Risk-Return Profiling of Altcoins

Evidence from Vectorized Backtesting

Executive Summary

The analysis evaluates a machine learning-enhanced trading strategy that integrates BB and EMA indicators with a Random Forest classifier to predict future return classes in crypto assets. Using macro recall as the tuning objective, the model demonstrated strong classification performance, especially in identifying high return signals. Coins like XRP and XLM showed the highest predictive alignment, making them prime candidates for further strategic focus. The results suggest that this hybrid approach can support more informed and adaptive decision-making for crypto portfolio management in dynamic markets.

Objective

This analysis aims to enhance cryptocurrency portfolio performance by integrating technical signal based strategies with machine learning classification models, enabling data driven asset allocation and optimized trading decisions across multiple altcoins. To ensure consistency and benchmark alignment, only cryptocurrencies with the highest prices in 2021 were selected. This corresponds with the inception year of the BITW benchmark and institutionally maintains a coherent time frame for backtesting and comparative evaluation (McGee, 2025).

Coin Selection

A selection of the top 10 highest-priced cryptocurrencies as of January 3, 2021, was presented to highlight the valuation of altcoins during a formative stage of the market cycle. Coins such as Bitcoin, Ethereum, and stable tokens like USDT and USDC were intentionally excluded to prevent dominance bias and allow a more balanced representation of alternative assets.

Name	Symbol	Approx. Price (USD)
Bitcoin Cash	BCH	**$343.98**
Bitcoin SV	BSV	**$164.98**
Litecoin	LTC	**$128.19**
Binance Coin	BNB	**$37.38**
Chainlink	LINK	**$11.73**
Polkadot	DOT	**$9.12**
EOS	EOS	**$2.63**

Name	Symbol	Approx. Price (USD)
Cardano	ADA	**$0.18**
XRP	XRP	**$0.23**
Stellar Lumens	XLM	**$0.13**

Strategy Selection

The Bollinger Bands (BB) strategy was chosen for its adaptability to volatility and clearer boundary-based signals in crypto markets, as noted by Otabek and Choi (2024). Unlike RSI and MACD, which often lag or misfire during rapid swings, BB adjusts dynamically to market shifts through its expanding and contracting bands. This responsiveness makes it more reliable for detecting overbought or oversold conditions, especially in volatile altcoins. Compared to moving averages, BB requires less subjective judgment and has demonstrated more consistent performance in both trending and ranging markets.

Parameter Selection

To identify the most effective configurations of the Bollinger Band (BB) strategy for each cryptocurrency, a grid search was conducted across varying parameters, including rolling window size, standard deviation multipliers, and entry signal thresholds. Signals were generated when price levels breached the lower BB band, and weights were dynamically adjusted based on signal strength and threshold filters. Each configuration was backtested and evaluated using four core performance metrics, like compound annual growth rate (CAGR), Sharpe, Sortino ratio, and maximum drawdown. The strategy identifies buying signals when a coin's price drops below a dynamic lower threshold, calculated as a moving average minus a volatility-based band. This approach adapts to market conditions and aims to capture potential rebounds during periods of price dips, adopted from Qureshi, et al. (2025).

<table>
<tr><th>Parameter Range</th><th>Bollinger Band Strategy</th></tr>
<tr><td>

```
window_range = [15, 20, 25, 30]
num_std_range = [1.5, 2.0, 2.5]
threshold_range = [0.005, 0.01, 0.015]
```

</td><td>

```
sma = coin_prices[coin].rolling(window=window).mean()
std = coin_prices[coin].rolling(window=window).std()
lower_band = sma - num_std * std

signal = (coin_prices[coin] < lower_band).astype(float)
```

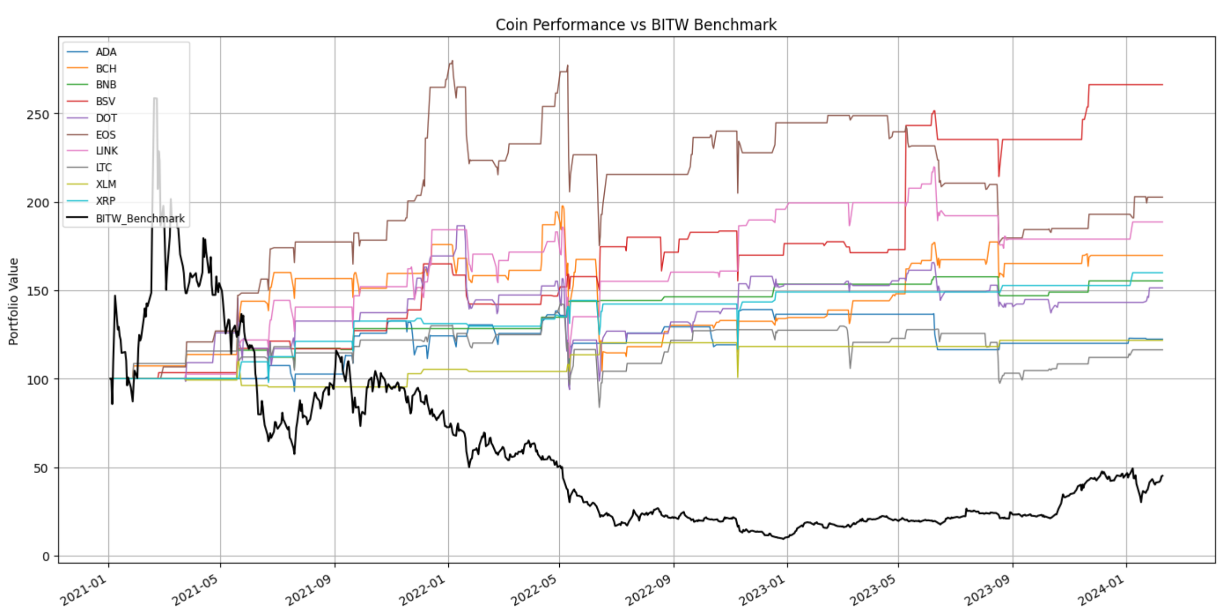
</td></tr>
</table>

The optimal parameter set for each coin was selected by maximizing CAGR, which reflects the strategy's long-term growth potential. As shown below, BSV and XLM achieved the strongest returns with CAGRs of 37% and 34% respectively, supported by high Sharpe and Sortino ratios and relatively moderate drawdowns. In contrast, LTC produced the weakest performance, with a CAGR of 5% and a Sharpe of only 0.26, indicating limited reward relative to risk. This was conducted for the training set from the beginning of 2021 to February 12, 2024, according to the 80 and 20 splits.

Coin	Window	Num_STD	Threshold	CAGR	Sharpe	Sortino	Max Drawdown
ADA	20	1.5	0.010	22.52%	0.63	1.05	-36.72%
BCH	25	1.5	0.010	18.51%	0.51	0.83	-47.24%
BNB	15	2.5	0.005	15.18%	0.86	2.55	-8.64%
BSV	15	2.0	0.005	36.96%	0.85	2.05	-17.75%
DOT	30	1.5	0.005	23.79%	0.58	0.90	-49.65%
EOS	20	1.5	0.005	17.87%	0.50	0.81	-47.17%
LINK	30	1.5	0.015	27.17%	0.65	1.09	-39.83%
LTC	25	1.5	0.005	4.98%	0.26	0.38	-41.03%
XLM	20	2.0	0.005	33.72%	0.97	1.96	-17.10%
XRP	30	2.0	0.010	21.37%	0.65	1.15	-17.98%

Bollinger Bands (BB) Strategy

A. BB Training Set

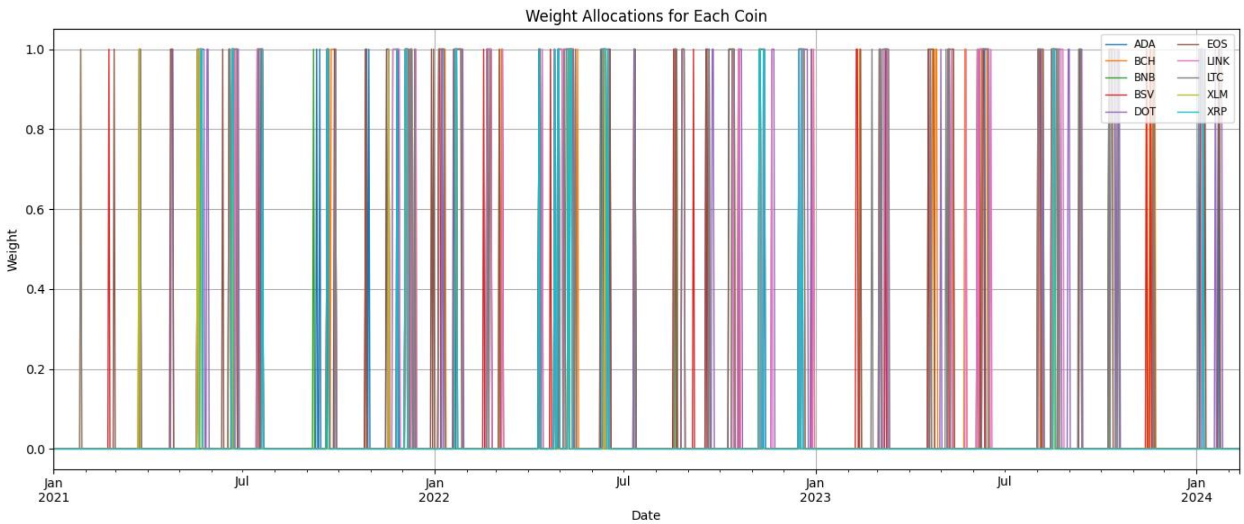


In this phase, optimized BB parameters were applied to each coin and backtested over the training set. Entry signals were generated when prices fell below the adjusted lower band, with dynamic weights assigned and forward-filled. Strategies were rebalanced daily and compared to the BITW benchmark, which followed a monthly equal-weight allocation.

The coins consistently outperformed the benchmark in both return and risk-adjusted terms. While BITW experienced a prolonged decline with a drawdown approaching full capital loss, coins like EOS and BSV achieved the top CAGR above 25%, with Sharpe ratios near or above 1.0, indicating strong performance relative to volatility.

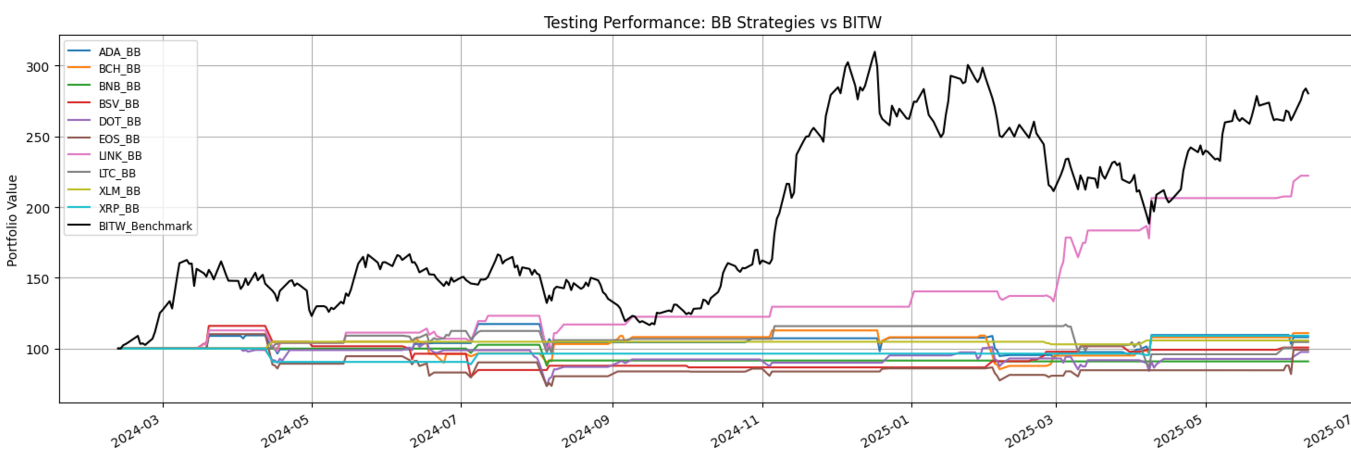
Coin	CAGR (%)	Sharpe	Sortino	Max Drawdown (%)
BSV	37.15	1.08	2.59	15.36
EOS	25.59	0.85	1.24	37.36
LINK	22.71	0.76	1.15	39.83
BCH	18.60	0.66	0.91	47.24
XRP	16.35	0.74	1.22	19.14
BNB	15.25	1.04	3.08	8.64
DOT	14.30	0.54	0.77	49.65
ADA	6.72	0.38	0.60	24.68
XLM	6.54	0.44	0.68	16.33
LTC	5.00	0.32	0.42	41.03
BITW (Benchmark)	−22.65	0.11	0.19	96.38

The weight allocation plot showed that most positions were activated selectively, with full weights applied only during clear signal conditions. This confirmed the strategy's ability to avoid overtrading, allocate capital efficiently, and capture breakout movements while filtering out noise in the crypto market.



B. BB Testing Set

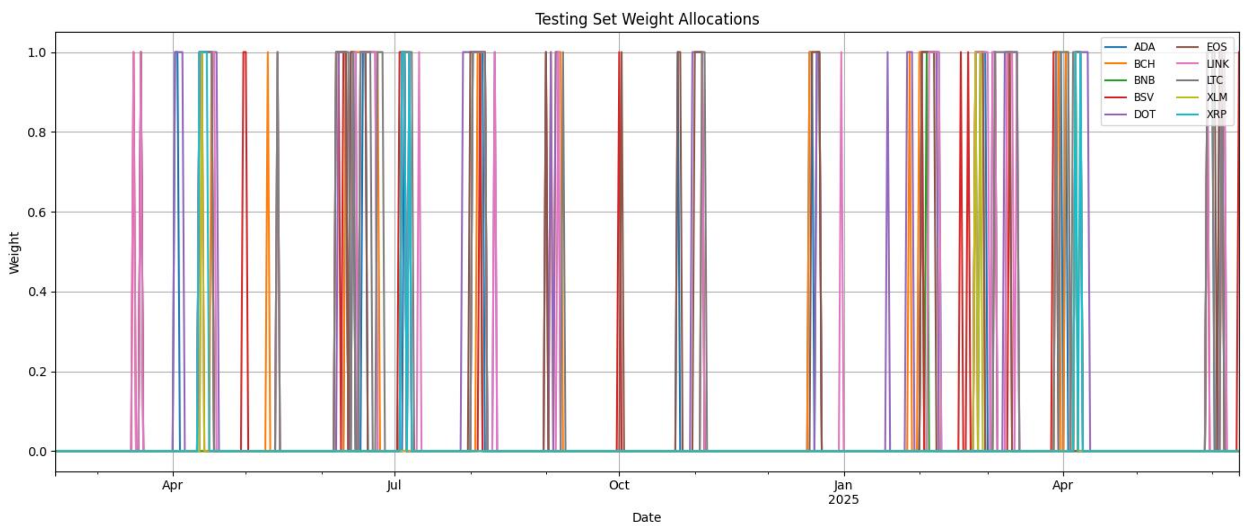
The testing phase was conducted from February 13, 2024 to June 13, 2025, using the BB parameters during training. Each coin was evaluated individually and compared against BITW, a diversified crypto benchmark.



During this period, BITW showed the strongest overall performance, with returns of over 100 percent and risk-adjusted metrics such as Sharpe and Sortino ratios well above 1.5 and 3 respectively. Among the BB strategies, LINK performed notably with returns close to 80 percent and strong risk metrics that aligned closely with the benchmark. XRP and XLM also showed moderate gains with stable downside control.

Coin	CAGR (%)	Sharpe	Sortino	Max Drawdown (%)
BITW (Benchmark)	117.05	1.65	3.17	39.19
LINK	82.22	1.68	3.03	20.41
BCH	8.09	0.42	0.63	24.38
XRP	6.74	0.47	0.96	11.12
ADA	5.99	0.35	0.52	20.21
XLM	4.29	0.89	4.07	1.73
LTC	3.45	0.27	0.34	25.46
BSV	0.55	0.15	0.19	31.14
EOS	−0.65	0.17	0.26	33.33
DOT	−1.82	0.10	0.14	29.85
BNB	−6.89	−0.42	−0.47	14.42

The weight allocation chart indicated that positions were selectively activated only when BB signal conditions were satisfied. Most exposures remained intermittent and concentrated. While assets like BNB**,** DOT**,** and EOS showed little to no gain during this window, the test confirmed that BB strategies, when precisely calibrated, can retain effectiveness in signal filtering and capital management under breakout conditions.



Strategy Adaptation

Further, to strengthen the BB strategy, the Exponential Moving Average was added as a trend confirmation layer within the bt framework. While Bollinger Bands capture volatility breakouts, the EMA aligns signals with momentum and filters out short-term noise. This combination improves entry precision and overall responsiveness.

This strategy blends two technical indicators—Bollinger Bands and EMAs—to create more reliable buy signals. It identifies entry points when a coin's price falls below a volatility-adjusted lower Bollinger Band and is simultaneously confirmed by a bullish EMA crossover. Once both conditions are met, the model assigns weight to the asset and rebalances the portfolio daily to reflect the updated signal.

Combined Strategy

```
sma = prices[coin].rolling(window).mean()
std_dev = prices[coin].rolling(window).std()
lower_band = sma - std * std_dev
ema_fast = prices[coin].ewm(span=ema_short, adjust=False).mean()
ema_slow = prices[coin].ewm(span=ema_long, adjust=False).mean()

bb_signal = (prices[coin] < (lower_band - threshold)).astype(float)
ema_signal = (ema_fast > ema_slow).astype(float)
combined_signal = ((bb_signal + ema_signal) >= 1).astype(float)

weights = combined_signal.ffill().fillna(0)
weights_df = pd.DataFrame(0.0, index=prices.index, columns=[coin])
weights_df.loc[weights.index, coin] = weights.values

strategy = bt.Strategy(f"{coin}_BBEMA",
                       [bt.algos.RunDaily(),
                        bt.algos.SelectThese([coin]),
                        bt.algos.WeighTarget(weights_df),
                        bt.algos.Rebalance()])
backtest = bt.Backtest(strategy, prices)
result = bt.run(backtest)[0]
stats = result.stats
```

Singh, Sharma, and Jain (2025) found that combining moving averages with Bollinger Bands enhances signal quality across different market conditions. Qureshi et al. (2025) further emphasized that well-tuned indicator combinations improve predictive accuracy and strategy robustness in cryptocurrency trading.

Parameter ranges followed standard practices. The BB window was set between 15 and 25, with standard deviation multipliers from 1.5 to 2.5. The EMA used a short span of 10 and longer spans from 30 to 50 to capture trend direction and price momentum.

Parameter Optimization Selection based Training

```
# === Setup ===
coins = {
    'ADA': 'Cardano', 'BCH': 'Bitcoin Cash', 'BNB': 'Binance Coin',
    'BSV': 'Bitcoin SV', 'DOT': 'Polkadot', 'EOS': 'EOS',
    'LINK': 'Chainlink', 'LTC': 'Litecoin', 'XLM': 'Stellar', 'XRP': 'XRP'
}
start_train = '2021-01-01'
end_train = '2024-02-12'

# === Download price data ===
tickers = [f"{coin}-USD" for coin in coins.keys()]
price_data = yf.download(tickers, start=start_train, end=end_train)['Close']
price_data.columns = [col.replace('-USD', '') for col in price_data.columns]
price_data.dropna(axis=1, how='any', inplace=True)

# === Parameter Ranges ===
window_range = [15, 20, 25]
std_range = [1.5, 2.0, 2.5]
threshold_range = [0.005, 0.01, 0.015]
ema_short_range = [10]
ema_long_range = [30, 50]
```

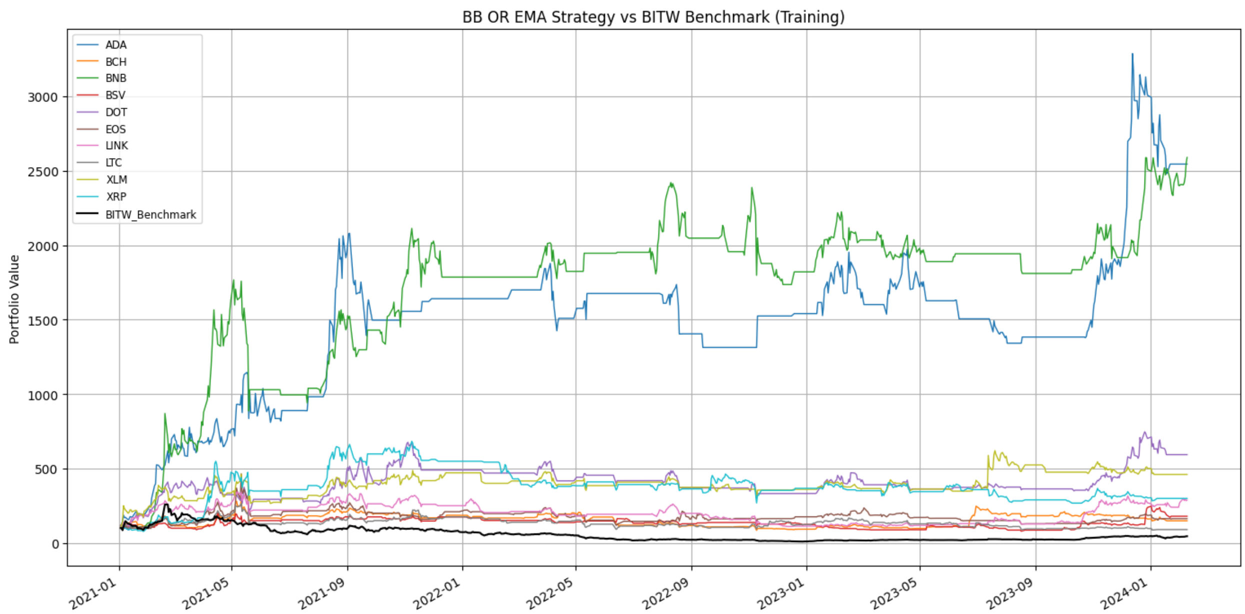
Training BB + EMA

The model was trained using a rule-based strategy that activated trades when either a BB breakout or an EMA crossover condition was met. Parameters were selected from previous optimization results and applied to each coin in the training set. Signals were forward-filled to simulate holding behavior, and capital was fully allocated only when a signal was present.

Combined Strategy Training with Optimized Parameters

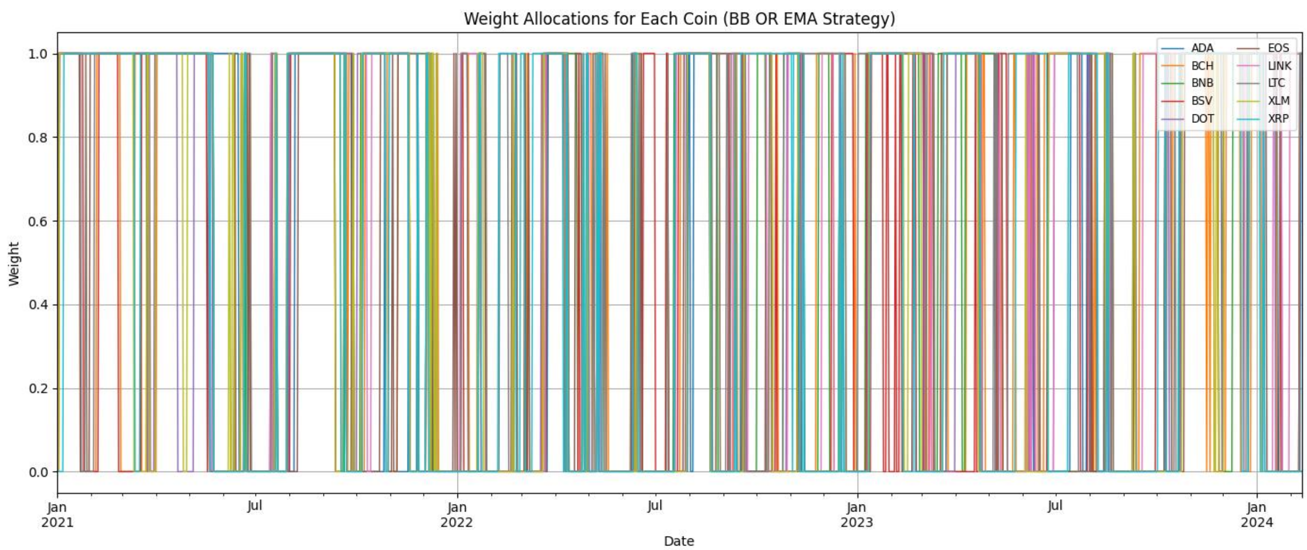
```
# === Optimized Parameters ===
optimized_params_or_strategy = {
    'ADA': (20, 2.0, 0.010, 10, 50),
    'BCH': (25, 1.5, 0.005, 10, 30),
    'BNB': (15, 2.5, 0.015, 10, 30),
    'BSV': (15, 2.0, 0.015, 10, 30),
    'DOT': (25, 2.5, 0.010, 10, 30),
    'EOS': (20, 1.5, 0.010, 10, 50),
    'LINK': (20, 2.0, 0.005, 10, 30),
    'LTC': (25, 1.5, 0.010, 10, 30),
    'XLM': (20, 1.5, 0.005, 10, 30),
    'XRP': (25, 2.0, 0.010, 10, 30)
}

start_train = '2021-01-01'
end_train = '2024-02-12'
tickers = [f"{coin}-USD" for coin in optimized_params_or_strategy]

# === Download Data ===
price_data = yf.download(tickers, start=start_train, end=end_train)['Close']
price_data.columns = [col.replace('-USD', '') for col in price_data.columns]
price_data.dropna(axis=1, inplace=True)
```

The results show that BNB and ADA grew the strongest, with cumulative returns increasing over twentyfold and Sharpe ratios well above one point five, delivering strong performance relative to volatility. DOT, XLM, and XRP also showed consistent returns with Sortino ratios around two or higher, suggesting good downside risk control. By contrast, LTC and BITW, the benchmark, produced flat or negative returns with high drawdowns and low risk-adjusted performance. Weight allocation patterns confirm that exposure was frequent across the period, but remained selective, only activating during qualifying trend or volatility signals. This strategy demonstrated the ability to outperform the benchmark by combining breakout sensitivity with trend confirmation in volatile market conditions.



Coin	CAGR (%)	Sharpe	Sortino	Max Drawdown (%)
BNB	179.04	1.64	3.47	49.82
ADA	171.19	1.68	3.23	36.87
DOT	72.75	1.08	1.91	55.42
XLM	63.63	0.95	1.93	42.71
XRP	42.39	0.81	1.52	60.81
LINK	35.70	0.78	1.28	68.35
BSV	20.73	0.61	1.13	61.37
EOS	17.14	0.61	1.00	74.50
BCH	7.55	0.48	0.80	70.55

Coin	CAGR (%)	Sharpe	Sortino	Max Drawdown (%)
LTC	−8.15	0.26	0.38	67.10
BITW (Benchmark)	−22.65	0.11	0.19	96.38

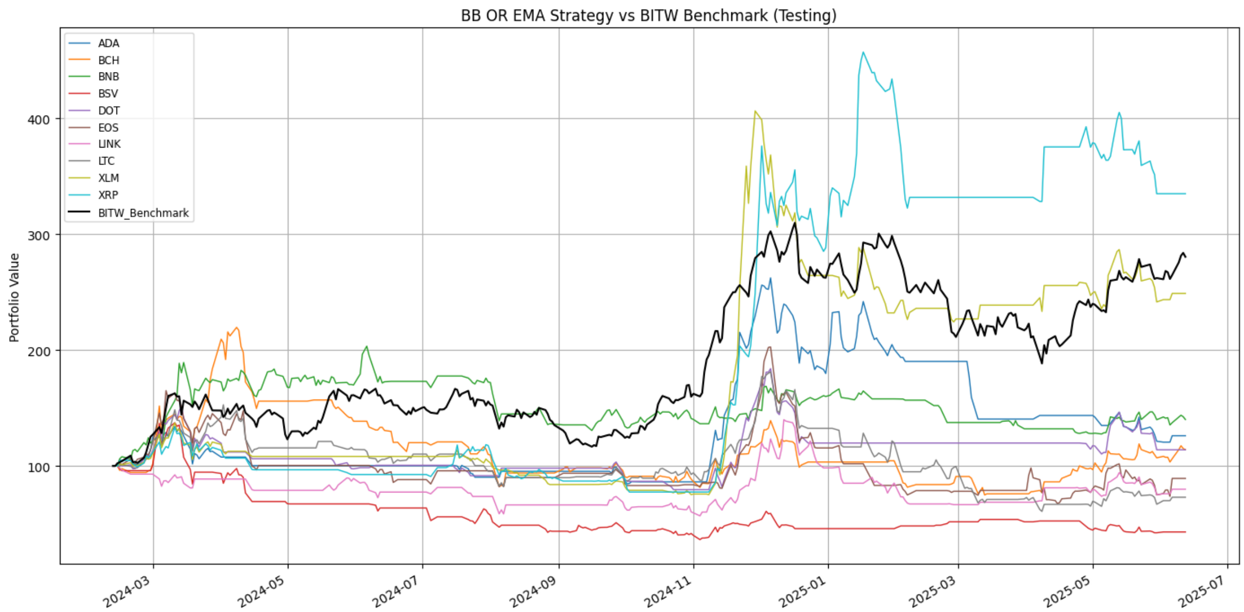


Testing BB + EMA

The model was trained using a rule-based strategy that activated trades when either a Bollinger Band breakout or an Exponential Moving Average crossover condition was met. Parameters were selected from previous optimization results and applied to each coin in the training set. Signals were forward-filled to simulate holding behavior, and

Combined Strategy Testing with Optimized Parameters

```
# === Optimized Parameters (from Training) ===
optimized_params_or_strategy = {
    'ADA': (20, 2.0, 0.010, 10, 50),
    'BCH': (25, 1.5, 0.005, 10, 30),
    'BNB': (15, 2.5, 0.015, 10, 30),
    'BSV': (15, 2.0, 0.015, 10, 30),
    'DOT': (25, 2.5, 0.010, 10, 30),
    'EOS': (20, 1.5, 0.010, 10, 50),
    'LINK': (20, 2.0, 0.005, 10, 30),
    'LTC': (25, 1.5, 0.010, 10, 30),
    'XLM': (20, 1.5, 0.005, 10, 30),
    'XRP': (25, 2.0, 0.010, 10, 30)
}

# === Testing Dates ===
start_test = '2024-02-13'
end_test = '2025-06-13'
tickers = [f"{coin}-USD" for coin in optimized_params_or_strategy]
```



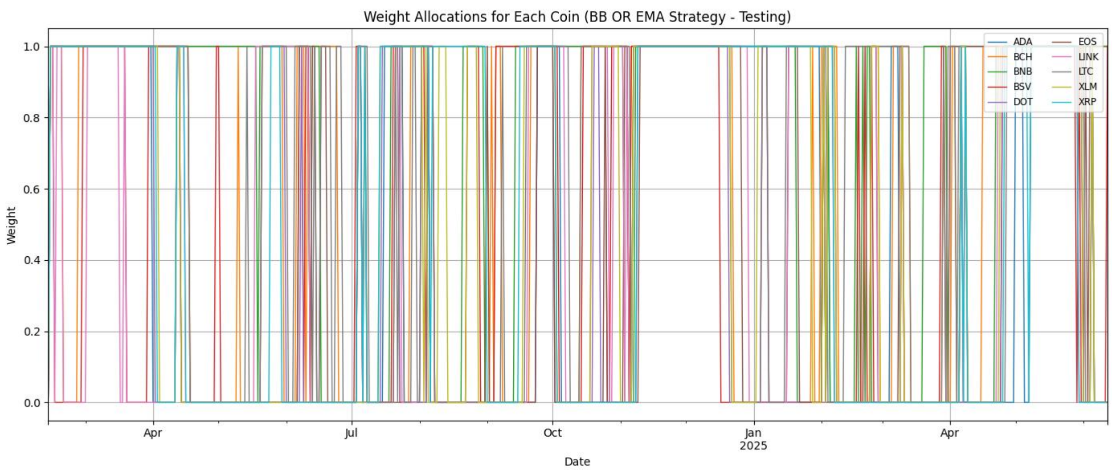
However, the result of the testing phase shows that XRP and XLM outperformed the benchmark, with XRP returning around 148% and XLM close to 98%, both posting high Sharpe and Sortino ratios above one and three respectively. These results suggest stable momentum and strong downside protection. BNB and ADA also delivered moderate returns with reasonable drawdowns and risk-adjusted metrics.

The combo strategy appears to have captured the broader trend price direction compared to a credible source (Trading View), especially during the strong upward movement around late 2024. This indicates that the model was responsive to volatility breakouts and trend confirmations without overexposing during short-term fluctuations, making it suitable for tactical portfolio allocation in volatile environments.

In contrast, BSV, LINK, and LTC performed poorly, with negative returns and weak Sharpe ratios, indicating unstable or inefficient signals during the test period. The benchmark BITW achieved over 117% return, making it difficult for most single-asset strategies to outperform. The weight allocation plot confirms that the strategy remained active throughout the test period but was more selective in signal activation. This suggests that while the combined logic is structurally sound, its effectiveness is more pronounced in certain coins and market conditions.

Coin	CAGR (%)	Sharpe	Sortino	Max Drawdown (%)
BITW (Benchmark)	117.05	1.65	3.17	39.19
XRP	148.03	1.49	3.64	41.86
XLM	98.42	1.16	3.15	45.17
BNB	28.82	0.76	1.31	37.26
ADA	19.04	0.58	1.07	54.04
BCH	10.44	0.49	0.93	65.85
DOT	10.32	0.45	0.80	47.18
EOS	−8.18	0.28	0.44	66.66
LINK	−15.49	0.09	0.16	52.40

Coin	CAGR (%)	Sharpe	Sortino	Max Drawdown (%)
LTC	−21.05	0.02	0.03	66.46
BSV	−46.91	−0.60	−0.94	73.45



Given the consistent outperformance of XRP and XLM, Random Forest provides a strong foundation for further analysis. Its ability to capture non-linear relationships and rank signal importance makes it ideal for refining entry logic on these winning coins. RF can also guide feature selection and inform more targeted strategies within BB and EMA frameworks.

Random Forest (RF)

A. Model Performance

To balance prediction across all return classes, macro recall was used as the tuning metric in Randomized Search CV. The best results were achieved with 100 trees, depth 3, split size 10, leaf size 4, and bootstrap enabled—optimizing recall while controlling overfitting.

RF Training Set with Optimized Parameters

```
# === Train RF Using Best Macro Recall Parameters ===
best_model = RandomForestClassifier(
    n_estimators=100,
    min_samples_split=10,
    min_samples_leaf=4,
    max_depth=3,
    bootstrap=True,
    random_state=42
)
best_model.fit(X_train, y_train)
```

In this method, a RF model was trained using signals derived from BB and EMA. The target variable was the 5-day forward return categorized into three quantile-based classes: low, mid, and high or decline (C0), flat (C1), and rise signals (C2). These labels were stored as Target and used to predict whether the asset would fall into the high-return class. Among the features, the BB signal showed the highest importance, followed by the combined BB or EMA signal and the EMA signal alone.

Target Variable

```
future_ret = price.pct_change(5).shift(-5)
label = pd.qcut(future_ret, q=3, labels=[0, 1, 2])
```

In the model, the data splits to classify future return levels using technical signals from the combined strategy. It is trained on one portion of the dataset and then tested on a separate holdout set, ensuring no data leakage. Signals predicting high returns are used to trigger buy positions, which are evaluated through backtesting for performance insights.

RF Engineering

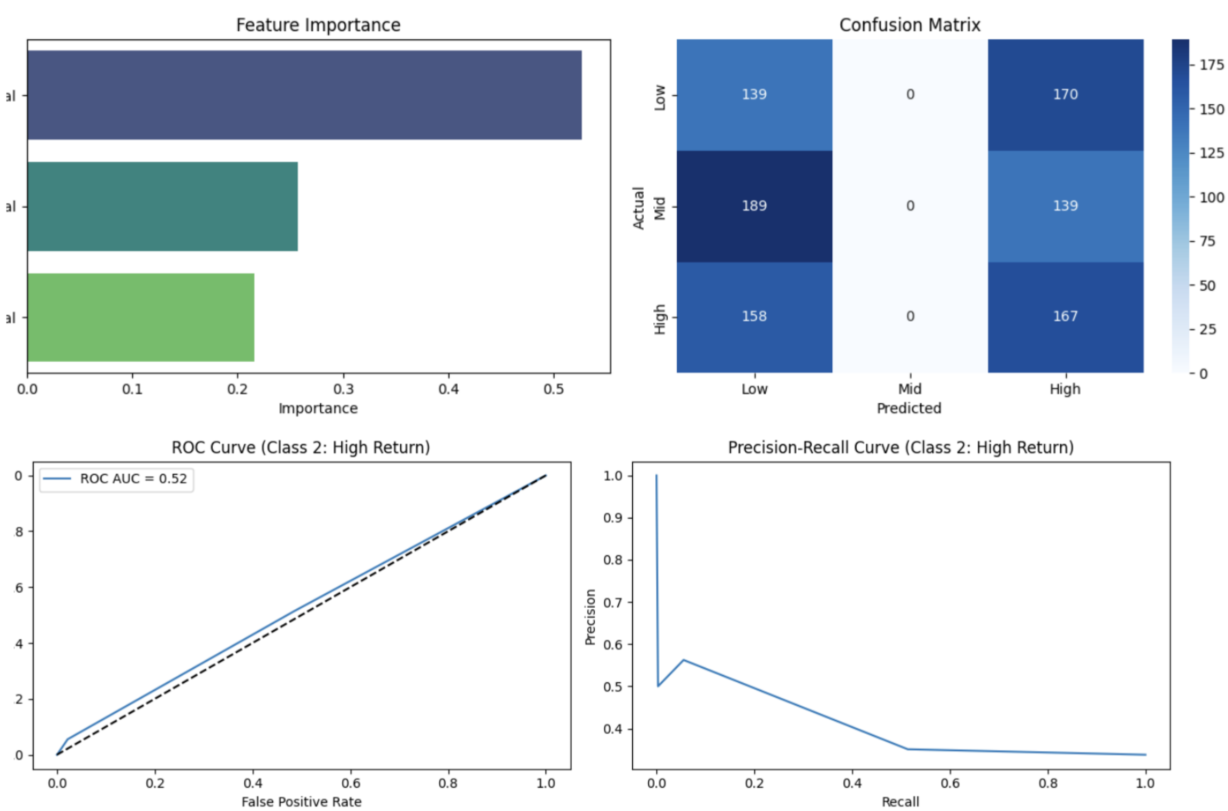
```
# === Date-Based Split ===
train_data = df_all[(df_all.index >= start_train) & (df_all.index <= end_train)]
test_data = df_all[(df_all.index >= start_test) & (df_all.index <= end_test)]

X_train = train_data[['BB_Signal', 'EMA_Signal', 'Combined_Signal']]
y_train = train_data['Target'].astype(int)
X_test = test_data[['BB_Signal', 'EMA_Signal', 'Combined_Signal']]
y_test = test_data['Target'].astype(int)

# === Train RF Using Best Macro Recall Parameters ===
best_model = RandomForestClassifier(
    n_estimators=100,
    min_samples_split=10,
    min_samples_leaf=4,
    max_depth=3,
    bootstrap=True,
    random_state=42
)
best_model.fit(X_train, y_train)

# === Predict on Test Set ===
test_data = test_data.copy()
test_data['Prediction'] = best_model.predict(X_test)
test_data['Signal'] = (test_data['Prediction'] == 2).astype(float)
```

In addition, backtests are constructed using the predicted signals from the model to simulate trading behavior. For each coin, the model's signal is matched with its price data, and a strategy is built where positions are taken only when a high-return class is predicted. This allows the evaluation of how well the model's classification translates into real-world trading performance.

Backtesting on Testing Set

```
# === Backtest Preparation ===
strategies = []
for coin in test_data['Coin'].unique():
    df_coin = test_data[test_data['Coin'] == coin].copy()
    prices = df_coin[['Price']].copy()
    prices.columns = [coin]

    signal = df_coin[['Signal']].copy()
    signal.columns = [coin]
    signal = signal.reindex(prices.index).fillna(0)

    strategy = bt.Strategy(f"RF_{coin}", [
        bt.algos.RunDaily(),
        bt.algos.SelectThese([coin]),
        bt.algos.WeighTarget(signal),
        bt.algos.Rebalance()
    ])
    strategies.append(bt.Backtest(strategy, prices))
```

Despite macro recall optimization, the model's classification performance was weak. The ROC AUC for detecting high returns was around 0.52, and the precision-recall curve reflected poor separability. The confusion matrix showed no predictions for the mid-return class, and overall accuracy remained close to 32%.



However, when the predicted signals were used to trigger trades, the backtest results were much stronger. XRP returned about 142% with a Sharpe ratio of 1.46 and a Sortino ratio over 3.5. XLM followed with around 95% return and a Sharpe ratio above 1.1. Both outperformed the benchmark BITW, which achieved roughly 110%. This highlights that while classification metrics were modest, BB and EMA signal combinations still produced effective trading outcomes.

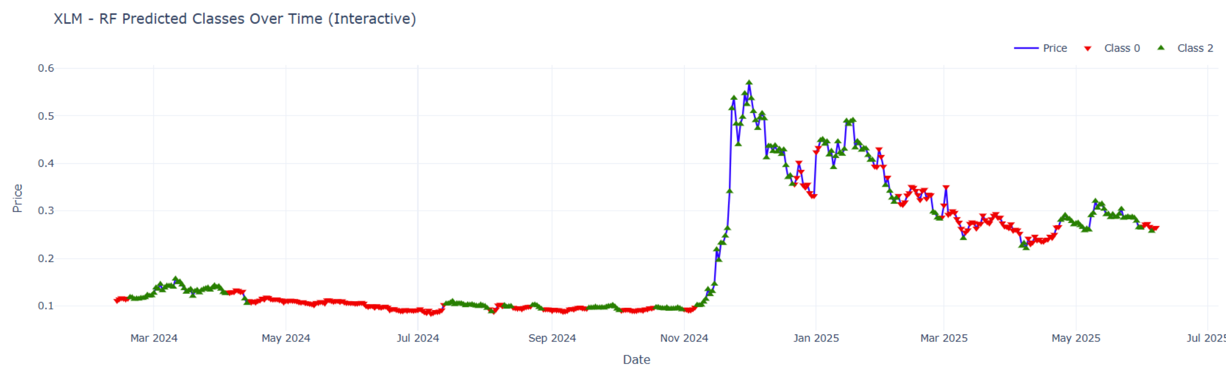
Classification Report (Test Set – 3-Class Return Prediction)

Metric	Low	Mid	High	Accuracy	Macro Avg	Weighted Avg
Precision	*0.29*	*0.00*	*0.35*	*0.32*	*0.21*	*0.21*
Recall	*0.45*	*0.00*	*0.51*	*0.32*	*0.32*	*0.32*
F1-Score	*0.35*	*0.00*	*0.42*	*0.32*	*0.26*	*0.25*
Support	*309*	*328*	*325*	*962*	*962*	*962*

Strategy Performance (Backtest: Feb 13, 2024 – Jun 13, 2025)

Coin	CAGR	Sharpe	Sortino	Max Drawdown
XLM	*94.87%*	*1.14*	*3.09*	*−45.17%*
XRP	*141.84%*	*1.46*	*3.56*	*−41.86%*
BITW (Benchmark)	*109.77%*	*1.58*	*3.04*	*−39.19%*

B. Prediction Results on Test Timeseries



The RF model effectively distinguishes between strong and weak return periods using C2 and C0 predictions. For both **XRP** and **XLM**, C2 signals consistently aligned with upward price movements, triggering ahead of major rallies and indicating strong momentum detection. In contrast, C0 predictions appeared during flat or declining price phases, helping the model avoid poorly timed entries. This selectivity shows that even with moderate classification accuracy, the model captures meaningful directional patterns that are critical for tactical decision-making.

From a business perspective, this dual-signal behavior makes the model highly applicable to momentum-driven crypto strategies and risk-aware allocation systems. C2 signals can guide confident entries, while C0 provides caution zones for position reduction or avoidance. This is especially valuable for trading desks, robo-advisors, and quantitative funds looking to integrate machine learning into their signal stacks. The model's structure also enables interpretability and scalability, offering firms a reliable tool for enhancing both offensive and defensive positioning in volatile crypto markets.

Conclusion

The results demonstrate that combining BB and EMA signals with a Random Forest classifier provides strong predictive power for identifying high return opportunities in crypto assets. With optimized parameters focusing on macro recall, the model effectively captured C2 signals, particularly in XRP and XLM, while maintaining balance across other classes. This strategic approach supports more accurate and timely trade signals, offering practical value for investment firms seeking data driven crypto strategies with improved momentum targeting and downside protection.

Recommendation

1. Prioritize High-Yield Altcoins with Consistent Signal Alignment

The assets XRP and XLM demonstrated superior performance across multiple evaluation metrics, including compound annual growth rate (CAGR exceeding 90%) and Sharpe ratios above 1.1. These results surpassed the benchmark index (BITW), despite moderate classification metrics from the Random Forest model.

- Allocate increased capital weights to XRP and XLM in multi-asset crypto portfolios.
- Utilize Class 2 predictions from the Random Forest classifier as activation triggers in systematic trading algorithms.
- Monitor feature importance over time to mitigate risks of signal degradation and concept drift.

2. Apply Bollinger Band and EMA Convergence as Tactical Entry Filters

The backtesting results confirmed that Bollinger Bands independently identify breakout zones; however, combining BB with EMA significantly enhanced signal precision and reduced drawdowns, particularly during volatile conditions.

- Integrate BB + EMA hybrid signals into real-time trade execution models for assets with erratic price action on coins, including ADA and DOT.
- Implement a volatility-adjusted allocation framework, where exposure scales based on the agreement between BB breakouts and EMA directionality.
- Deploy this configuration specifically in ranging or low-volatility conditions to optimize entry efficiency.

3. Reinforce Machine Learning with Strategy-Driven Feedback Validation

RF classification exhibited limited predictive accuracy in traditional metrics (precision, recall); however, the predicted labels corresponded closely with profitable trading outcomes when applied in backtests. This indicates that classification metrics alone may not fully capture a model's trading utility.

- Evaluate machine learning models using both conventional metrics, such as macro recall, and financial performance indicators, like Sharpe ratio and max drawdown
- Employ rolling retraining with walk-forward validation to ensure models remain calibrated to evolving market conditions.
- Incorporate Class 0 predictions as a risk-off signal to reduce exposure during anticipated downturns.

4. Adopt Dual Benchmarking for Relative Performance Assessment

While BITW was effective for basic benchmarking, the use of a synthetic Crypto20 index provided enhanced comparative analysis, especially for altcoins not covered by major institutional indices.

- Maintain parallel performance tracking against both BITW and the synthetic Crypto20 basket to enable robust peer-relative assessment.
- Construct dynamic benchmarks for volatility-weighted or liquidity-adjusted portfolios for enhanced institutional relevance.
- Integrate benchmark overlays into performance dashboards to facilitate automated asset selection and risk-adjusted decision-making.

5. Extend Backtesting Coverage Across Temporal Regimes and Holding Horizons

The existing strategy was optimized for 5-day forward returns; however, digital assets often transition between directional, choppy, and illiquid states.

- Segment historical data by market regime (bullish, bearish, range-bound) to perform regime-specific stress testing.
- Conduct sensitivity analyses across multiple holding periods, including 1-day, 3-day, or 7-day to evaluate time horizon robustness.
- Simulate execution slippage and latency to quantify deviations in live trading versus theoretical backtest results.

6. Commercialize via Strategic Financial Products and Data Services

The underlying strategy and model architecture support multiple monetization paths across the algorithmic trading, digital advisory, and data services sectors.

Suggested Business Models

Product/Service	Description	Monetization Structure
Signal Subscription Platform	Periodic delivery of altcoin trade recommendations via BB+EMA+RF pipeline	Tiered SaaS subscriptions
Portfolio Enhancement Toolkit	Integration of BB/EMA signals into client trading portfolios	Advisory fees or performance-linked
Crypto Risk Analytics Suite	Real-time monitoring of Sharpe, Sortino, and drawdown metrics	API licensing or enterprise dashboards
Backtest Engine (BaaS)	Client-accessible infrastructure for strategy validation on user inputs	Pay-per-use or platform credits

Reference

McGee, S. (2025, May 15). *Institutional investors juggle bitcoin ETF holdings, US filings show*. Reuters. https://www.reuters.com/business/institutional-investors-juggle-bitcoin-etf-holdings-us-filings-show-2025-05-15

Otabek, S., Choi, J. (2024). From Prediction to Profit: A Comprehensive Review of Cryptocurrency Trading Strategies and Price Forecasting Techniques. IEEE Access 12, 87039–87064.. https://doi.org/10.1109/access.2024.3417449

Qureshi, S. M., Saeed, A., Ahmad, F., Khattak, A. R., Almotiri, S. H., Al Ghamdi, M. A., & Rukh, M. S. (2025). Evaluating machine learning models for predictive accuracy in cryptocurrency price forecasting. *PeerJ Computer Science*, *11*, e2626. https://doi.org/10.7717/peerj-cs.2626

Singh, R. K., Sharma, S., & Jain, M. (2025). Analyzing the effectiveness of moving average and bollinger bands in trading strategies. *International Academic Research Journal of Science and Technology (IARJSET)*, 12(4).