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Hybrid Deep Learning and Statistical Modeling for Multi-Asset Price Prediction

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Abstract - *This technique is a combination of LSTM neural networks and time series analyses of the Prophet in order to predict three commodity markets for the year 2015-2024-the hybrid prediction framework. Risk measures are integrated into the rolling window analyses-VaR, CVaR, and maximum drawdown-which help in calculating volatility and in cross-asset correlation analysis.While the LSTM model captures short-range dynamics in price movements, Prophet identifies long-term trends. The empirical results sufficiently confirm the approach in independently assessing price movements over five years, thus producing findings that would be valuable to market participants. The work presents a novel hybrid model for predicting multiple assets that incorporate consideration of market conditions and granularity of the data used.*

Key words: *commodity markets, price prediction, LSTM, Prophet, hybrid modeling, risk metrics, deep learning, time series analysis*

1.INTRODUCTION

The very nature of financial markets comprises intricate dynamics that are a composite of several diverse macroeconomic, geopolitical, and other market-specific factors.

Financial markets operate in an extremely complex manner. Their price formation is affected by macroeconomic factors, geopolitical events, and market-specific ones. Accurate prediction of price movements is necessary for the management of various portfolios, for risk assessment, and for investment strategies. Traditional financial models, like autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroskedasticity (GARCH), were extensively applied to time series forecasting. However, these methods usually fall short when capturing nonlinear dependencies, long-range memory effects, and regime shifts in market data[1]. Hybrid forecasting mechanisms constructed through statistical time series analysis and neural networks for enhancing forecast accuracy have been drastically improved through the advancement of machine learning and deep learning. RNNs and LSTMs have been useful in capturing sequential dependencies in financial time-series applications [2]. Furthermore, there are slow and steady applications of statistical methods including Prophet, which was originally developed for time-series forecasting with seasonal and trend components, in the steadily FinMarkets[3].

The research study concerned here investigates hybrid forecasting through the LSTM neural network and the Prophet model with the aim of improving price prediction accuracy for different asset classes. These asset classes are Bitcoin, the S&P500 Index, and Gold, which vary in terms of market volatility and behaviors. Our study covers a nine-year period (2015-2024) employing high-frequency trading data to certify themselves against the various market conditions that they experienced.

In addition to enhancing predictive accuracy, this study introduces an improved risk assessment framework using a Value at Risk (VaR) modeling approach.:

- We proposed a hybrid framework for forecasting multi-asset price movements using deep learning (LSTM) and statistical modeling (Prophet).
- To empirically validate our framework, we obtained and tested it using high-frequency trading data over nine years to cover a wide array of market conditions and asset-specific behavior.
- The assessment of model performance considering risk by VaR, CVaR, and drawdown is a measure of the strength of the working model across various market regimes.

Interpretability analysis along with other visualizations is offered by comparing history with forecast price movements and confidence intervals.

2. STATISTICAL AND RISK METRICS ANALYSIS

Accurate financial forecasting requires vast knowledge of market behavior, statistical properties, and risk factors. The present section affirms the dataset analysis, with the study of descriptive statistics, risk assessment metrics, and market regime classification. It provides insights into the nature of Bitcoin, S&P 500, and Gold based on some of the key indicators, namely, mean returns, volatility, skewness, kurtosis, and risk-adjusted performance measures.

2.1. Descriptive Statistics of Returns

One basic step of financial modeling is to study the statistical properties of asset returns. From 2015 to 2024, the average returns, standard deviation, skewness, and kurtosis for Bitcoin, S&P 500, and Gold are listed in Table I.

Mean Return: This indicates the average daily return of the asset during the study period, where Bitcoin has the highest mean return (0.225%) while Gold, the lowest (0.017%).

Standard Deviation: This indicates the measure of volatility, so higher values would mean greater price movements. Bitcoin is most volatile (3.65%) while Gold had least volatility (0.74%).

Skewness: This is concerned with the asymmetry of the return distributions; a negative skew (say-0.58 for S&P 500) indicates a greater probability of extreme negative returns while near-zero skewness for example Gold (0.03) would indicate relatively balanced distribution.

Kurtosis: This refers to how heavy-tailed return distributions really are. Higher kurtosis means greater chances of extreme price movement. The S&P 500 has the highest kurtosis (22.43), with the implication that extreme events occur with higher-than-normal frequency (in a normal distribution, kurtosis equals 3).

Asset	Mean Return	Std. Dev.	Skewness	Kurtosis
Bitcoin	0.00225	0.03652	-0.11150	7.67590
S&P500	0.00031	0.00956	-0.58426	22.43149
Gold	0.00017	0.00739	0.03670	6.26388

Table-1: Descriptive Statistics of Daily Returns

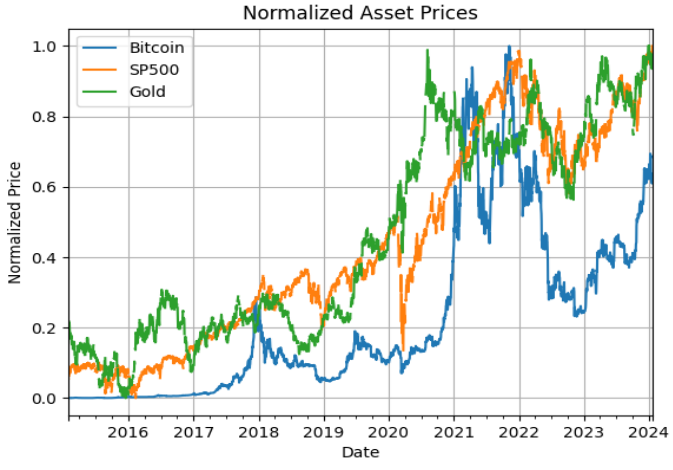

Chart -1: Normalized Asset

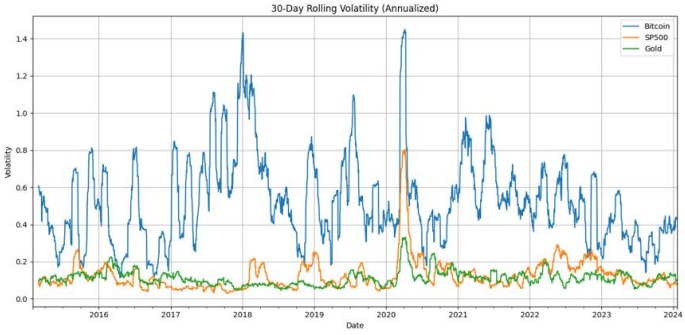

Chart -2: 30 Day Rolling Volatility

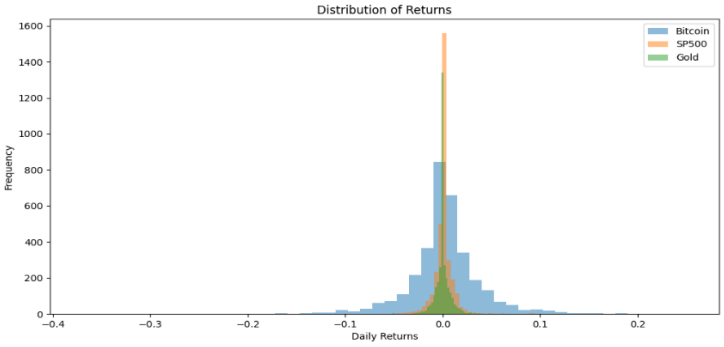

Chart -3: Distribution of Returns

2.2. Risk Metrics and Performance Indicators

The Risk Assessment for each of these assets is studied through Value at Risk (VaR), Conditional Value at Risk (CVaR), Maximum Drawdown (MDD), Sortino Ratio, and Information Ratio. These are the indicators that actually tell in detail about the downside risk of each asset and risk-adjusted performance.

1) Value at Risk (VaR)-

VaR assesses the maximum expected loss (over a given time horizon, i.e., one day in this instance) with 95% confidence. For example, for Bitcoin, -5.73% would imply that there exists a 5% probability that its loss in one day exceeds 5.73% or more. It, therefore, means Bitcoin exhibited maximum downside risk, while Gold showed it the least.

2) Conditional Value at Risk (CVaR)-

CVaR, known among financial analysts as the Expected Shortfall, estimates the average loss once the loss crosses over the absorbent VaR threshold. Since it is extreme losses that define more importance in assessing risk than that which comes from the standard parametric assumption, thus CVaR is more suitable for tail events. The -8.56% for Bitcoin means that when losses are the worst, that is, when losses exceed the loss amount considered in VaR, Bitcoin's average loss would become 8.56%, which

drags the average losses onto a comparatively higher return for S&P 500 and Gold.

3) Maximum Drawdown (MDD)-

MDD describes the greatest observed decline from peak to trough in the value of an asset. Bitcoin registered the highest MDD of (-83.4%), meaning that its price fell by 83.4% from its highest point before recovering. This speaks for Bitcoin's high volatility relative to the S&P 500 (-33.9%) and Gold (-21.2%).

4) Sortino Ratio

The Sortino ratio measures risk-adjusted return, but it considers only one side of volatility, i.e., downside, while the Sharpe ratio takes account of volatility on both sides, i.e., gains and losses. So, a higher Sortino ratio value indicates higher return per unit of downside risk. Thus, Bitcoin, with the highest Sortino ratio, of 1.24, has the highest risk-adjusted return, while gold has the lowest of 0.23. The implication is that Bitcoin, despite its volatility, compensates more for that risk.

5) Information Ratio

The information ratio measures the excess return of an asset over and above that of a benchmark (S&P 500) against the risk of that excess return. In this regard, it is interesting to note that Bitcoin has a positive information ratio of 0.86, which means it has beat the benchmark relative to its tracking error. And gold, on the contrary, has a negative information ratio of -0.19, which shows underperformance.

Table-2: Risk Metrics and Performance Indicators

Metric	Bitcoin	S&P500	Gold
Var (95%)	-0.057251	-0.014159	-0.011629
CVar (95%)	-0.085576	-0.024261	-0.017655
Max Drawdown	-0.833990	-0.339250	-0.212074
Sortino Ratio	1.244850	0.388613	0.236186
Information Ratio	0.859553	NaN	-0.192842

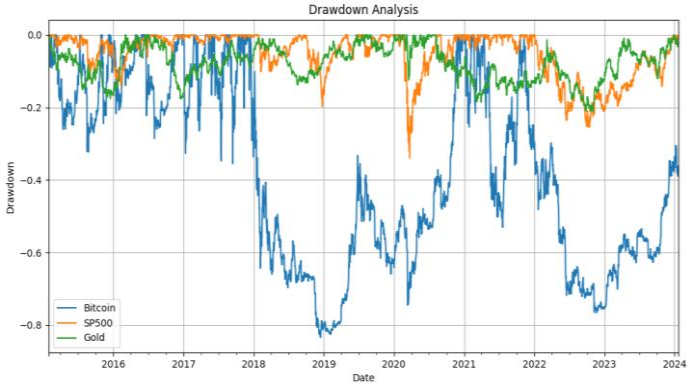

Chart -4: Drawdown Analysis

2.3. Market Regime Classification

In financial markets, volatility regimes used for classification typically fall into the categories of low, medium, and high volatility phases. Analysis of the recent individual market conditions for Bitcoin, S&P500 & Gold has been performed through rolling windows of 21 days by quantile classification.

The classification shows that the S&P500 changed from low-volatility to medium-volatility, while Bitcoin and Gold remained firmly in the medium-volatility classification range. These classifications are essential to bring to light market calm periods versus havoc periods, which help in risk management and forecasting.

Table-3: Market Regime Classification (Last 5 Periods)

Date	Bitcoin	S&P500	Gold
2024-01-17	Medium	Low	Medium
2024-01-18	Medium	Low	Medium
2024-01-19	Medium	Medium	Medium
2024-01-20	Medium	Medium	Medium
2024-01-21	Medium	Medium	Medium

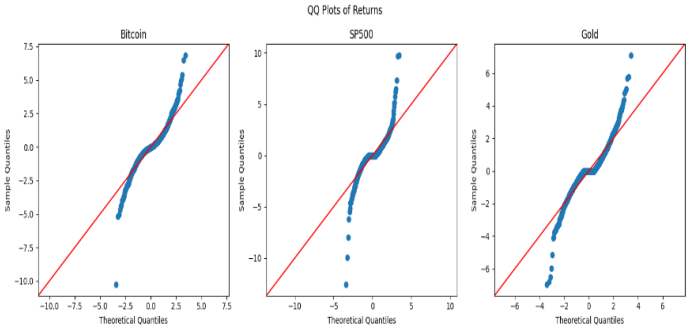

Chart -5: QQ Plots

3. SUMMARY OF FINDINGS

- Bitcoin exhibits the highest volatility and risk, but also the highest risk-adjusted returns.
- The S&P 500, despite lower volatility, experiences significant tail events, as reflected in its high kurtosis.
- Gold is the least volatile asset but provides limited returns compared to Bitcoin and the S&P 500.
- Regime analysis suggests a shift in volatility trends, with the S&P 500 recently moving into a medium volatility state.

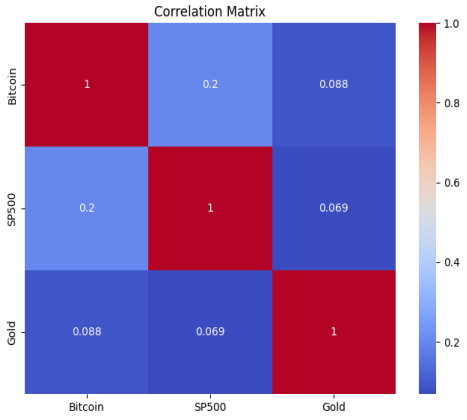

Chart -6: Correlation Matrix

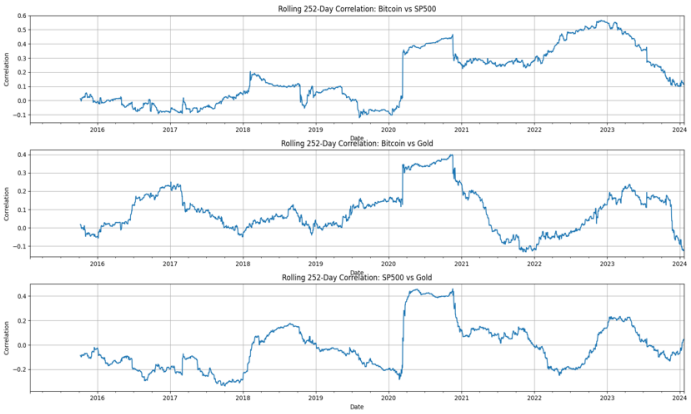

Chart -7: Rolling Correlation

4. CONCLUSIONS

The present work detailed a hybrid forecasting model combining LSTM and Prophet toward the goal of improving multi-asset price predictions. The analysis covers Bitcoin, S&P 500, and Gold over a period of nine years, successfully capturing short-term volatility as well as long-term trends.

Results point to Bitcoin having high volatility and risk-adjusted returns; the S&P 500 marks significant tail risks; and Gold renders stability with lower returns. Risk measures such as VaR and MDD confirmed the same observations. These five-period forecasts still indicate variability, with Bitcoin having the widest confidence intervals.

This study illustrates the viability of hybrid models in forecasting financial markets. Future research will enhance accuracy by introducing macroeconomic variables and state-of-the-art neural network mechanisms to support risk-aware decision-making on the part of the investors.

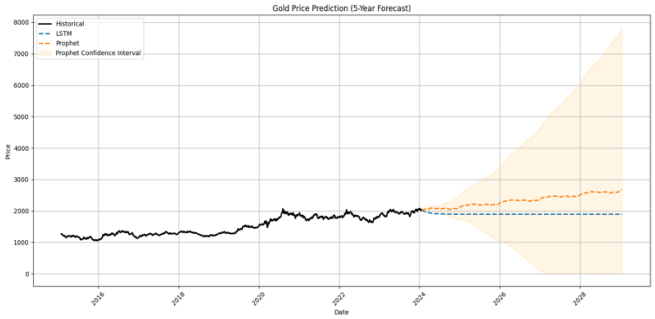

Chart-8: 5 year Forecast for Gold

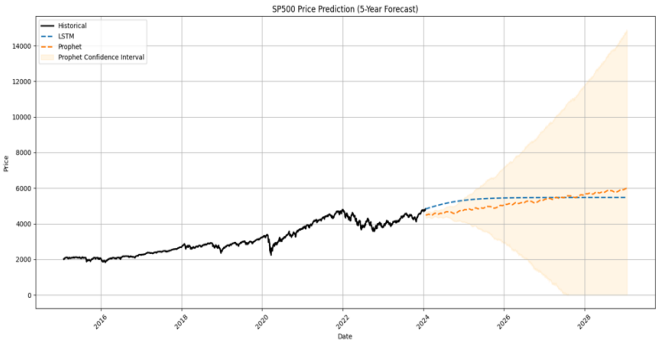

Chart-9: 5 year Forecast for S&P500

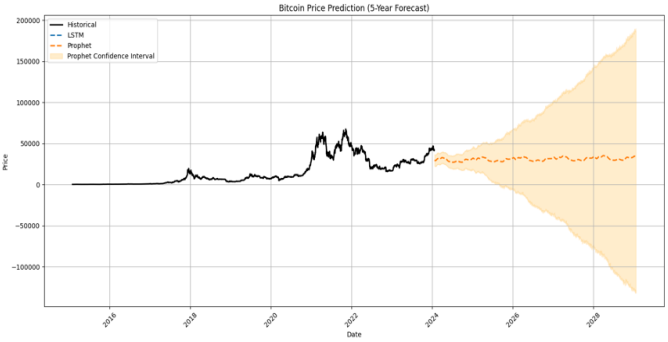

Chart -10: 5 year Forecast for Bitcoin

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