moving Average Crossover.
- * Other ML models (Random Forest, XGBoost).

This is how backtesting a daily DNN based strategy is executed.

BACKTESTING AN INTRADAY DNN BASED STRATEGY:

Backtesting an Intraday Deep Neural Network (DNN) - Based strategy is more complex than daily strategies due to high-frequency data, faster decision-making, and greater sensitivity to latency and transaction costs. Here's how to approach it:

Step-by-step guide:

(1) Data Collection:

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Collecting a high-frequency data for assets (stocks, crypto, etc). at intraday intervals like 1-minute, 5-minute or 15-minute candles.

→ Data Needed are OHLCV → Open, High, Low, Close, Volume.

(2) Feature Engineering:

You need to turn raw data into inputs that a model can learn from:

Examples:

Price returns: % change or log returns over 1 or more intervals.

→ Technical indicators: RSI, MACD etc.

→ Volume indicators: VWAP, volume delta, spikes.

→ Time features: Time of day (trading behaviour changes hourly).

→ Lag features: Include data from past n minutes (rolling window).

Windowing:-

Create a fixed-size sliding window of data. For example.

→ Input: Data from minute $t-10$ to t .

→ Predict: Price direction or return at $t+1$.

(3) DNN model design:

MLP (Fully connected DNN): Good for static data.

LSTM/GRU: Recurrent Neural networks for time-series forecasting.

CNN: Detect patterns in sequences like price waves.

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Semester: VIIISubject: AI/EBAcademic Year: 2024-25Architecture Example:

model = Sequential([

Input (shape = (10, 6), ~~10~~ # 10 time steps, 6 features

LSTM(64) # It adds LSTM layer with 64 units (neurons)

Dropout (0.2) # It randomly disables 20% of neurons during each training step to prevent overfitting.

Dense(1, activation = "sigmoid") # Dense(1) means

a scalar output for single neuron. sigmoid squashes the output between 0 and 1. If 1 then buy else sell (0).

(4) Training Strategy:

→ Split by time: Train → validate → test

→ Walk forward: Retrain the model regularly using most recent data.

→ Avoid data leakage: Don't let future data into training or validation.

(5) Backtesting Framework:

Simulate what would happen if you used your model to trade in the past.

(6) Feed model the latest window of features.

* Make a prediction: buy/sell/hold.

* Simulate the trade.

* Update capital and portfolio.

* Repeat for next time step.

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(b) Performance Metrics:

To measure:

- * Cumulative return: Total percentage gain/loss over the period.
- * Sharpe Ratio: Return relative to risk.
- * Sortino Ratio: Sharpe with focus on downside volatility.
- * Max Drawdown: Worst capital drop from a peak.
- * Hit rate: % of correct predictions.
- * Profit factor: Gross profit / gross loss.

The Full Workflow:

Raw Intraday Data



Feature Engineering (Indicators, Lagged Returns, Volume)



Create sliding Windows (Supervised-format)



Train DNN (LSTM, CNN, MLP)



Use model to predict on Historical Data



BackTest Simulation



Evaluate Metrics.