# KAILASA CAPITAL – ALGORITHMIC TRADING STRATEGIES REPORT

## EXECUTIVE SUMMARY

This report provides a comprehensive analysis of the algorithmic trading strategies developed and implemented by Kailasa Capital for the Indian equity market, specifically focused on Nifty 50 and Nifty Bank indices. The strategies are designed to capitalize on different market conditions and timeframes, utilizing various technical indicators, pattern recognition techniques, and mathematical models to generate trading signals.

The three core strategies implemented are:   
1. **Strategy 1: Indicator-Based** - Applied to daily timeframes   
2. **Strategy 2: Trend-Based** - Applied to 15-minute timeframes   
3. **Strategy 3: Momentum-Based** - Applied to 60-minute timeframes

Each strategy has been thoroughly back-tested against historical data spanning from 2020 to 2025, with performance metrics demonstrating their effectiveness in generating consistent returns while managing risk effectively.

## TABLE OF CONTENTS

1. Data Overview and Preparation
2. Strategy 1: Indicator-Based Approach – BackTesting
3. Strategy 2: Trend-Based Approach
4. Strategy 3: Momentum-Based Approach
5. Mathematical Foundations
6. Performance Metrics and Back-testing Results
7. Risk Management Framework
8. Implementation Considerations
9. Conclusion and Recommendations

## 1. DATA OVERVIEW AND PREPARATION

### Data Sources

The strategies utilize historical OHLCV (Open, High, Low, Close, Volume) data for Nifty 50 and Nifty Bank indices across multiple timeframes: - Daily data: January 2020 to February 2025 - 60-minute data: Approximately 8,855 bars (equivalent to ~4 years of market data) - 15-minute data: 31,638 bars (equivalent to ~5 years of market data)

### Data Preparation Process

For all strategies, the data preparation follows a consistent workflow:   
1. Loading raw CSV files containing historical OHLCV data   
2. Converting date and time columns to appropriate datetime formats   
3. Sorting data chronologically   
4. Computing derived fields and indicators specific to each strategy

Example code snippet for data preparation:

*# Data loading and preparation for 15-minute timeframe*

|  |
| --- |
| **df = pd.read\_csv('datasets/NF\_15.csv') df["datetime"] = pd.to\_datetime(df["date"] + " " + df["time"]) df = df.sort\_values("datetime").reset\_index(drop=True)** |

## 2. STRATEGY 1: INDICATOR-BASED APPROACH (DAILY TIMEFRAME)

### Strategy Overview

Strategy 1 employs a combination of technical indicators to identify potential trading opportunities on a daily time frame. It utilizes the relationship between price action, momentum indicators, and moving averages to generate signals.

### Key Components

#### Indicators Used:

* **Relative Strength Index (RSI)** - 14-period RSI to measure momentum
* **Moving Average Convergence Divergence (MACD)** - To identify changes in strength, direction, momentum, and duration of trends
* **Simple Moving Average (SMA)** - 50-period SMA to identify the overall trend direction

#### Signal Generation Logic:

* **Long Signal**: RSI > 55, MACD histogram > 0 and increasing, price above 50-period SMA
* **Short Signal**: RSI < 45, MACD histogram < 0 and decreasing, price below 50-period SMA

#### Entry and Exit Mechanisms:

* **Entry**: Open of next candle or previous high/low (whichever is more conservative)
* **Exit**: Fixed profit target of 400 points or stop loss of 75 points for long positions and 50 points for short positions

### Implementation Details

*# CALCULATION FOR INDICATORS*

|  |
| --- |
| **df['rsi'] = RSIIndicator(close=df['close'], window=14).rsi() macd = MACD(close=df['close'], window\_slow=26, window\_fast=12, window\_sign=9) df['macd\_hist'] = macd.macd\_diff() df['macd\_increasing'] = df['macd\_hist'].diff() > 0 df['macd\_decreasing'] = df['macd\_hist'].diff() < 0 df['ma'] = SMAIndicator(close=df['close'], window=ma\_length).sma\_indicator()  # GENERATING SIGNALS df['long\_signal'] = (df['rsi'] > 55) & (df['macd\_hist'] > 0) & df['macd\_increasing'] & (df['close'] > df['ma']) df['short\_signal'] = (df['rsi'] < 45) & (df['macd\_hist'] < 0) & df['macd\_decreasing'] & (df['close'] < df['ma'])** |

## 3. STRATEGY 2: TREND-BASED APPROACH (15-MINUTE TIMEFRAME)

### Strategy Overview

Strategy 2 is designed to capture intraday trends using 15-minute data. It employs a custom Renko chart implementation combined with specific time-of-day filters to identify high-probability trading opportunities.

### Key Components

#### Technical Elements:

* **Renko Charts**: Custom implementation with 10-point brick size
* **Trend Detection**: Sequence of consecutive up/down bricks to identify strong trends
* **Time Filters**: Specific trading windows during high liquidity periods
* **ATR-based volatility adjustments**: To adapt to changing market conditions

#### Signal Generation Logic:

* **Long Signal**: Uptrend detected in Renko chart during optimal trading hours
* **Short Signal**: Downtrend detected in Renko chart during optimal trading hours

#### Entry and Exit Mechanisms:

* **Entry**: Market order at the open of the bar following the signal
* **Exit**: Trailing stop loss based on Renko brick reversal or time-based exit at end of session

### Implementation Details

*# CALCULATING TRADITIONAL RENKO*

|  |
| --- |
| **brick\_size = 10 df['renko'] = df['close'].copy()  # Create Renko bricks renko\_prices = [] renko\_directions = []  current\_price = df['close'].iloc[0] renko\_prices.append(current\_price) renko\_directions.append(0) # Initial brick has no direction  for i in range(1, len(df)):  close = df['close'].iloc[i]    # Determine if we need to add new bricks  while True:  if close >= current\_price + brick\_size:  current\_price += brick\_size  renko\_prices.append(current\_price)  renko\_directions.append(1) # Up brick  elif close <= current\_price - brick\_size:  current\_price -= brick\_size  renko\_prices.append(current\_price)  renko\_directions.append(-1) # Down brick  else:  break  df['renko\_direction'] = 0  # Assign the directions to the dataframe for i in range(1, len(df)):  if df['close'].iloc[i] > df['close'].iloc[i-1] + brick\_size:  df.loc[i, 'renko\_direction'] = 1  elif df['close'].iloc[i] < df['close'].iloc[i-1] - brick\_size:  df.loc[i, 'renko\_direction'] = -1** |

## 4. STRATEGY 3: MOMENTUM-BASED APPROACH (60-MINUTE TIMEFRAME)

### Strategy Overview

Strategy 3 is designed to capture medium-term momentum on an hourly timeframe using Renko charts and supertrend indicators. This approach is particularly effective in capturing sustained price movements while filtering out noise.

### Key Components

#### Technical Elements:

* **Renko Charts**: Using the stocktrends library with adaptive brick sizing
* **Supertrend Indicator**: A trend-following overlay that combines ATR and price action
* **ADX Filter**: To confirm trend strength before entering positions

#### Signal Generation Logic:

* **Long Signal**: Uptrend in Renko chart combined with bullish Supertrend and strong ADX
* **Short Signal**: Downtrend in Renko chart combined with bearish Supertrend and strong ADX

#### Entry and Exit Mechanisms:

* **Entry**: Market order at the open of the next bar after signal generation
* **Exit**: Reversal of signal, trailing stop loss, or time-based exit

### Implementation Details

*# CONVERTING DATA TO RENKO CHART*

|  |
| --- |
| **def df\_to\_renko(data, n):  data.reset\_index(inplace=True)  data.columns = [i.lower() for i in data.columns]  df = Renko(data)  df.brick\_size = n  renko\_df = df.get\_ohlc\_data()  return renko\_df  # Calculate Supertrend def supertrend(df, period=7, multiplier=3):  atr = df['high'].rolling(period).max() - df['low'].rolling(period).min()    # Calculate Upper and Lower Bands  df['upperband'] = ((df['high'] + df['low']) / 2) + (multiplier \* atr)  df['lowerband'] = ((df['high'] + df['low']) / 2) - (multiplier \* atr)    # Initialize Supertrend  df['supertrend'] = 0  df['direction'] = 1 # 1 for uptrend, -1 for downtrend    # Calculate Supertrend  for i in range(period, len(df)):  if df['close'].iloc[i] > df['upperband'].iloc[i-1]:  df.loc[df.index[i], 'direction'] = 1  elif df['close'].iloc[i] < df['lowerband'].iloc[i-1]:  df.loc[df.index[i], 'direction'] = -1  else:  df.loc[df.index[i], 'direction'] = df['direction'].iloc[i-1]    if df['direction'].iloc[i] == 1:  df.loc[df.index[i], 'supertrend'] = df['lowerband'].iloc[i]  else:  df.loc[df.index[i], 'supertrend'] = df['upperband'].iloc[i]    return df** |

## 5. MATHEMATICAL FOUNDATIONS

### Risk-Reward Calculations

For all strategies, the risk-reward calculations are determined by: - Fixed profit targets - Stop-loss levels - Position sizing adjusted to maintain consistent risk per trade

The general formula used for position sizing is:

**Position Size = (Capital × Risk per Trade) ÷ (Entry Price × Stop-Loss in Points)**

Where: - Capital is the available trading capital - Risk per Trade is typically set at 1-2% of capital - Entry Price is the price at which the trade is executed - Stop-Loss in Points is the distance from entry to stop-loss level

### Slippage Modeling

In back-testing, slippage is modeled as a percentage of the trade price:

**Adjusted Entry Price = Entry Price × (1 + Slippage%)**

For all strategies, a default slippage of 0.01% is used to approximate real-world trading conditions.

### Leverage Considerations

The strategies employ leverage to enhance returns:

**Effective Capital = Initial Capital × Leverage**

For example, with an initial capital of 1,500,000 and 5× leverage, the effective capital becomes 7,500,000, allowing for larger position sizes while maintaining the same percentage risk per trade.

## 6. PERFORMANCE METRICS AND BACKTESTING RESULTS

### Key Performance Indicators

For each strategy, the following metrics are calculated:

1. **Profit and Loss Metrics**:
   * Total Net Profit
   * Profit Factor (Gross Profit ÷ Gross Loss)
   * Average Profit per Trade
   * Maximum Consecutive Winners/Losers
2. **Risk Metrics**:
   * Maximum Drawdown
   * Sharpe Ratio
   * Sortino Ratio
   * Calmar Ratio (Annual Return ÷ Maximum Drawdown)
3. **Statistical Measures**:
   * Win Rate
   * Average Win ÷ Average Loss
   * Standard Deviation of Returns
   * Skewness and Kurtosis of Return Distribution

### Comparative Performance Analysis Strategy-1 (Daily data)

| **Metric** | **Nifty-50** | **Bank-Nifty** |
| --- | --- | --- |
| Total Net Profit | ₹5,866,281.37 | ₹2,646,401.13 |
| Number of Trades | 168 | 170 |
| Trade Frequency  (trades/month) | 2.70 | 2.74 |
| Win Rate | 22.62% | 24.71 |
| CAGR (%) | 512.19% | 351.42% |
| Maximum Drawdown | ₹608,842.98 | ₹238,798.40 |
| Total Drawdown Duration (days) | 140 | 136 |
| Sharpe Ratio | 3.53 | 4.55 |
| Calmar Ratio | 9.64 | 11.08 |

### Strategy-2 (15 Min data)

| **Metric** | **Nifty-50** | **Bank-Nifty** |
| --- | --- | --- |
| Initial Capital | ₹1,000,000 | ₹1,000,000 |
| Effective Capital | ₹5,000,000 | ₹5,000,000 |
| Total Net Profit | ₹9,186,786 | ₹6,351,652 |
| Profit Factor | 1.55 | 1.44 |
| Win Rate | 36.07% | 31.98% |
| Maximum Drawdown | ₹441,363 | ₹750,243 |
| Max Drawdown Duration (days) | 111 | 151 |
| Sharpe Ratio | 2.22 | 1.81 |
| Calmar Ratio | 4.08 | 1.66 |

### Strategy-3 (60 Min data)

| **Metric** | **Nifty-50** | **Bank-Nifty** |
| --- | --- | --- |
| Total Net Profit | ₹11,378,571 | ₹17,533,065 |
| Win Rate | 54.10% | 38.14% |
| Profit Factor | 2.18 | 2.11 |
| Maximum Drawdown | ₹236,281 | ₹319,477 |
| Total Drawdown Duration (days) | 20 | 60 |
| Sharpe Ratio | 4.95 | 3.78 |
| Calmar Ratio | 9.45 | 10.75 |

## 7. RISK MANAGEMENT FRAMEWORK

### Per-Trade Risk Control

Each strategy incorporates specific risk management techniques: - Fixed stop-loss levels (varying by strategy) - Maximum position sizing limited to 5% of total capital - Time-based exits for intraday strategies

### Portfolio-Level Risk Management

At the portfolio level, additional risk controls include: - Maximum open trades limited to 3 per strategy - Correlation analysis to avoid overexposure to similar market conditions - Daily loss limits of 3% of total capital - Maximum drawdown threshold of 15%, triggering strategy re-evaluation

### Volatility Adjustments

Position sizing is dynamically adjusted based on market volatility: - Higher ATR values result in reduced position sizes - Strategic pauses during extreme volatility events - Reduced leverage during high VIX periods

## 8. INSIGHTS GAINED

### What Worked

1. Multi-timeframe approach gave **strong diversification**
2. Renko charts helped **reduce noise** in intraday setups
3. Time-based filters **improved win rates**
4. **Strict risk management** (fixed SL/TP) was effective
5. **Leverage** was used efficiently with **proper position sizing**

### What Didn’t Work

1. Bank Nifty strategies had **higher drawdowns**
2. Intraday setups showed **lower win rates**
3. **Missed trades** in volatile spikes
4. Fixed targets occasionally **limited profit potential**

### Suprises

1. **Daily timeframe** outperformed intraday trades consistently
2. Renko strategy showed **resilience in choppy markets**
3. Time filters had **more impact than expected**
4. Bank Nifty required **frequent parameter tuning**

## 9. CONCLUSION AND RECOMMENDATIONS

The three strategies presented in this report offer a robust approach to algorithmic trading in the Indian equity markets. By combining different timeframes and methodologies, the system provides diversification benefits while maintaining strong overall performance metrics.

### Key Strengths

* Multi-timeframe approach provides trading opportunities in various market conditions
* Strong risk management framework protects capital during adverse market movements
* Comprehensive back-testing demonstrates strategy viability across market cycles

### Recommendations for Deployment

1. Implement strategies sequentially, starting with Strategy 1 (Daily)
2. Allocate capital proportionally based on strategy Sharpe ratios
3. Consider deploying on Nifty 50 initially before expanding to Nifty Bank
4. Maintain strict adherence to risk management protocols
5. Conduct monthly strategy reviews and quarterly parameter optimizations

### Future Enhancements

* Integration of machine learning for pattern recognition
* Development of hybrid strategies combining technical and statistical approaches
* Exploration of multi-asset models incorporating correlations with global markets
* Implementation of advanced execution algorithms to minimize slippage

Thank You