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Using Machine Learning in Swing or Intraday Trading

Why predictions are difficult

Financial markets are highly stochastic – prices are influenced by human behaviour, news, macro-economic data and even weather. A 2025 review notes that stock prices exhibit **volatile and irrational behaviour**, making them hard to predict precisely [1]. Models can identify patterns and generate probabilities, but they **do not guarantee profits** and can suffer during unusual market regimes. A research paper using Indian 5-minute NIFTY data showed that even sophisticated bots produced modest profits; a permutation decision-tree strategy gained **1.35 % in 12 days**, whereas an LSTM bot returned **0.12 %**, and a recurrent neural network (RNN) bot returned **0.31 %**, although all still beat a buy-and-hold strategy [2]. Another 2025 study on S&P 500 data found that simple **linear regression** outperformed both artificial neural networks and long-short-term memory (LSTM) models when predicting next-day closing prices [3].

Process for building a trading model

1. **Data collection:** Obtain high-quality historical data. For swing trading (positions held a few days), daily OHLCV (Open/High/Low/Close/Volume) data is common. For intraday trading, minute-level or tick data is necessary. Some studies also incorporate technical indicators, order-book depth and news sentiment [4].

2. **Feature engineering:** Create features that capture patterns. Examples include price returns, moving averages, RSI, MACD, volatility bands, volume-weighted price, rolling highs/lows or technical levels. For next-day open/close prediction, lagged features (previous day's open, high, low, close, volume) can be useful; one study trained models using only **1-day lagged features** and achieved reasonable performance [3]. For intraday models, features such as order-flow imbalance, bid-ask spread and time-of-day effect are often added.

3. **Preprocessing:** Clean missing or corrupt values, align data by timestamp, and **normalize or standardize** features to ensure the model focuses on trends rather than scale [5]. For sequence models, create sliding windows (e.g., previous 60 periods to predict the next period) [6].

4. **Model selection and training:** Split the data into training/validation/test sets and tune hyper-parameters using cross-validation [7]. Back-test the strategy using historical data to assess realistic returns, including transaction costs and slippage [8]. Evaluate using metrics like mean absolute error (MAE), root mean squared error (RMSE) and risk–adjusted measures (Sharpe ratio). Always incorporate risk management (stop-loss, position sizing) to limit potential losses [9].

5. **Deployment:** Once a model shows acceptable performance, implement it in a paper-trading environment before risking real capital. Monitor out-of-sample results and retrain periodically as market regimes change.

Common algorithms and their use cases

Algorithm	Type	Suitable for	Strengths	Limitations
Linear Regression	Statistical regression	Predicting next-day prices based on a few lagged features	Simple, interpretable; performed best among linear regression, ANN and LSTM in predicting next-day S&P 500 closing prices [3]	Assumes linear relationships; may underperform when market dynamics are non-linear
Random Forest	Ensemble of decision trees	Non-linear regression/ classification tasks	Robust to over-fitting; handles mixed data types; good baseline for swing-trading signals [10]	Less interpretable; may not capture temporal order unless features include lags
Gradient Boosting (XGBoost/ LightGBM)	Ensemble boosting	Ranking trade opportunities; probability estimates	High accuracy on structured data; often wins machine-learning competitions [11]	Requires careful tuning; computationally heavier
Support Vector Machine (SVM)	Classifier/ regressor	Classifying market direction (up/ down) [12]	Effective in high-dimensional spaces; robust to over-fitting	Not ideal for very large datasets; less suited for multi-step forecasting
Artificial Neural Network (ANN)	Feed-forward neural network	Capturing non-linear relationships in daily data	Can model complex patterns; some research shows PCA-ANN hybrids achieve high accuracy [13]	Requires tuning; risk of over-fitting; black box

Algorithm	Type	Suitable for	Strengths	Limitations
LSTM (Long-Short-Term Memory)	Recurrent neural network	Time-series forecasting; capturing long-range dependencies	Handles sequential data well and is widely used in deep learning [14]	Computationally intensive; may underperform simple models on next-day predictions; a 2025 study reported that LSTM performed worse than linear regression for S&P 500 next-day closing prices [3]
Permutation Decision Tree (PDT)	Variant of decision tree designed to reduce over-fitting	High-frequency intraday trading	In a 2025 study on NIFTY 50 5-minute data, a PDT bot achieved **1.35 %** profit in 12 days, outperforming LSTM and RNN bots [2]	Requires custom implementation; performance depends on specific market conditions
Other models (ARIMA, GARCH, ANFIS)	Time-series/ statistical/ hybrid	Forecasting mean and volatility	ARIMA/GARCH capture auto-correlations and volatility clustering; ANFIS (adaptive neuro-fuzzy inference) can model fuzzy logic [15]	Often require stationarity; may not adapt quickly to regime changes

Considerations for swing vs. intraday trading

- **Time frame:** Swing trading uses daily or hourly bars and aims to catch multi-day trends. In this context, technical indicators (moving averages, momentum oscillators) combined with tree-based models (Random Forest, Gradient Boosting) or simple regression can be effective. The S&P 500 study suggests starting with linear regression and exploring ANN or gradient boosting [3] .

- **Intraday trading:** Intraday models operate on minute-level data and must react quickly. Sequential models like LSTM or other recurrent networks are often used because they can capture temporal dependencies. However, the high noise in intraday data means prediction accuracy is usually low; risk management and back-testing are crucial. The NIFTY 5-minute study found that a permutation decision-tree approach with a trailing stop-loss outperformed LSTM and RNN models [2] .

- **Feature richness:** Incorporating additional data (earnings announcements, macro indicators, social-media sentiment) can improve models but also increases complexity. Always evaluate whether additional features meaningfully improve predictive power.

Practical advice and cautions

- **Start simple:** Use a basic linear regression or decision-tree model as a benchmark. If these models cannot beat a naïve baseline (e.g., predicting that tomorrow's open/close equals today's close), more complex models may not either.

- **Back-testing and validation:** Always back-test strategies on unseen historical data and include transaction costs and slippage [8]. Many academic models show high accuracy on paper but underperform in live trading.

- **Risk management:** ML models should be part of a broader trading plan that includes stop-losses, position sizing and diversification. The 3Commas guide emphasises that bots must adhere to strict risk rules and that ML complements rather than replaces human judgement [9].

- **No guarantee of profit:** Even sophisticated models can fail when market conditions change abruptly. The goal of ML in trading is to improve the probability of success, not to predict exact prices. Consult a qualified financial adviser before committing capital.

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